Self-referencing Prioritizes Moral Character on Perceptual Matching

Abstract

Evidence for the prioritization of moral information in cognitive processes is mixed. We examined this question using a series of ten experiments where participants first learned associations between moral characters and geometric shapes and then performed simple speed tasks. In the first five experiments, we tested and validated a robust prioritization of good characters over bad and neutral characters. To pin down the processes that are critical to the prioritization effects, in the second round of five experiments, we tested two opposing hypotheses: the valence hypothesis suggests that a general positivity bias towards all underpins the prioritization effects, while the self-binding account posits that self-referencing, rather than other-referencing is the fundamental driver of the effects. The data support the latter. Together, these results show a robust prioritization effect of good character through self-referencing processes, indicating the innate connection between morality and oneself and how humans use self-reference to explore the world and learn morality.

Keywords: Perceptual matching, self positivity bias, primacy of morality, Bayesian hierarchical models

Word count: X

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Introduction

Morality is central to human life (Haidt & Kesebir, 2010). Thus, gathering information about morality efficiently and accurately is crucial for individuals to navigate the social world (Brambilla, Sacchi, Rusconi, & Goodwin, 2021). The importance of morality naturally leads to the hypothesis that morality-related information is prioritized in information processing, especially when attentional resources are limited. This hypothesis is plausible because a large volume of studies has reported that valuable stimuli are prioritized, e.g., threatening stimuli (e.g., Ohman, Lundqvist, & Esteves, 2001), rewards (B. A. Anderson, Laurent, & Yantis, 2011), or self-related stimuli (Sui & Rotshtein, 2019). Consistent with this hypothesis, a few studies reported a prioritization effect of negative moral information in visual processing: negative moral trait words (Gantman & Van Bavel, 2014; Ybarra, Chan, & Park, 2001; **fiske_1980?**) and faces associated with bad behaviors (E. Anderson, Siegel, Bliss-Moreau, & Barrett, 2011; Eiserbeck & Abdel Rahman, 2020) attracted more attention and were responded faster.

However, evidence for this negative moral bias effect is mixed. First, the opposite effect was also reported. For example, Shore and Heerey (2013) found that faces with positive interaction in a trust game were prioritized in the pre-attentive process. Also, Abele and Bruckmueller found faster responses to moral words were not moderated by valence (Abele & Bruckmüller, 2011). Second, the robustness of the negative moral bias effect is questioned, a direct replication study failed to support the conclusion that faces associated with bad social behaviors dominate visual awareness (eg., Stein, Grubb, Bertrand, Suh, & Verosky, 2017). Third, the prioritization effect of morality might be confounded with other factors, such as the priming effect (Firestone & Scholl, 2015, 2016b; Jussim, Crawford, Anglin, Stevens, & Duarte, 2016) or differences between lexical characteristics [Larsen et al., 2006]. As a result, while the importance of morality is widely recognized and there is initial evidence for a negative moral bias, whether moral information is prioritized in perceptual processing is still an open question.

Here, we conducted a series of well-controlled experiments to examine the prioritization effect of morality and its potential mechanisms. To eliminate the priming effect and other potential confounding factors, we employed a task where participants first acquired moral meanings of geometric shapes during the instruction phase and then performed a simple perceptual matching task. The instruction-based associative learning task is based on the fact that humans can rapidly learn based on verbal instructions (e.g., Cole, Braver, & Meiran, 2017). This instruction-based associative learning task is widely used in aversive learning, value-based learning, and other tasks [Atlas (2023); Deltomme, Mertens, Tibboel, and Braem (2018); cole_nbr_2017]. Unlike previous studies relies on faces or words, stimuli in the current study are geometric shapes, whose moral meanings were acquired right before the perceptual matching task. By counter-balancing associations between shapes and valence of moral characters across different participants, we controlled the effect of these shapes on the matching task. Also, in the matching task, we repeatedly present a few pairs of shapes and labels to participants, the results can not be explained by semantic priming (Unkelbach, Alves, & Koch, 2020), which is the center of the debate on previous results (Firestone & Scholl, 2015, 2016a; Gantman & Bavel, 2015, 2016; Jussim et al., 2016). Finally, we conducted a series of control experiments and established that moral content, rather than other factors such as familiarity of stimuli, drove the prioritization effects.

To pin down the factors that are central to the prioritization effects, two competing hypotheses were examined. One is the valence-based account, suggesting that a general positivity bias towards all underpins the prioritization effects. In fact, the account has been applied to explain not only positivity biases but also negativity biases. For example, the negative bias toward moral information was explained by a threat detection mechanism which might be general for all negative information (B. A. Anderson et al., 2011). The positive bias toward moral information, on the other hand, was explained by the positive valence of the stimuli because the stimuli imply potential benefits (Shore & Heerey, 2013). However, these explanations often ignore the fact that valence is subjective *per se* (Juechems & Summerfield, 2019). That is, being related to a person is the premise of a stimulus or outcome being of value to the person. The subjective value is "a broader concept that refers to the personal significance or importance that a person assigns to a particular stimulus or outcome" and when the outcome is affective or emotional, researchers refer to it as "valence", i.e., positive or negative (Carruthers, 2021). The subjectivity of valence leads to an alternative explanation: self-binding account (Sui & Humphreys, 2015). The self-binding account suggests that merely associating with the self can prioritize stimuli in perception, attention, working memory, and long-term memory (Sui & Humphreys, 2015; Sui & Rotshtein, 2019), especially for positive information (**Hu_2020_goodme?**). According to the self-binding account, the prioritization of good character is a result of spontaneous self-referencing.

To test the valence account and self-binding account in the prioritization effect of good character, we manipulated self-relevance and instructed participants on which moral character is self-referencing and which is not. We then tested whether the prioritization of moral character is by valence or by the associations between self-relevance and moral valence. The results revealed that the prioritization effect only occurred when shapes of good characters referred to the self of participants. We confirmed these results in the subsequent experiments, where shapes of good characters did not explicitly refer to the self or others but were merely presented with labels of the self or others. Together, these data revealed a mutual facilitation effect of good character and the self, suggesting a spontaneous self-referential process as a novel mechanism underlying the prioritization of good character in perceptual matching.

Disclosures

We reported all the measurements, analyses, and results in all the experiments in the current study. Participants whose overall accuracy was lower than 60% were excluded from analyses. Also, accurate responses with less than 200ms reaction times were excluded from the analysis. These excluded data can be found in the shared raw data files (see https://doi.org/10.5281/zenodo.8031086).

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 at Tsinghua University, Beijing, China. Participants in these experiments were recruited from the local community. To increase the sample size of experiments to 50 or more (Simmons, Nelson, & Simonsohn, 2013), we recruited additional participants from Wenzhou University, Wenzhou, China, in 2017 for experiments 1a, 1b, 4a, and 4b. Experiment 3b was finished at Wenzhou University in 2017 (See Table 1 for an overview of these experiments).

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

General methods

Design and Procedure

This series of experiments used the perceptual matching paradigm (or self-tagging paradigm, see Sui, He, and Humphreys (2012)), in which participants first learned the associations between geometric shapes and labels of different moral characters (e.g., in the first three studies, the triangle, square, and circle for shapes and Chinese words for “good person”, “neutral person”, and “bad person”, respectively). The associations of shapes and labels were counterbalanced across participants. The paradigm consists of a brief learning stage and a test stage. During the learning stage, participants were instructed about the association between shapes and labels. Participants started the test stage with a practice phase to familiarize themselves with the task, in which they viewed one of the shapes above the fixation while one of the labels below the fixation and judged whether the shape and the label matched the association they learned. If the overall accuracy reached 60% or higher at the end of the practicing session, participants proceeded to the experimental task of the test stage. Otherwise, they finished another practices sessions until the overall accuracy was equal to or greater than 60%. The experimental task shared the same trial structure as in the practice.

Experiments 1a, 1b, 1c, 2, 5, and 6a were designed to explore and confirm the effect of moral character on perceptual matching. All these experiments 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 of studies, which aimed to examine the prioritization of moral character and found that shapes associated with good character were prioritized. Experiments 1b, 1c, and 2 were to confirm that it is the moral character that caused the effect. More specifically, experiment 1b used different Chinese words as labels to test whether the effect was contaminated by familiarity. Experiment 1c manipulated the moral character indirectly: participants first learned to associate different moral behaviors with different Chinese names, after remembering the association, they then associated the names with different shapes and finished the perceptual matching task. Experiment 2 further tested whether the way we presented the stimuli influenced the prioritization of moral character, by sequentially presenting labels and shapes instead of simultaneous presentation. Note that a few participants in Experiment 2 also participated in Experiment 1a because we originally planned a cross-task comparison. Experiment 5 was designed to compare the prioritization of good character with other important social values (aesthetics and emotion). All social values had three levels, positive, neutral, and negative, and were associated with different shapes. Participants finished the associative learning task for different social values in different blocks, and the order of the social values was counterbalanced. Only the data from moral character blocks, which shared the design of experiment 1a, were reported here. Experiment 6a, which shared the same design as Experiment 2, was an EEG experiment aimed at exploring the neural mechanism of the prioritization of good character. Only behavioral results of Experiment 6a were reported here.

Experiments 3a, 3b, and 6b were designed to test whether the prioritization of good character can be explained by the valence account or by the self-binding account. For this purpose, we included self-reference as another within-subject variable. For example, Experiment 3a extended 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). 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), participants finished Experiment 6b in two days. On the first day, participants completed the perceptual matching task as a practice, and on 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 test whether the effect found in Experiments 3a and 6b is robust if we separately present the self-referencing trials and other-referential trials. That is, participants finished two types of blocks: in the self-referencing blocks, they only made matching judgments to shape-label pairs that related to the self (i.e., shapes and labels of good-self, neutral-self, and bad-self), in the other-referential blocks, they only responded to shape-label pairs that related to the other (i.e., shapes and labels of good-other, neutral-other, and bad-other).

Experiments 4a and 4b were designed to test whether the self and the good character bind spontaneously. In Experiment 4a, participants were instructed to learn the association between two shapes (circle and square) with two labels (self vs. other) in the learning stage. In the test stage, they were instructed only respond to the shape and label during the test stage. However, we presented the labels of different moral characters in the shapes and instructed participants to ignore these labels when making matching judgments. If the self and good character bind together spontaneously, then the mere presence of good character will facilitate the response to shapes associated with the self. In the Experiment 4b, we reversed the role of self and moral character in the task: Participants learned associations between three moral labels (good-person, neutral-person, and bad-person) and three shapes (circle, square, and triangle) and made matching judgments about the shape and label of moral character, while words related to identity, "self" or "other", were presented within the shapes. As in Experiment 4a, participants were told to ignore the words inside the shape during the perceptual matching task. In the same vein, if the self and good character bind together spontaneously, then the mere presence of the self will facilitate the response to shapes associated with good character.

Stimuli and Materials

We used E-prime 2.0 for presenting stimuli and collecting behavioral responses. Data were collected from two universities located in two different cities in China. Participants recruited from Tsinghua University, Beijing, finished the experiment individually in a dim-lighted chamber. Stimuli were presented on 22-inch CRT monitors and participants rested their chins on a brace to fix the distance between their eyes and the screen around 60 cm. The visual angle of geometric shapes was about $3.7° \times 3.7°$, the fixation cross is of $0.8° \times 0.8°$ visual angle at the center of the screen. The words were of $3.6° \times 1.6°$ visual angle. The distance between the center of shapes or images of labels and the fixation cross was of $3.5°$ visual angle. Participants from Wenzhou University, Wenzhou, finished the experiment in a group consisting of $3 \sim 12$ participants in a dim-lighted testing room. They were instructed to complete the whole experiment independently. Also, they were told to start the experiment at the same time so that the distraction between participants was minimized. The stimuli were presented on 19-inch CRT monitors with the same set of parameters in E-prime 2.0 as in Tsinghua University, however, the visual angles could not be controlled because participants' chins were not fixed.

In most of these experiments, participants were also asked to fill out questionnaires after finishing the behavioral tasks. All the questionnaire data were open (see, dataset 4 in Liu et al., 2020). See Table 1 for a summary of information about all the experiments.

Data analysis

We used the `tidyverse` of r (see script `Load_save_data.r`) to preprocess the data. The data from all experiments 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 estimates the posterior distributions of parameters for statistical inference, therefore providing uncertainty in estimation (Rouder & Lu, 2005). Second, BHM, where generalized linear mixed models could be easily implemented, can use distributions that fit the data, instead of using the normal distribution for all data. Using appropriate distributions for the data will avoid misleading results and provide a better fitting of the data. For example, Reaction times are not normally distributed but are often right skewed, and the linear assumption in ANOVAs is not satisfied (Rousselet & Wilcox, 2020). Third, BHM provides a unified framework to analyze data from different levels and different sources, avoiding information loss when we need to combine data from different experiments.

We used the `r` package `BRMs` (Bürkner, 2017), which used Stan (Carpenter et al.,

Table 1

Information about all experiments.

ExpID	Time	Location	N	n.of.trials	Self.ref	Stim.for.Morality	Presenting.order
Exp_1a_1	2014-04	Beijing	38 (35)	60	NA	words	Simultaneously
Exp_1a_2	2017-04	Wenzhou	18 (16)	120	NA	words	Simultaneously
Exp_1b_1	2014-10	Beijing	39 (27)	60	NA	words	Simultaneously
Exp_1b_2	2017-04	Wenzhou	33 (25)	120	NA	words	Simultaneously
Exp_1c	2014-10	Beijing	23 (23)	60	NA	descriptions	Simultaneously
Exp_2	2014-05	Beijing	35 (34)	60	NA	words	Sequentially
Exp_3a	2014-11	Beijing	38 (35)	60	explicit	words	Simultaneously
Exp_3b	2017-04	Wenzhou	61 (56)	60	explicit	words	Simultaneously
Exp_4a_1	2015-06	Beijing	32 (29)	30	implicit	words	Simultaneously
Exp_4a_2	2017-04	Wenzhou	32 (30)	60	implicit	words	Simultaneously
Exp_4b_1	2015-10	Beijing	34 (32)	60	implicit	words	Simultaneously
Exp_4b_2	2017-04	Wenzhou	19 (13)	60	implicit	words	Simultaneously
Exp_5	2016-01	Beijing	43 (38)	60	NA	words	Simultaneously
Exp_6a	2014-12	Beijing	24 (24)	180	NA	words	Sequentially
Exp_6b	2016-01	Beijing	23 (22)	90	explicit	words	Sequentially

Note. Stim.for.Morality = How moral character was manipulated; Presenting.order = How shapes & labels were presented. Number in () for N is number of participants are included in the analysis. In the current analysis, we only remain participants' data when they participate the experiment for the first time.

2017) as the back-end, for the BHM analyses. We estimated the overall effect across experiments that shared the same experimental design using one model, instead of a two-step approach that was adopted in mini-meta-analysis (e.g., Goh, Hall, & Rosenthal, 2016). More specifically, a three-level model was used to estimate the overall effect of prioritization of good character, which included data from five experiments: 1a, 1b, 1c, 2, 5, and 6a. Similarly, a three-level HBM model is used for experiments 3a, 3b, and 6b. Results of individual experiments can be found in the supplementary results. For experiments 4a and 4b, which tested the implicit interaction between the self and good character, we used HBM for each experiment separately.

For questionnaire data, we only reported the subjective distance between different persons or moral characters in the supplementary results and did not analyze other questionnaire data in the present study, which were described in (Liu et al., 2020).

Response data. We followed previous studies (Hu, Lan, Macrae, & Sui, 2020; Sui et al., 2012) and used the signal detection theory approach to analyze the response accuracy. More specifically, the match trials are treated as signals and non-match trials are noise. The sensitivity and criterion of signal detection theory are modeled through BHM (Rouder & Lu, 2005).

We used the Bernoulli distribution for the signal detection theory. The probability that the jth subject responded "match" ($y_{ij} = 1$) at the ith trial p_{ij} is distributed as a Bernoulli distribution with parameter p_{ij}:

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

The reparameterized value of p_{ij} is a linear regression of the independent variables:

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

where the probits (z-scores; Φ, "Phi") of ps is used for the regression.

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

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

We used the following formula for Experiments 1a, 1b, 1c, 2, 5, and 6a, which have a 2 (matching: match vs. mismatch) by 3 (moral character: good vs. neutral vs. bad) within-subject design:

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

in which the `saymatch` is the response data whether participants pressed the key corresponding to "match", `mismatch` is the independent variable of matching, `Valence` is the independent variable of moral character, `Subject` is the index of participants, and `Exp_ID_new` is the index of different experiments. Not that we distinguished data collected from two universities.

For experiments 3a, 3b, and 6b, an additional variable, i.e., reference (self vs. other), was included in the formula:

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

in which the `ID` is the independent variable "reference", which means whether the stimulus was self-referencing or other-referential.

Reaction times. We used log-normal distribution (https://lindeloev.github.io/shiny-rt/#34_(shifted)_log-normal) to model the RT data. This means we need to estimate the posterior of two parameters: μ, and σ. μ is the mean of the `logNormal` distribution, and σ is the disperse of the distribution.

The reaction time of the jth subject on ith trial, y_{ij}, is log-normal distributed:

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

The parameter μ_j is a linear regression of the independent variables:

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

and the parameter σ_j does not vary with independent variables:

$$\sigma_j \sim HalfNormal()$$

The subjective-specific intercepts (β_{0j}) and slopes (β_{1j}) are described by multivariate normal with means and a covariance matrix for the parameters.

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

The formula used for experiments 1a, 1b, 1c, 2, 5, and 6a, which have a 2 (matching: match vs. non-match) by 3 (moral character: good vs. neutral vs. bad) within-subject design, is as follows:

`RT_sec ~ 1 + Valence*ismatch + (Valence*ismatch | Subject) + (Valence*ismatch | ExpID_new:Subject), family = lognormal()` in which `RT_sec` is the reaction times data with the second as a unit. The other variables in this formula have the same meaning as the response data.

For experiments 3a, 3b, and 6b, which have a 2 by 2 by 3 within-subject design, the formula is as follows: `RT_sec ~ 1 + ID*Valence + (ID*Valence | Subject) + (ID*Valence | ExpID_new:Subject), family = lognormal()`

Note that for experiments 3a, 3b, and 6b, the three-level model for reaction times only included the matched trials to avoid divergence when estimating the posterior of the parameters.

Testing hypotheses. To test hypotheses, we used the Sequential Effect eXistence and sIgnificance Testing (SEXIT) framework suggested by Makowski, Ben-Shachar, Chen, and Lüdecke (2019). In this approach, we used the posterior distributions of model parameters or other effects that can be derived from posterior distributions. The SEXIT approach reports centrality, uncertainty, existence, significance, and size of the input posterior, which is intuitive for making statistical inferences. We used `bayestestR` for implementing this approach (Makowski, Ben-Shachar, & Lüdecke, 2019).

Prioritization of moral character. We tested whether moral characters are prioritized by examining the population-level effects (also called fixed effect) of the three-level Bayesian hierarchical model of Experiments 1a, 1b, 1c, 2, 5, and 6a. More specifically, we calculated the differences between the posterior distributions of the good/bad character and the neutral character and then tested these posterior distributions with the SEXIT approach.

Modulation of self-relevance. We tested the modulation effect of the self-referencing process by examining the interaction between moral character and the self-referencing process for the three-level Bayesian hierarchical model of Experiments 3a, 3b, and 6b. More specifically, we tested two possible explanations for the prioritization of good character: the valence effect alone or an interaction between the valence effect and self-relevance. If the former is correct, then there will be no interaction between moral character and self-relevance, i.e., the prioritization effect exhibits a similar pattern for both self- and other-referential conditions. Otherwise, there will be an interaction between the two factors, i.e., the prioritization effect exhibits different patterns for self- and other-referencing conditions. To test the interaction, we calculated the posterior distribution of the difference of difference: $(good - neutral)_{self}$ vs. $(good - neutral)_{other}$. We then tested the difference of difference with SEXIT approach.

Spontaneous binding between the self and good character. For data from Experiments 4a and 4b, we further examined whether the self-referencing process is spontaneous (i.e., whether the good character is spontaneously bound with the self). For Experiment 4a, if there exists a spontaneous binding between self and good character, there should be an interaction between moral character and self-relevance. More specifically, we tested the posterior distributions of $good_{self} - neutral_{self}$ and $good_{other} - neutral_{other}$, as well as the difference between these differences with the SEXIT framework. For Experiment 4b, if there exists a spontaneous binding between self-relevance and good character, then, there will be a self-other difference for some moral character conditions but not for other moral character conditions. More specifically, we tested the posteriors of $good_{self} - good_{other}$, $neutral_{self} - neutral_{other}$, and $bad_{self} - bad_{other}$ as well as the difference between them with SEXIT framework.

Results

Prioritization of good character

To test whether moral characters are prioritized, we modeled data from Experiments 1a, 1b, 1c, 2, 5, and 6a with three-level Bayesian hierarchical models. All these experiments shared similar designs, with a total sample size of 192. Note that for both experiments 1a and 1b, two datasets were collected at different time points and locations, thus we treated them as independent samples. Here we only reported the population-level results of three-level Bayesian models, the results of each experiment can be found in supplementary materials.

For the d prime, results from the Bayesian model revealed a robust effect of moral character. Shapes associated with good characters ("good person", "kind person" or a name associated with good behaviors) have higher sensitivity (median = 2.45, 95% HDI = [2.24 2.72]) than shapes associated with neutral characters (median = 2.15, 95% HDI = [1.92 2.45]), the difference ($median_{diff}$ = 0.31, 95% HDI [0, 0.62]) has a 97.31% probability of being positive (> 0), 94.91% of being significant (> 0.05). But we did not find a difference between shapes associated with bad characters (median = 2.21, 95% HDI = [2.00 2.48]) and neutral character, the difference ($median_{diff}$ = 0.05, 95% HDI [-0.27, 0.38]) only has a 60.56% probability of being positive (> 0), 49.34% of being significant (> 0.05).

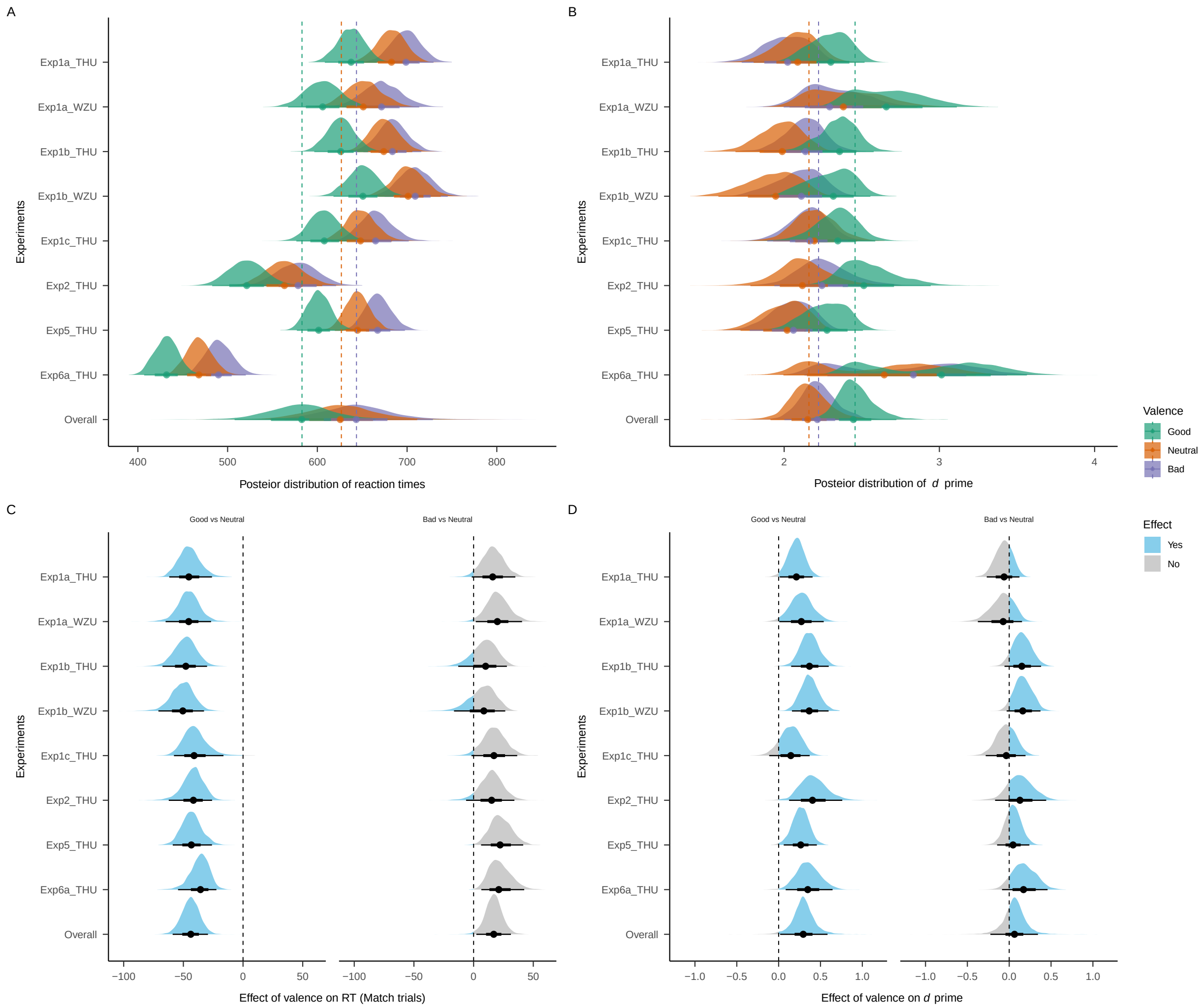

Figure 1. Effect of moral character on perceptual matching. (A) Experimental level (five experiments, with eight independent samples) and population level posterior distributions of RT under different conditions; (B) Experimental level and population level posterior distributions of *d*-prime under different conditions; (C) Experimental level and population level posterior distributions of the RT differences between conditions (left, Good vs. Neutral; right, Bad vs. Neutral); (D) Experimental level and population level posterior distributions of the *d*-prime differences between conditions (left, Good vs. Neutral; right, Bad vs. Neutral).

The results from reaction times also found a robust effect of moral character for both match trials (see figure 1 C) and mismatch trials (**see supplementary materials**). For match trials, shapes associated with good characters were faster (median = 583 ms, 95% HDI = [506 663]) than shapes associated with neutral characters (median = 626 ms, 95% HDI = [547 710]), the effect ($median_{diff}$ = -44, 95% HDI [-67, -24]) has a 99.94% probability of being negative (< 0), 99.94% of being significant (< -0.05). We also found that RTs to shapes associated with bad characters (median = 643 ms, 95% HDI = [564 729]) were slower as compared to the neutral character, the effect ($median_{diff}$ = 17, 95% HDI [-6, 36]) has a 93.58% probability of being positive (> 0), 93.55% of being significant (> 0.05).

For the mismatch trials, we found a similar pattern but a much smaller effect size. Shapes associated with good characters (median = 657 ms, 95% HDI = [571 739]) were faster than shapes associated with neutral characters (median = 673 ms, 95% HDI = [589 761]), the difference ($median_{diff}$ = -18, 95% HDI [-27, -8]) has a 99.91% probability of being negative (< 0), 99.91% of being significant (< -0.05). In contrast, the shapes associated with bad characters (median = 678 ms, 95% HDI = [592 764]) were slower than shapes associated with neutral characters, the effect ($median_{diff}$ = 5, 95% HDI [-3, 13]) has a 92.43% probability of being positive (> 0), 92.31% of being significant (> 0.05).

Modulation effect self-referential processing

To test the modulation effect of self-relevance, we also modeled data from three experiments (3a, 3b, and 6b) with three-level Bayesian models. These three experiments included 108 unique participants. We focused on the population-level effect of the interaction between self-referential processing and moral valence. Also, we examined the differences of differences, i.e., how the differences between good/bad characters and the neutral character under the self-referencing conditions differ from that under other-referencing conditions. The results of each experiment can be found in supplementary materials.

For the *d* prime, we found an interaction between the moral valence and self-relevance: the good-neutral differences are larger for the self-referencing condition than for the other-referencing condition, the difference ($median_{diff}$ = 0.48, 95% HDI [-0.62, 1.65]) has a 93.04% probability of being positive (> 0), 91.92% of being significant (> 0.05). However, the bad-neutral differences ($median_{diff}$ = 0.0087, 95% HDI [-0.96, 1.00]) only have a 51.85% probability of being positive (> 0), 41.29% of being significant (> 0.05). Further analyses revealed that the prioritization effect of good character (as compared to neutral) only appeared for self-referencing conditions but not other-referential conditions. The estimated *d* prime for good-self was greater than neutral-self ($median_{diff}$ = 0.54, 95% HDI [-0.30, 1.41]), with a 95.99% probability of being positive (> 0), 95.36% of being significant (> 0.05). The differences between bad-self and neutral-self, good-other and neutral-other, and bad-other and neutral-other are all centered around zero (see Figure 2, B, D).

For the RTs of matched trials, we also found an interaction between moral valence and self-relevance: the good-neutral differences were larger for the self- than the other-referencing conditions ($median_{diff}$ = -148, 95% HDI [-413, 73]) has a 96.05% probability of being negative (< 0), 96.05% of being significant (< -0.05). However, this pattern was much weaker for bad-neutral differences ($median_{diff}$ = -47, 95% HDI [-280, 182]) has a 79.91% probability of being negative (< 0) and 79.88% of being significant (< -0.05). Further analyses revealed a robust good-self prioritization effect as compared to neutral-self ($median_{diff}$ = -59, 95% HDI [-115, -22]) has a 98.87% probability of being negative (< 0) and 98.87% of being significant (< -0.05)) and good-other ($median_{diff}$ = -109, 95% HDI [-227, -31]) has a 98.65% probability of being negative (< 0) and 98.65% of being significant (< -0.05)) conditions. Similar to the results of *d'*, we found that participants responded slower for both good character than for the neutral character when they referred to others, $median_{diff}$ = 85.01, 95% HDI [-112, 328]) has a 92.16%

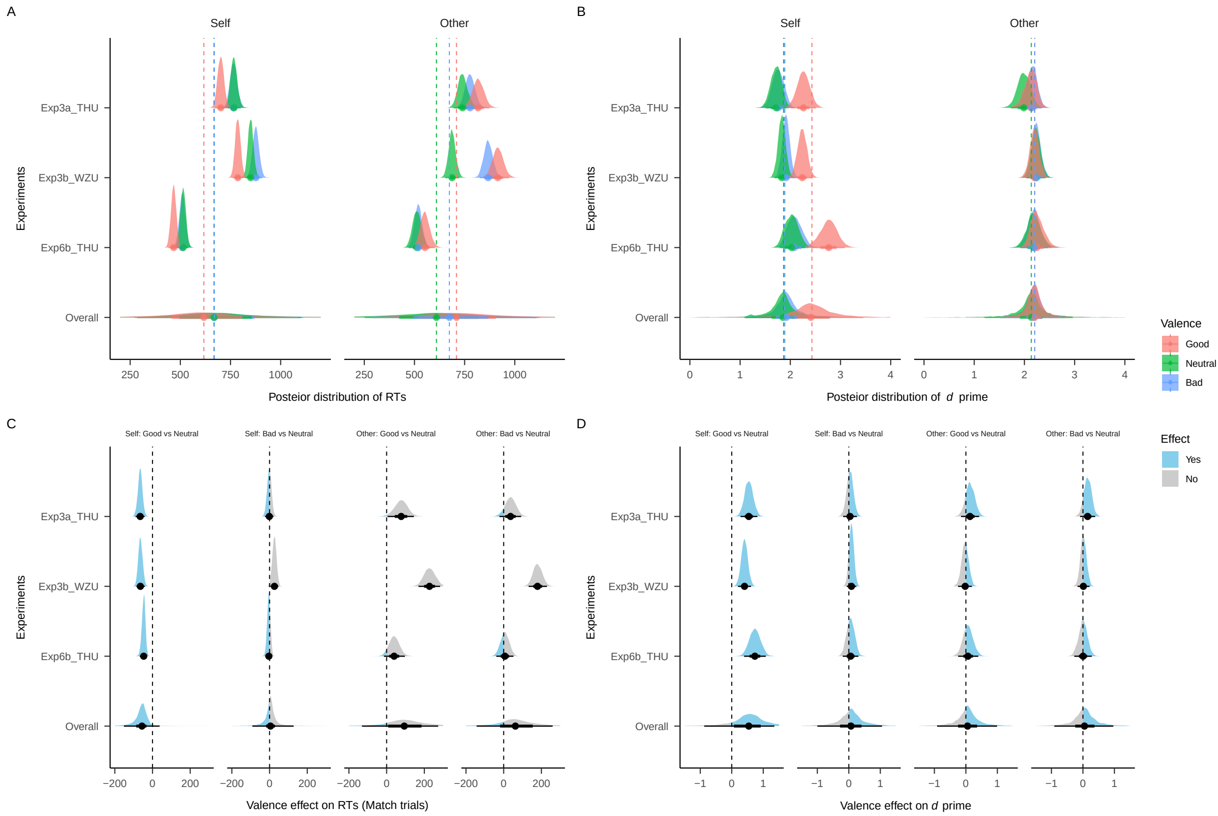

Figure 2. Interaction between moral character and self-referential. (A) Experimental level (three experiments) and population level posterior distributions of RT under different conditions; (B) Experimental level and population level posterior distributions of *d*-prime under different conditions; (C) Experimental level and population level posterior distributions of the RT differences between conditions, from left to right: Good-self vs. Neutral-self, Bad-self vs. Neutral-self, Good-other vs. Neutral-other, Bad-other vs. Neutral-other; (D) Experimental level and population level posterior distributions of the *d*-prime differences between conditions, from left to right: Good-self vs. Neutral-self, Bad-self vs. Neutral-self, Good-other vs. Neutral-other, Bad-other vs. Neutral-other.

probability of being positive (> 0) and 92.15% of being significant (> 0.05). A similar pattern was also found for the bad character when referred to others: bad-other responded slower than neutral-other, $median_{diff}$ = 44, 95% HDI [-146, 268]) has an 80.03% probability of being positive (> 0) and 79.99% of being significant (> 0.05). See Figure 2.

These results suggested that the prioritization of good character is not solely driven by the valence of moral character. Instead, self-relevance modulated the prioritization of good character: good character was prioritized only when it referred to the self. When the moral character referred to others, responses to both good and bad characters were slowed down.

The link between oneself and good character

Experiments 4a and 4b were designed to test whether the good character and the self bind together spontaneously. Because these two experiments have different experimental designs, we model their data separately.

In experiment 4a, where "self" vs. "other" were task-relevant and moral character were task-irrelevant, we found the "self" conditions performed better than the "other" conditions for both *d* prime and reaction times. This pattern is consistent with previous studies (e.g., Sui et al. (2012)).

More importantly, we found evidence that task-irrelevant moral character also played a role. For shapes associated with "self", *d'* was greater when shapes had a good character inside (median = 2.82, 95% HDI [2.64 3.03]) than shapes that have neutral character (median = 2.74, 95% HDI [2.58 2.94]), the difference (median = 0.08, 95% HDI [-0.10, 0.27]) has an 81.60% probability of being positive (> 0), 64.33% of being significant (> 0.05). For shapes associated with "other", the pattern reversed: *d* prime was smaller when shapes had a good character inside (median = 1.87, 95% HDI [1.70 2.04]) than had neutral (median = 1.96, 95% HDI [1.79 2.14]), the difference (median = -0.09, 95% HDI [-0.25, 0.05]) has an 89.03% probability of being negative (< 0), 71.38% of being significant (< -0.05). The difference between these two effects (median = 0.18, 95% HDI [-0.06, 0.43]) has a 92.88% probability of being positive (> 0), 85.08% being significant (> 0.05). See Figure 3.

A similar but more robust pattern was found for RTs in matched trials. For the "self" condition, when a good character was presented inside the shapes, the RTs (median = 633, 95% HDI [614 654]) were faster than when a neutral character (median = 647, 95% HDI [628 666]) was inside, the effect (median = -8, 95% HDI [-17, 2]) has a 94.55% probability of being negative (< 0) and 94.50% of being significant (< -0.05). In contrast, when the shapes referred to other, RTs for shapes with good character inside (median = 733, 95% HDI [707 756]) were slower than those with neutral character inside (median = 713, 95% HDI [691 734]), the effect (median = 12, 95% HDI [-4, 28]) has a 93.00% probability of being positive (> 0) and 92.83% of being significant (> 0.05). The difference between these effects (median = -19, 95% HDI [-43, 4]) has a 94.90% probability of being negative (< 0) and 94.88% of being significant (< -0.05).

In experiment 4b, where moral characters were task-relevant and "self" vs "other" were task-irrelevant, we found a main effect of moral character: performance for shapes associated with good characters was better than other-related conditions on both *d'* and reaction times. This pattern, again, shows a robust prioritization effect of good character.

Most importantly, we found evidence that task-irrelevant labels, "self" or "other", also played a role. For shapes associated with good character, the *d* prime was greater when shapes had a "self" inside than with "other" inside ($mean_{diff}$ = 0.14, 95% HDI [-0.05, 0.34]) has a 92.35% probability of being positive (> 0) and 81.80% of being significant (> 0.05). However, the difference did not occur when the target shape where associated with "neutral" ($mean_{diff}$ = 0.04, 95% HDI [-0.13, 0.22]) and has a 67.20% probability of being positive (> 0) and 44.80% of being significant (> 0.05). Neither for the "bad" person condition: $mean_{diff} = 0.10$, 95% HDI [-0.16, 0.37]) has a 77.03% probability of being positive (> 0) and 64.62% of being significant (> 0.05).

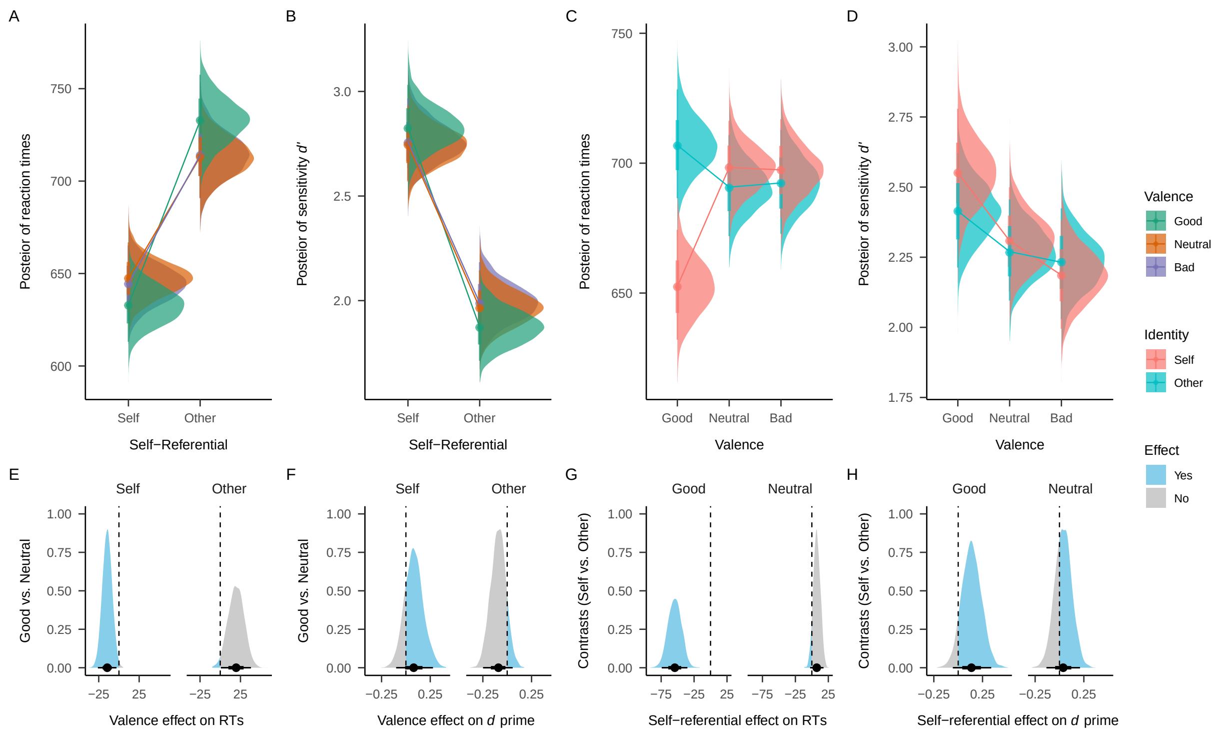

Figure 3. Implicit binding between self and good characters. (A) Posterior distributions of RT under different conditions of Experiment 4a; (B) Posterior distributions of *d*-prime under different conditions of Experiment 4a; (C) Posterior distributions of RT under different conditions of Experiment 4b; (D) Posterior distributions of *d*-prime under different conditions of Experiment 4b; (E) Posterior distributions of the RT differences between good character and neutral character when self (left) and other (right) were presented inside the shapes; (F) Posterior distributions of the *d*-prime differences between good character and neutral character when self (left) and other (right) were presented inside the shapes; (G) Posterior distributions of the RT differences between self- and other-referencing conditions when good character (left) and neutral character (right) were presented inside the shapes; (H) Posterior distributions of the *d*-prime differences between self- and other-referencing conditions when good character (left) and neutral character (right) were presented inside the shapes.

The same trend appeared for the RT data. For shapes associated with good character, having a "self" inside shapes reduced the reaction times as compared to having an "other" inside the shapes ($mean_{diff}$ = -55, 95% HDI [-75, -35]) has a 100% probability of being negative (< 0) and 100.00% of being significant (< -0.05). However, when the shapes were associated with the neutral character, having a "self" inside shapes increased the RTs: $mean_{diff}$ = 11, 95% HDI [1, 21]) has a 98.20% probability of being positive (> 0) and 98.15% of being significant (> 0.05). While having "self" slightly increased the RT than having "other" inside the shapes for the bad character: $mean_{diff}$ = 5, 95% HDI [-17, 27]) has a 69.45% probability of being positive (> 0) and 69.27% of being significant (> 0.05), See Figure 3.

Discussion

Across ten well-controlled experiments, we tested the primacy of morality in perceptual matching tasks. First, we found a robust prioritization of good character in the shape-label matching task across five experiments. Second, across three experiments, we found that the prioritization of good character was not solely driven by moral valence, i.e., "good" vs "bad". Instead, this effect was modulated by self-relevance: prioritization only occurred when moral characters are self-referential. Finally, the prioritization of the combination of good character and self occurred, albeit weak, even when either the self- or character-related information was irrelevant to the experimental task (experiments 4a and 4b). In contrast, performance to the combination of good character and "other", explicitly or implicitly, was worse than the combination of neutral character and "other". Together, these results highlighted the importance of self-relevance in perceiving information related to moral characters, suggesting a self-binding process when making perceptual decision-making for moral characters. These results are in line with a growing literature on the social and relational nature of perception (Xiao, Coppin, and Bavel (2016); Freeman, Stolier, and Brooks (2020); hafri_perception_2021) and deepened our understanding of mechanisms of perceptual decision-making of moral information.

The current study provided robust evidence for the prioritization of good character in perceptual decision-making. Though the primacy of morality has been argued in social psychology, whether morality is prioritized in information processing had been disputed. For instance, (E. Anderson et al., 2011) reported that faces associated with bad social behavior capture attention more rapidly, but an independent team failed to replicate the effect (Stein et al., 2017). In another study, Gantman and Van Bavel (2014) found that moral words are more likely to be judged as words when it was presented subliminally. But this effect may be caused by semantic priming instead of morality (Firestone & Scholl, 2015; Jussim et al., 2016). In the current study, we employed an associative learning task, which allowed us to eliminate the semantic priming effect for two reasons. First, associations between shapes and moral characters were acquired right before the perceptual matching task, semantic priming from pre-existed knowledge was impossible. Second, there were only a few pairs of stimuli were used and each stimulus represented different conditions, making it impossible for priming between trials. Importantly, a series of control experiments (1b, 1c, and 2) further excluded other confounding factors such as familiarity, presenting sequence, or words-based associations, suggesting that it was the moral content that drove the prioritization of good character.

The robust prioritization of good character found in the current study was incongruent with previous moral perception studies, which usually reported a negativity bias, i.e., information related to bad character is processed preferentially (E. Anderson et al., 2011; Eiserbeck & Abdel Rahman, 2020). This discrepancy may be caused by the experimental task: while in many previous moral perception studies, the participants were asked to detect the existence of a stimulus, the current task asked participants to recognize a pattern. In other words, previous studies targeted early stages of perception while the current task focused more on decision-making at a relatively later stage of information processing. This discrepancy is consistent with the pattern found in studies with emotional stimuli (Pool, Brosch, Delplanque, & Sander, 2016).

We expanded previous moral perception studies by focusing on the agent who made the perceptual decision-making and examined the interaction between moral valence and self-relevance. Our results revealed that prioritization of good character is modulated by self-relevance: good character was prioritized when it was related to the "self", even when the self-relatedness was task-irrelevant. By contrast, good character information was not prioritized when it was associated with "other". The modulation effect of self-relevance was large when the relationship between moral character and the self was explicit, which is consistent with previous studies that only positive aspects of the self are prioritized (Hu et al., 2020). More importantly, the effect persisted when the relationship between moral character and self-information was implicit, suggesting a spontaneous self-binding process when both pieces of information were presented. A possible explanation for this spontaneous self-binding of good character is that the positive moral self-view is central to our identity (Freitas, Cikara, Grossmann, & Schlegel, 2017; Strohminger, Knobe, & Newman, 2017) and the motivation to maintain a moral self-view influences how we perceive (e.g., Ma & Han, 2010) and remember (e.g., Carlson, Maréchal, Oud, Fehr, & Crockett, 2020; Stanley, Henne, & De Brigard, 2019).

Although the results here revealed the prioritization of good character in perceptual decision-making, we did not claim that the motivation of a moral self-view *penetrates* perception. The perceptual decision-making process involves processes more than just encoding the sensory inputs. To fully account for the nuance of behavioral data and/or related data collected from other modules (e.g., Sui, He, Golubickis, Svensson, & Neil Macrae, 2023), we may need computational models and an integrative experimental approach (**Almaatouq_BBS_2022?**). For example, sequential sampling models suggest that, when making a perceptual decision, the agent continuously accumulates evidence until the amount of evidence passed a threshold, then a decision is made (Chuan-Peng et al., 2022; Forstmann, Ratcliff, & Wagenmakers, 2016; Ratcliff, Smith, Brown, & McKoon, 2016). In these models, the evidence, or decision variable, can accumulate from both sensory information but also memory (Shadlen & Shohamy, 2016). Recently, applications of sequential sample models to perceptual matching tasks also suggest that different processes may contribute to the prioritization effect of self (Golubickis et al., 2017) or good self (Hu et al., 2020). Similarly, reinforcement learning models also revealed that the key difference between self- and other-referential learning lies in the learning rate (Lockwood et al., 2018). These studies suggest that computational models are needed to disentangle the cognitive processes underlying the prioritization of good character.

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