Positivity bias in perceptual matching may reflect a spontaneous self-referential processing

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Abstract

To navigate in a complex social world, individual has learnt to prioritize valuable information. Previous studies suggested the moral related stimuli was prioritized (Anderson, Siegel, Bliss-Moreau, & Barrett, 2011; Gantman & Van Bavel, 2014). Using social associative learning paradigm (self-tagging paradigm), we found that when geometric shapes, without soical meaning, were associated with different moral valence (morally good, neutral, or bad), the shapes that associated with positive moral valence were prioritized in a perceptual matching task. This patterns of results were robust across different procedures. Further, we tested whether this positive effect was modulated by self-relevance by manipulating the self-referential explicitly and found that this moral positivity effect only occured when the moral valence are self-relevant but evidence to support such effect when the moral valence are other-relevant is weak. We further found that this effect exist even when the self-relevance or the moral valence were presented as a task-irrelevant information, though the effect size become much smaller. We also tested whether the positivity effect only exist in moral domain and found that this effect was not limited to moral domain. Exploratory analyses on task-questionnaire relationship found that moral self-image score (how closely one feel they are to the ideal moral image of themselves) is positively correlated to the *d'* of morally positive condition in singal detection and the drift rate using DDM, while the self-esteem is negatively correlated with *d'* of neutral and morally negative conditions. These results suggest that the positive self prioritzation in perceptual decision-making may reflect …

Keywords: Perceptual decision-making, Self, positive bias, morality

Word count: X

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Introduction

XXXX In perceptual matching, same is faster than different (Farell, 1985; Krueger, 1978). Automatic processing (Spruyt & Houwer, 2017)

Van Zandt, Colonius, and Proctor (2000): A comparison of two response time models applied to perceptual matching

Yakushijin, ReikoJacobs, Robert A (2020), Are People Successful at Learning Sequential Decisions on a Perceptual Matching Task?

Schooler, L. J., Shiffrin, R. M., & Raaijmakers, J. G. W. (2001). A Bayesian model for implicit effects in perceptual identification. Psychological Review, 108(1), 257–272. https://doi.org/10.1037/0033-295X.108.1.257

We reported results from eleven experiments. In first set of experiments, we found that shapes associated with morally positive person label were responded faster and more accurately. In the second set of experiments, we explore the potential role of good self in perceptual matching task and added one more independent variable, we found that the effect was mainly on good self. In the third part we tested whether the morality will automatically binds with person-relevance. Finally, we explore the correlation between behavioral task and questionnaire scores.

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 ~ 6b, except experiment 3b) reported in the current study were first finished between 2014 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 two experiments (experiment 7a, 7b) that were reported in Hu, Lan, Macrae, and Sui (2020) (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 Tsinghua University.

General methods

Design and Procedure

This series of experiments started to test the effect of instantly acquired true self (moral self) on perceptual decision-making. For this purpose, we used 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, and 6a shared a 2 (matching: match vs. nonmatch) by 3 (moral valence: good vs. neutral vs. bad) within-subject design. Experiment 1a was the first one of the whole series studies and 1b, 1c, and 2 were conducted to exclude the potential confounding factors. More specifically, experiment 1b used different Chinese words as label to test whether the effect only occurred with certain familiar words. Experiment 1c manipulated the moral valence indirectly: participants first learned to associate different moral behaviors with different neutral 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 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, 4a, 4b, 6b, 7a, and 7b, 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 (matchness: match vs. nonmatch) by 2 (reference: self vs. other) by 3 (moral valence: 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 extended from 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. Experiment 3b was designed to separate the self-referential trials and other-referential trials. That is, participants finished two different blocks: in the self-referential blocks, they only responded to good-self, neutral-self, and bad-self, with half match trials and half non-match trials; for the other-reference blocks, they only responded to good-other, neutral-other, and bad-other. Experiment 7a and 7b were designed to test the cross task robustness of the effect we observed in the aforementioned experiments (see, Hu et al., 2020). The matching task in these two experiments shared the same design with experiment 3a, but only with two moral valence, i.e., good vs. bad. We didn't include the neutral condition in experiment 7a and 7b because we found that the neutral and bad conditions constantly showed non-significant results in experiment 1 ~ 6.

Experiment 4a and 4b were design to test the automaticity of the binding between self/other and moral valence. In 4a, we used only two labels (self vs. other) and two shapes (circle, square). To manipulate the moral valence, 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 valence in the task: participant learnt 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.

Finally, experiment 5 was design to test the specificity of the moral valence. We extended experiment 1a with an additional independent variable: domains of the valence words. More specifically, besides the moral valence, we also added valence from other domains: appearance of person (beautiful, neutral, ugly), appearance of a scene (beautiful, neutral, ugly), and emotion (happy, neutral, and sad). Label-shape pairs from different domains were separated into different blocks.

E-prime 2.0 was used for presenting stimuli and collecting behavioral responses, except that experiment 7a and 7b used Matlab Psychtoolbox (Brainard, 1997; Pelli, 1997). 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 ($0.8^\circ \times 0.8^\circ$ of 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° of visual angle. For participants recruited in Wenzhou University, they finished the experiment in a group consisted of $3 \sim 12$ 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's 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

Analysis of individual study. We used the `tidyverse` of r (see script `Load_save_data.r`) to exclude the practicing trials, invalid trials of each participants, and invalid participants, if there were any, in the raw data. Results of each experiment were then analyzed in three different approaches.

Classic NHST.

First, as in Sui et al. (2012), we analyzed the accuracy and reaction times using classic repeated measures ANOVA in the Null Hypothesis Significance Test (NHST) framework. Repeated measures ANOVAs is essentially a two-step mixed model. In the first step, we estimate the parameter on individual level, and in the second step, we used repeated ANOVA to test the Null hypothesis. More specifically, for the accuracy, we used a signal detection approach, in which individual' sensitivity *d'* was estimated first. To estimate the sensitivity, we treated the match condition as the signal while the nonmatch conditions as noise. Trials without response were coded either as "miss" (match trials) or "false alarm" (nonmatch trials). Given that the match and nonmatch trials are presented in the same way and had same number of trials across all studies, we assume that participants' inner distribution of these two types of trials had equal variance but may had different means. That is, we used the equal variance Gaussian SDT model (EVSDT) here (Rouder & Lu, 2005). The d' was then estimated as the difference of the standardized hit and false alarm rats (Stanislaw & Todorov, 1999):

$$d' = zHR - zFAR = \Phi^{-1}(HR) - \Phi^{-1}(FAR)$$

where the HR means hit rate and the FAR mean false alarm rate. zHR and $zFAR$ are the standardized hit rate and false alarm rates, respectively. These two z-scores were converted from proportion (i.e., hit rate or false alarm rate) by inverse cumulative normal density function, Φ^{-1} (Φ is the cumulative normal density function, and is used convert z score into probabilities). Another parameter of signal detection theory, response criterion c, is defined by the negative standardized false alarm rate (DeCarlo, 1998): $-zFAR$.

For the reaction times (RTs), only RTs of accurate trials were analyzed. We first calculate the mean RTs of each participant and then subject the mean RTs of each participant to repeated measures ANOVA. Note that we set the alpha as .05. The repeated measure ANOVA was done by `afex` package (https://github.com/singmann/afex).

To control the false positive rate when conducting the post-hoc comparisons, we used Bonferroni correction.

Bayesian hierarchical generalized linear model (GLM).

The classic NHST approach may ignore the uncertainty in estimate of the parameters for SDT (Rouder & Lu, 2005), and using mean RT assumes normal distribution of RT data, which is always not true because RTs distribution is skewed (Rousselet & Wilcox, 2019). To better estimate the uncertainty and use a more appropriate model, we also tried Bayesian hierarchical generalized linear model to analyze each experiment's accuracy and RTs data. We used BRMs (Bürkner, 2017) to build the model, which used Stan (Carpenter et al., 2017) to estimate the posterior.

In the GLM model, we assume that the accuracy of each trial is Bernoulli distributed (binomial with 1 trial), with probability p_i that $y_i = 1$.

$$y_i \sim Bernoulli(p_i)$$

In the perceptual matching task, the probability p_i can then be modeled as a function of the trial type:

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

The outcomes y_i are 0 if the participant responded "nonmatch" on trial i, 1 if they responded "match". The probability of the "match" response for trial i for a participant is p_i. We then write the generalized linear model on the probits (z-scores; Φ, "Phi") of ps. Φ is the cumulative normal density function and maps z scores to probabilities. Given this parameterization, the intercept of the model (β_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 (β_1) is the increase of saying 1 when predictor is 1, in z-scores, which is another expression of d'. Therefore, c = -zHR $= -\beta_0$, and $d' = \beta_1$.

In each experiment, we had multiple participants, then we need also consider the variations between subjects, i.e., a hierarchical mode in which individual's parameter and the the population level parameter are estimated simultaneously. We assume that the outcome of each trial is Bernoulli distributed (binomial with 1 trial), with probability p_{ij} that $y_{ij} = 1$.

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

Similarly, the generalized linear model was extended to two levels:

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

The outcomes y_{ij} are 0 if participant j responded “nonmatch” on trial i, 1 if they responded “match”. The probability of the “match” response for trial i for subject j is p_{ij}. We again can write the generalized linear model on the probits (z-scores; Φ, “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.

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

For the reaction time, we used the log normal distribution (https://lindeloev.github.io/shiny-rt/#34_(shifted)_log-normal). This distribution has two parameters: μ, σ. μ is the mean of the logNormal distribution, and σ is the disperse of the distribution. The log normal distribution can be extended to shifted log normal distribution, with one more parameter: shift, which is the earliest possible response.

$$y_i = \beta_0 + \beta_1 * IsMatch_i * Valence_i$$

Shifted log-normal distribution:

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

y_{ij} is the RT of the ith trial of the jth participants.

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

$$\sigma_j \sim Cauchy()$$

Hierarchical drift diffusion model (HDDM).

To further explore the psychological mechanism under perceptual decision-making, we used HDDM (Wiecki, Sofer, & Frank, 2013) to model our RTs and accuracy data. We used the prior implemented in HDDM, that is, informative priors that constrains parameter estimates to be in the range of plausible values based on past literature (Matzke & Wagenmakers, 2009). As reported in Hu et al. (2020), we used the response code approach, match response were coded as 1 and nonmatch responses were coded as 0. To fully explore all parameters, we allow all four parameters of DDM free to vary. We then extracted the estimation of all the four parameters for each participants for the correlation analyses. However, because the starting point is only related to response (match vs. non-match) but not the valence of the stimuli, we didn't included it in correlation analysis.

Synthesized results. We also reported the synthesized results from the experiments, because many of them shared the similar experimental design. We reported the results in five parts: valence effect, explicit interaction between valence and self-relevance, implicit interaction between valence and self-relevance, specificity of valence effect, and behavior-questionnaire correlation.

For the first two parts, we reported the synthesized results from Frequestist's approach(mini-meta-analysis, Goh, Hall, & Rosenthal, 2016). The mini meta-analyses were carried out by using `metafor` package (Viechtbauer, 2010). We first calculated the mean of d' and RT of each condition for each participant, then calculate the effect size (Cohen's d) and variance of the effect size for all contrast we interested: Good v. Bad, Good v. Neutral, and Bad v. Neutral for the effect of valence, and self vs. other for the effect of self-relevance. Cohen's d and its variance were estimated using the following formula (Cooper, Hedges, & Valentine, 2009):

$$d = \frac{(M_1 - M_2)}{\sqrt{(sd_1^2 + sd_2^2) - 2rsd_1sd_2}}\sqrt{2(1-r)}$$

$$var.d = 2(1-r)(\frac{1}{n} + \frac{d^2}{2n})$$

M_1 is the mean of the first condition, sd_1 is the standard deviation of the first condition, while M_2 is the mean of the second condition, sd_2 is the standard deviation of the second condition. r is the correlation coefficient between data from first and second condition. n is the number of data point (in our case the number of participants included in our research).

The effect size from each experiment were then synthesized by random effect model using `metafor` (Viechtbauer, 2010). Note that to avoid the cases that some participants participated more than one experiments, we inspected the all available information of participants and only included participants' results from their first participation. As mentioned above, 24 participants were intentionally recruited to participate both exp 1a and exp 2, we only included their results from experiment 1a in the meta-analysis.

We also estimated the synthesized effect size using Bayesian hierarchical model, which extended the two-level hierarchical model in each experiment into three-level model, which experiment as an additional level. For SDT, we can use a nested hierarchical model to model all the experiment with similar design:

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

where

$$\Phi(p_{ijk}) = \beta_{0jk} + \beta_{1jk} IsMatch_{ijk}$$

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

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

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

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

in which μ_0 and μ_1 means the population level parameter.

This model can be easily expand to 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 ith trial of the jth participants in the kth experiment.

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

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

$$\theta_{jk} \sim Cauchy()$$

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

Using the Bayesian hierarchical model, we can directly estimate the over-all effect of valence on d' across all experiments with similar experimental design, instead of using a two-step approach where we first estimate the d' for each participant and then use a random effect model meta-analysis (Goh et al., 2016).

Valence effect.

We synthesized effect size of d' and RT from experiment 1a, 1b, 1c, 2, 5 and 6a for the valence effect. We reported the synthesized the effect across all experiments that tested the valence effect, using the mini meta-analysis approach (Goh et al., 2016).

Explicit interaction between Valence and self-relevance.

The results from experiment 3a, 3b, 6b, 7a, and 7b. These experiments explicitly included both moral valence and self-reference.

Implicit interaction between valence and self-relevance.

In the third part, we focused on experiment 4a and 4b, which were designed to examine the implicit effect of the interaction between moral valence and self-referential processing. We are interested in one particular question: will self-referential and morally positive valence had a mutual facilitation effect. That is, when moral valence (experiment 4a) or self-referential (experiment 4a) was presented as task-irrelevant stimuli, whether they would facilitate self-referential or valence effect on perceptual decision-making. For experiment 4a, we reported the comparisons between different valence conditions under the self-referential task and other-referential task. For experiment 4b, we first calculated the effect of valence for both self- and other-referential conditions and then compared the effect size of these three contrast from self-referential condition and from other-referential condition. Note that the results were also analyzed in a standard repeated measure ANOVA (see supplementary materials).

Specificity of the valence effect.

In this part, we reported the data from experiment 5, which included positive, neutral, and negative valence from four different domains: morality, aesthetic of person, aesthetic of scene, and emotion. This experiment was design to test whether the positive bias is specific to morality.

Behavior-Questionnaire correlation.

Finally, we explored correlation between results from behavioral results and self-reported measures.

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 data were reported in (Liu et al., 2020).

For the behavioral task part, we derived different indices. First, we used the mean of the RT and *d'* from each participants of each condition. Second, we used three parameters from drift diffusion model: drift rate (v), boundary separation (a), and non decision-making time (t). Third, we calculated the differences between different conditions (valence effect: good-self vs. bad-self, good-self vs. neutral-self, bad-self vs. neutral-self; good-other vs. bad-other, good-other vs. neutral-other, bad-other vs. neutral-other; Self-reference effect: good-self vs. good-other, neutral-self vs. neutral-other, bad-self vs. bad-other), as indexed by Cohen's d and standard error (SE) of Cohen's d.

$$Cohen' sd_z = \frac{(M_1 - M_2)}{\sqrt{(SD_1^2 + SD_2^2)/2}}$$

Given that the task difficulty were different across experiments, we z-transformed all these indices so that they become unit-free.

We used the mean of parameter posterior distribtion as the estimate of each parameter for each participants in the correlation analysis.

We used Pearson correlation to quantify the correlation. For those correlation that is significant ($p < 0.05$), we further tested the robustness of the correlation using bootstrap by `BootES` package (Kirby & Gerlanc, 2013). To avoid false positive, we further determined the threshold for significant by permutation. More specifically, for each pairs that initially with $p < .05$, we randomly shuffle the participants data of each score and calculated the correlation between the shuffled vectors. After repeating this procedure for 5000 times, we choose arrange these 5000 correlation coefficients and use the 95% percentile number as our threshold.

Part 1: Moral valence effect

In this part, we report five experiments that aimed at testing whether the instantly acquired association between shapes and good person would be prioritized in perceptual decision-making.

Experiment 1a

Methods.

Participants.

57 college students (38 female, age = 20.75 ± 2.54 years) participated. 39 of them were recruited from Tsinghua University community in 2014; 18 were recruited from Wenzhou University in 2017. All participants were right-handed except one, and all had normal or corrected-to-normal vision. Informed consent was obtained from all participants prior to the experiment according to procedures approved by the local ethics committees. 6 participant's data were excluded from analysis because nearly random level of accuracy, leaving 51 participants (34 female, age = 20.72 ± 2.44 years).

Stimuli and Tasks.

Three geometric shapes were used in this experiment: triangle, square, and circle. These shapes were paired with three labels (bad person, good person or neutral person). The pairs were counterbalanced across participants.

Procedure.

This experiment had two phases. First, there was a brief learning stage. Participants were asked to learn the relationship between geometric shapes (triangle, square, and circle) and different person (bad person, a good person, or a neutral person). For example, a participant was told, "bad person is a circle; good person is a triangle; and a neutral person is represented by a square." After participant remember the associations (usually in a few minutes), participants started a practicing phase of matching task which has the exact task as in the experimental task. In the experimental task, participants judged whether shape–label pairs, which were subsequently presented, were correct. Each trial started with the presentation of a central fixation cross for 500 ms. Subsequently, a pairing of a shape and label (good person, bad person, and neutral person) was presented for 100 ms. The pair presented could confirm to the verbal instruction for each pairing given in the training stage, or it could be a recombination of a shape with a different label, with the shape–label pairings being generated at random. The next frame showed a blank for 1100ms. Participants were expected to judge whether the shape was correctly assigned to the person by pressing one of the two response buttons as quickly and accurately as possible within this timeframe (to encourage immediate responding). Feedback (correct or incorrect) was given on the screen for 500 ms at the end of each trial, if no response detected, "too slow" was presented to remind participants to accelerate. Participants were informed of their overall accuracy at the end of each block. The practice phase finished and the experimental task began after the overall performance of accuracy during practice phase achieved 60%. For participants from the Tsinghua community, they completed 6 experimental blocks of 60 trials. Thus, there were 60 trials in each condition (bad-person match, bad-person nonmatch, good-person match, good-person nonmatch, neutral-person match, and neutral-person nonmatch). For the participants from Wenzhou University, they finished 6 blocks of 120 trials, therefore, 120 trials for each condition.

Data analysis.

As described in general methods section, this experiment used three approaches to analyze the behavioral data: Classical NHST, Bayesian Hierarchical Generalized Linear Model, and Hierarchical drift diffusion model.

Results.

Classic NHST.

d *prime.*

Figure 1 shows *d* prime and reaction times during the perceptual matching task. We conducted a single factor (valence: good, neutral, bad) repeated measure ANOVA.

We found the effect of Valence ($F(1.96, 97.84) = 6.19$, $MSE = 0.27$, $p = .003$, $\hat{\eta}^2_G = .020$). The post-hoc comparison with multiple comparison correction revealed that the shapes associated with Good-person (2.11, SE = 0.14) has greater *d* prime than shapes associated with Bad-person (1.75, SE = 0.14), $t(50) = 3.304$, $p = 0.0049$. The Good-person condition was also greater than the Neutral-person condition (1.95, SE = 0.16), but didn't reach statistical significant, $t(50) = 1.54$, $p = 0.28$. Neither the Neutral-person condition is significantly greater than the Bad-person condition, $t(50) = 2.109$, $p = .098$.

Reaction times.

We conducted 2 (Matchness: match v. nonmatch) by 3 (Valence: good, neutral, bad) repeated measure ANOVA. We found the main effect of Matchness ($F(1, 50) = 232.39$, $MSE = 948.92$, $p < .001$, $\hat{\eta}^2_G = .104$), main effect of valence ($F(1.87, 93.31) = 9.62$, $MSE = 1,673.86$, $p < .001$, $\hat{\eta}^2_G = .016$), and interaction between Matchness and Valence ($F(1.73, 86.65) = 8.52$, $MSE = 1,441.75$, $p = .001$, $\hat{\eta}^2_G = .011$).

We then carried out two separate ANOVA for Match and Mismatched trials. For matched trials, we found the effect of valence . We further examined the effect of valence for both self and other for matched trials. We found that shapes associated with Good Person (684 ms, SE = 11.5) responded faster than Neutral (709 ms, SE = 11.5), $t(50) =$

-2.265, p = 0.0702) and Bad Person (728 ms, SE = 11.7), $t(50)$ = -4.41, p = 0.0002), and the Neutral condition was faster than the Bad condition, $t(50)$ = -2.495, p = 0.0415). For non-matched trials, there was no significant effect of Valence ().

Bayesian hierarchical GLM.

d prime.

We fitted a Bayesian hierarchical GLM for signal detection theory approach. The results showed that when the shapes were tagged with labels with different moral valence, the sensitivity (d') and criteria (c) were both influence. For the d', we found that the shapes tagged with morally good person (2.46, 95% CI[2.21 2.72]) is greater than shapes tagged with moral bad (2.07, 95% CI[1.83 2.32]), $P_{PosteriorComparison} = 1$. Shape tagged with morally good person is also greater than shapes tagged with neutral person (2.23, 95% CI[1.95 2.49]), $P_{PosteriorComparison} = 0.97$. Also, the shapes tagged with neutral person is greater than shapes tagged with morally bad person, $P_{PosteriorComparison} = 0.92$.

Interesting, we also found the criteria for three conditions also differ, the shapes tagged with good person has the highest criteria (-1.01, [-1.14 -0.88]), followed by shapes tagged with neutral person(-1.06, [-1.21 -0.92]), and then the shapes tagged with bad person(-1.11, [-1.25 -0.97]). However, pair-wise comparison showed that only showed strong evidence for the difference between good and bad conditions.

Reaction times.

We fitted a Bayesian hierarchical GLM for RTs, with a log-normal distribution as the link function. We used the posterior distribution of the regression coefficient to make statistical inferences. As in previous studies, the matched conditions are much faster than the mismatched trials ($P_{PosteriorComparison} = 1$). We focused on matched trials only, and compared different conditions: Good is faster than the neutral, $P_{PosteriorComparison} = .99$, it was also faster than the Bad condition, $P_{PosteriorComparison} = 1$. And the neutral condition is faster than the bad condition, $P_{PosteriorComparison} = .99$. However, the mismatched trials are largely overlapped. See Figure 2.

HDDM.

We fitted our data with HDDM, using the response-coding (See also, Hu et al., 2020). We estimated separate drift rate (v), non-decision time (T_0), and boundary separation (a) for each condition. We found that the shapes tagged with good person has higher drift rate and higher boundary separation than shapes tagged with both neutral and bad person. Also, the shapes tagged with neutral person has a higher drift rate than shapes tagged with bad person, but not for the boundary separation. Finally, we found that shapes tagged with bad person had longer non-decision time (see Figure 3).

Experiment 1b

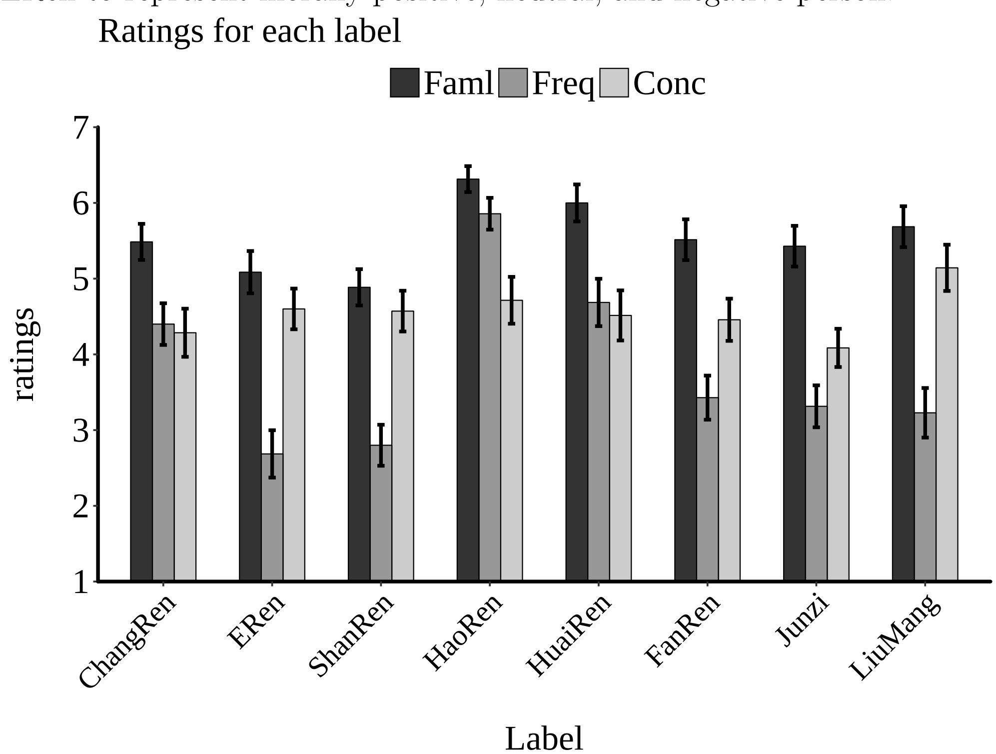
In this study, we aimed at excluding the potential confounding factor of the familiarity of words we used in experiment 1a, by matching the familiarity of the words.

Method.

Participants.

72 college students (49 female, age = 20.17 $\pm$ 2.08 years) participated. 39 of them were recruited from Tsinghua University community in 2014; 33 were recruited from Wenzhou University in 2017. All participants were right-handed except one, and all had normal or corrected-to-normal vision. Informed consent was obtained from all participants prior to the experiment according to procedures approved by the local ethics committees. 20 participant's data were excluded from analysis because nearly random level of accuracy, leaving 52 participants (36 female, age = 20.25 $\pm$ 2.31 years).

Stimuli and Tasks. Three geometric shapes (triangle, square, and circle, with 3.7º $\times$ 3.7º of visual angle) were presented above a white fixation cross subtending 0.8º $\times$ 0.8º of visual angle at the center of the screen. The three shapes were randomly assigned to three labels with different moral valence: a morally bad person (“ ”, ERen), a morally good person (“ ”, ShanRen) or a morally neutral person (“ ”, ChangRen). The order of the associations between shapes and labels was counterbalanced across participants. Three labels used in this experiment is selected based on the rating results from an independent survey, in which participants rated the familiarity, frequency, and concreteness of eight different words online. Of the eight words, three of them are morally positive (HaoRen, ShanRen, Junzi), two of them are morally neutral (ChangRen, FanRen), and three of them are morally negative (HuaiRen, ERen, LiuMang). An independent sample consist of 35 participants (22 females, age 20.6 ± 3.11) were recruited to rate these words. Based on the ratings (see supplementary materials Figure S1), we selected ShanRen, ChangRen, and ERen to represent morally positive, neutral, and negative person.



Procedure.

For participants from both Tsinghua community and Wenzhou community, the procedure in the current study was exactly same as in experiment 1a.

Data Analysis. Data was analyzed as in experiment 1a.

Results.

NHST.

Figure 4 shows d prime and reaction times of experiment 1b.

d prime.

Repeated measures ANOVA revealed main effect of valence, $F(1.83, 93.20) = 14.98$, $MSE = 0.18$, $p < .001$, $\hat{\eta}^2_G = .053$. Paired t test showed that the Good-Person condition (1.87 ± 0.102) was with greater d prime than Neutral condition (1.44 ± 0.101, $t(51) = 5.945$, $p < 0.001$). We also found that the Bad-Person condition (1.67 ± 0.11) has also greater d prime than neutral condition , $t(51) = 3.132$, $p = 0.008$). There Good-person condition was also slightly greater than the bad condition, $t(51) = 2.265$, $p = 0.0701$.

Reaction times.

We found interaction between Matchness and Valence ($F(1.95, 99.31) = 19.71$, $MSE = 960.92$, $p < .001$, $\hat{\eta}^2_G = .031$) and then analyzed the matched trials and mismatched trials separately, as in experiment 1a. For matched trials, we found the effect of valence $F(1.94, 99.10) = 33.97$, $MSE = 1,343.19$, $p < .001$, $\hat{\eta}^2_G = .115$. Post-hoc t-tests revealed that shapes associated with Good Person (684 ± 8.77) were responded faster than Neutral-Person (740 ± 9.84), ($t(51) = -8.167$, $p < 0.001$) and Bad Person (728 ± 9.15), $t(51) = -5.724$, $p < 0.0001$). While there was no significant differences between Neutral and Bad-Person condition ($t(51) = 1.686$, $p = 0.221$). For non-matched trials, there was no significant effect of Valence ($F(1.90, 97.13) = 1.80$, $MSE = 430.15$, $p = .173$, $\hat{\eta}^2_G = .003$).

BGLM.

Signal detection theory analysis of accuracy.

We fitted a Bayesian hierarchical GLM for SDT. The results showed that when the shapes were tagged with labels with different moral valence, the sensitivity (d') and criteria (c) were both influence. For the d', we found that the shapes tagged with morally good person (2.46, 95% CI[2.21 2.72]) is greater than shapes tagged with moral bad (2.07, 95% CI[1.83 2.32]), $P_{PosteriorComparison} = 1$. Shape tagged with morally good person is also greater than shapes tagged with neutral person (2.23, 95% CI[1.95 2.49]), $P_{PosteriorComparison} = 0.97$. Also, the shapes tagged with neutral person is greater than shapes tagged with morally bad person, $P_{PosteriorComparison} = 0.92$.

Interesting, we also found the criteria for three conditions also differ, the shapes tagged with good person has the highest criteria (-1.01, [-1.14 -0.88]), followed by shapes tagged with neutral person(1.06, [-1.21 -0.92]), and then the shapes tagged with bad person(-1.11, [-1.25 -0.97]). However, pair-wise comparison showed that only showed strong evidence for the difference between good and bad conditions.

Reaction time.

We fitted a Bayesian hierarchical GLM for RTs, with a log-normal distribution as the link function. We used the posterior distribution of the regression coefficient to make statistical inferences. As in previous studies, the matched conditions are much faster than the mismatched trials ($P_{PosteriorComparison} = 1$). We focused on matched trials only, and compared different conditions: Good is faster than the neutral, $P_{PosteriorComparison} = .99$, it was also faster than the Bad condition, $P_{PosteriorComparison} = 1$. And the neutral condition is faster than the bad condition, $P_{PosteriorComparison} = .99$. However, the mismatched trials are largely overlapped. See Figure 5.

HDDM.

We found that the shapes tagged with good person has higher drift rate and higher boundary separation than shapes tagged with both neutral and bad person. Also, the shapes tagged with neutral person has a higher drift rate than shapes tagged with bad person, but not for the boundary separation. Finally, we found that shapes tagged with bad person had longer non-decision time (see figure 6).

Discussion. These results confirmed the facilitation effect of positive moral valence on the perceptual matching task. This pattern of results mimic prior results demonstrating self-bias effect on perceptual matching (Sui et al., 2012) and in line with previous studies that indirect learning of other's moral reputation do have influence on our subsequent behavior (Fouragnan et al., 2013).

Experiment 1c

In this study, we further control the valence of words using in our experiment. Instead of using label with moral valence, we used valence-neutral names in China. Participant first learn behaviors of the different person, then, they associate the names and shapes. And then they perform a name-shape matching task.

Method.

Participants.

23 college students (15 female, age = 22.61 $\pm$ 2.62 years) participated. All of them were recruited from Tsinghua University community in 2014. Informed consent was obtained from all participants prior to the experiment according to procedures approved by the local ethics committees. No participant was excluded because they overall accuracy were above 0.6.

Stimuli and Tasks.

Three geometric shapes (triangle, square, and circle, with 3.7º $\times$ 3.7º of visual angle) were presented above a white fixation cross subtending 0.8º $\times$ 0.8º of visual angle at the center of the screen. The three most common names were chosen, which are neutral in moral valence before the manipulation. Three names (Zhang, Wang, Li) were first paired with three paragraphs of behavioral description. Each description includes one sentence of biographic information and four sentences that describing the moral behavioral under that name. To assess the that these three descriptions represented good, neutral, and bad valence, we collected the ratings of three person on six dimensions: morality, likability, trustworthiness, dominance, competence, and aggressiveness, from an independent sample (n = 34, 18 female, age = 19.6 ± 2.05). The rating results showed that the person with morally good behavioral description has higher score on morality (M = 3.59, SD = 0.66) than neutral (M = 0.88, SD = 1.1), $t(33) = 12.94$, $p < .001$, and bad conditions (M = -3.4, SD = 1.1), $t(33) = 30.78$, $p < .001$. Neutral condition was also significant higher than bad conditions $t(33) = 13.9$, $p < .001$ (See supplementary materials).

Procedure.

After arriving the lab, participants were informed to complete two experimental tasks, first a social memory task to remember three person and their behaviors, after tested for their memory, they will finish a perceptual matching task. In the social memory task, the descriptions of three person were presented without time limitation. Participant self-paced to memorized the behaviors of each person. After they memorizing, a recognition task was used to test their memory effect. Each participant was required to have over 95% accuracy before preceding to matching task. The perceptual learning task was followed, three names were randomly paired with geometric shapes. Participants were required to learn the association and perform a practicing task before they start the formal experimental blocks. They kept practicing until they reached 70% accuracy. Then, they would start the perceptual matching task as in experiment 1a. They finished 6 blocks of perceptual matching trials, each have 120 trials.

Data Analysis. Data was analyzed as in experiment 1a.

Results. Figure 7 shows d prime and reaction times of experiment 1c. We conducted same analysis as in Experiment 1a. Our analysis didn't should effect of valence on d prime, $F(1.93, 42.56) = 0.23$, $MSE = 0.41$, $p = .791$, $\hat{\eta}^2_G = .005$. Neither the effect of valence on RT ($F(1.63, 35.81) = 0.22$, $MSE = 2,212.71$, $p = .761$, $\hat{\eta}^2_G = .001$) or interaction between valence and matchness on RT ($F(1.79, 39.43) = 1.20$,

$MSE = 1,973.91$, $p = .308$, $\hat{\eta}^2_G = .005$).

Signal detection theory analysis of accuracy.

We fitted a Bayesian hierarchical GLM for SDT. The results showed that when the shapes were tagged with labels with different moral valence, the sensitivity (d') and criteria (c) were both influenced. For the d', we found that the shapes tagged with morally good person (2.30, 95% CI[1.93 2.70]) is greater than shapes tagged with moral bad (2.11, 95% CI[1.83 2.42]), $P_{PosteriorComparison} = 0.8$. Shape tagged with morally good person is also greater than shapes tagged with neutral person (2.16, 95% CI[1.88 2.45]), $P_{PosteriorComparison} = 0.75$.

Interesting, we also found the criteria for three conditions also differ, the shapes tagged with good person has the highest criteria (-0.97, [-1.12 -0.82]), followed by shapes tagged with neutral person(-0.96, [-1.09 -0.83]), and then the shapes tagged with bad person(-1.03, [-1.22 -0.84]). However, pair-wise comparison showed that only showed strong evidence for the difference between good and bad conditions.

Reaction time.

We fitted a Bayesian hierarchical GLM for RTs, with a log-normal distribution as the link function. We used the posterior distribution of the regression coefficient to make statistical inferences. As in previous studies, the matched conditions are much faster than the mismatched trials ($P_{PosteriorComparison} = .75$). We focused on matched trials only, and compared different conditions: Good () is not faster than the neutral (), $P_{PosteriorComparison} = .5$, it was faster than the Bad condition (), $P_{PosteriorComparison} = .88$. And the neutral condition is faster than the bad condition, $P_{PosteriorComparison} = .95$. However, the mismatched trials are largely overlapped.

HDDM. We fitted our data with HDDM, using the response-coding (also see Hu et al., 2020). We estimated separate drift rate (v), non-decision time (T_0), and boundary separation (a) for each condition. We found that the shapes tagged with good person has higher drift rate and higher boundary separation than shapes tagged with both neutral and bad person. Also, the shapes tagged with neutral person has a higher drift rate than shapes tagged with bad person, but not for the boundary separation. Finally, we found that shapes tagged with bad person had longer non-decision time (see figure 9)).

Experiment 2: Sequential presenting

Experiment 2 was conducted for two purpose: (1) to further confirm the facilitation effect of positive moral associations; (2) to test the effect of expectation of occurrence of each pair. In this experiment, after participant learned the association between labels and shapes, they were presented a label first and then a shape, they then asked to judge whether the shape matched the label or not (see (Sui, Sun, Peng, & Humphreys, 2014). Previous studies showed that when the labels presented before the shapes, participants formed expectations about the shape, and therefore a top-down process were introduced into the perceptual matching processing. If the facilitation effect of positive moral valence we found in experiment 1 was mainly drive by top-down processes, this sequential presenting paradigm may eliminate or attenuate this effect; if, however, the facilitation effect occurred because of button-up processes, then, similar facilitation effect will appear even with sequential presenting paradigm.

Method.

Participants.

35 participants (17 female, age = 21.66 ± 3.03) were recruited. 24 of them had participated in Experiment 1a (9 male, mean age = 21.9, s.d. = 2.9), and the time gap between these experiment 1a and experiment 2 is at least six weeks. The results of 1 participants were excluded from analysis because of less than 60% overall accuracy, remains 34 participants (17 female, age = 21.74 ± 3.04).

Procedure.

In Experiment 2, the sequential presenting makes the matching task much easier than experiment 1. To avoid ceiling effect on behavioral data, we did a few pilot experiments to get optimal parameters, i.e., the conditions under which participant have similar accuracy as in Experiment 1 (around 70 ~ 80% accuracy). In the final procedure, the label (good person, bad person, or neutral person) was presented for 50 ms and then masked by a scrambled image for 200 ms. A geometric shape followed the scrambled mask for 50 ms in a noisy background (which was produced by first decomposing a square with $\frac{3}{4}$ gray area and $\frac{1}{4}$ white area to small squares with a size of 2×2 pixels and then re-combine these small pieces randomly), instead of pure gray background in Experiment 1. After that, a blank screen was presented 1100 ms, during which participants should press a button to indicate the label and the shape match the original association or not. Feedback was given, as in study 1. The next trial then started after 700 ~ 1100 ms blank. Other aspects of study 2 were identical to study 1.

Data analysis.

Data was analyzed as in study 1a.

Results.

NHST.

Figure 10 shows d prime and reaction times of experiment 2. Less than 0.2% correct trials with less than 200ms reaction times were excluded.

d prime.

There was evidence for the main effect of valence, $F(1.83, 60.36) = 14.41$, $MSE = 0.23$, $p < .001$, $\hat{\eta}^2_G = .066$. Paired t test showed that the Good-Person condition (2.79 ± 0.17) was with greater d prime than Netural condition (2.21 ± 0.16, $t(33) = 4.723$, $p = 0.001$) and Bad-person condition (2.41 ± 0.14), $t(33) = 4.067$, $p = 0.008$). There was no-significant difference between Neutral-person and Bad-person conidition, $t(33) =$ -1,802, $p = 0.185$.

Reaction time.

The results of reaction times of matchness trials showed similar pattern as the d prime data.

We found interaction between Matchness and Valence ($F(1.99, 65.70) = 9.53$, $MSE = 605.36$, $p < .001$, $\hat{\eta}^2_G = .017$) and then analyzed the matched trials and mismatched trials separately, as in experiment 1a. For matched trials, we found the effect of valence $F(1.99, 65.76) = 10.57$, $MSE = 1,192.65$, $p < .001$, $\hat{\eta}^2_G = .067$. Post-hoc t-tests revealed that shapes associated with Good Person (548 $\pm$ 9.4) were responded faster than Neutral-Person (582 $\pm$ 10.9), ($t(33)$ = -3.95, p = 0.0011) and Bad Person (582 $\pm$ 10.2), $t(33)$ = -3.9, p = 0.0013). While there was no significant differences between Neutral and Bad-Person condition ($t(33)$ = -0.01, p = 0.999). For non-matched trials, there was no significant effect of Valence ($F(1.99, 65.83) = 0.17$, $MSE = 489.80$, $p = .843$, $\hat{\eta}^2_G = .001$).

BGLMM.

Signal detection theory analysis of accuracy.

We fitted a Bayesian hierarchical GLM for SDT. The results showed that when the shapes were tagged with labels with different moral valence, the sensitivity (d') and criteria (c) were both influence. For the d', we found that the shapes tagged with morally good person (2.46, 95% CI[2.21 2.72]) is greater than shapes tagged with moral bad (2.07, 95% CI[1.83 2.32]), $P_{PosteriorComparison} = 1$. Shape tagged with morally good person is also greater than shapes tagged with neutral person (2.23, 95% CI[1.95 2.49]), $P_{PosteriorComparison} = 0.97$. Also, the shapes tagged with neutral person is greater than shapes tagged with morally bad person, $P_{PosteriorComparison} = 0.92$.

Interesting, we also found the criteria for three conditions also differ, the shapes tagged with good person has the highest criteria (-1.01, [-1.14 -0.88]), followed by shapes tagged with neutral person(1.06, [-1.21 -0.92]), and then the shapes tagged with bad person(-1.11, [-1.25 -0.97]). However, pair-wise comparison showed that only showed strong evidence for the difference between good and bad conditions.

Reaction times.

We fitted a Bayesian hierarchical GLM for RTs, with a log-normal distribution as the link function. We used the posterior distribution of the regression coefficient to make statistical inferences. As in previous studies, the matched conditions are much faster than the mismatched trials ($P_{PosteriorComparison} = .75$). We focused on matched trials only, and compared different conditions: Good () is not faster than the neutral (), $P_{PosteriorComparison} = .5$, it was faster than the Bad condition (), $P_{PosteriorComparison} = .88$. And the neutral condition is faster than the bad condition, $P_{PosteriorComparison} = .95$. However, the mismatched trials are largely overlapped.

HDDM. We fitted our data with HDDM, using the response-coding (also see Hu et al., 2020). We estimated separate drift rate (v), non-decision time (T_0), and boundary separation (a) for each condition. We found that the shapes tagged with good person has higher drift rate and higher boundary separation than shapes tagged with both neutral and bad person. Also, the shapes tagged with neutral person has a higher drift rate than shapes tagged with bad person, but not for the boundary separation. Finally, we found that shapes tagged with bad person had longer non-decision time (see figure @ref(fig:plot-exp1c -HDDM))).

Discussion

In this experiment, we repeated the results pattern that the positive moral valenced stimuli has an advantage over the neutral or the negative valence association. Moreover, with a cross-task analysis, we didn't found evidence that the experiment task interacted with moral valence, suggesting that the effect might not be effect by experiment task. These findings suggested that the facilitation effect of positive moral valence is robust and not affected by task. This robust effect detected by the associative learning is unexpected.

Experiment 6a: EEG study 1

Experiment 6a was conducted to study the neural correlates of the positive prioritization effect. The behavioral paradigm is same as experiment 2.

Method.

Participants.

24 college students (8 female, age = 22.88 ± 2.79) participated the current study, all of them were from Tsinghua University in 2014. Informed consent was obtained from all participants prior to the experiment according to procedures approved by a local ethics committee. No participant was excluded from behavioral analysis.

Experimental design. The experimental design of this experiment is same as experiment 2: a 3×2 within-subject design with moral valence (good, neutral and bad associations) and matchness between shape and label (match vs. mismatch for the personal association) as within-subject variables.

Stimuli.

Three geometric shapes (triangle, square and circle, each $4.6^{\circ} \times 4.6^{\circ}$ of visual angle) were presented at the center of screen for 50 ms after 500ms of fixation ($0.8^{\circ} \times 0.8^{\circ}$ of visual angle). The association of the three shapes to bad person (“ , HuaiRen”), good person (“ , HaoRen”) or ordinary person (“ , ChangRen”) was counterbalanced across participants. The words bad person, good person or ordinary person ($3.6^{\circ} \times 1.6^{\circ}$) was also displayed at the center fo the screen. Participants had to judge whether the pairings of label and shape matched (e.g., Does the circle represent a bad person?). The experiment was run on a PC using E-prime software (version 2.0). These stimuli were displayed on a 22-in CRT monitor (1024×768 at 100Hz). We used backward masking to avoid over-processing of the moral words, in which a scrambled picture were presented for 900 ms after the label. Also, to avoid the ceiling effect on accuracy, shapes were presented on a noisy background based on our pilot studies. The noisy images were made by scrambling a picture of 3/4gray and ¼ white at resolution of 2 × 2 pixel.

Procedure.

The procedure was similar to Experiment 2. Participants finished 9 blocks of trial, each with 120 trials. In total, participants finished 180 trials for each combination of condition.

As in experiment 2 (Sui, He, & Humphreys, 2012), subjects first learned the associations between labels and shapes and then completed a shape-label matching task (e.g., good person-triangle). In each trial of the matching task, a fixation were first presented for 500 ms, followed by a 50 ms label; then, a scrambled picture presented 900 ms. After the backward mask, the shape were presented on a noisy background for 50ms. Participant have to response in 1000ms after the presentation of the shape, and finally, a feedback screen was presented for 500 ms (see figure 1). The inter-trial interval (ITI) were randomly varied at the range of 1000 ~ 1400 ms.

All the stimuli were presented on a gray background (RGB: 127, 127, 127). E-primed 2.0 was used to present stimuli and collect behavioral results. Data were collected and analyzed when accuracy performance in total reached 60%.

Data Analysis. Data was analyzed as in experiment 1a.

Results.

NHST.

Only the behavioral results were reported here. Figure 13 shows *d* prime and reaction times of experiment 6a.

d prime.

We conducted repeated measures ANOVA, with moral valence as independent variable. The results revealed the main effect of valence ($F(1.74, 40.05) = 3.76$,

$MSE = 0.10$, $p = .037$, $\hat{\eta}^2_G = .021$). Post-hoc analysis revealed that shapes link with Good person (mean = 3.13, SE = 0.109) is greater than Neutral condition (mean = 2.88, SE = 0.14),t = 2.916, *df* = 24, p = 0.02, p-value adjusted by Tukey method, but the d prime between Good and bad (mean = 3.03, SE = 0.142) (t = 1.512, *df* = 24, p = 0.3034, p-value adjusted by Tukey method), bad and neutral (t = 1.599, *df* = 24, p = 0.2655, p-value adjusted by Tukey method) were not significant.

Reaction times.

The results of reaction times of matchness trials showed similar pattern as the d prime data.

We found intercation between Matchness and Valence ($F(1.97, 45.20) = 20.45$, $MSE = 450.47$, $p < .001$, $\hat{\eta}^2_G = .021$) and then analyzed the matched trials and mismatched trials separately, as in experiment 2. For matched trials, we found the effect of valence $F(1.97, 45.25) = 32.37$, $MSE = 522.42$, $p < .001$, $\hat{\eta}^2_G = .078$. For non-matched trials, there was no significant effect of Valence ($F(1.77, 40.67) = 0.35$, $MSE = 242.15$, $p = .679$, $\hat{\eta}^2_G = .000$). Post-hoc t-tests revealed that shapes associated with Good Person (mean = 550, SE = 13.8) were responded faster than Neutral-Person (501, SE = 14.7), (t(24) = -5.171, p = 0.0001) and Bad Person (523, SE = 16.3), t(24) = -8.137, p < 0.0001)., and Neutral is faster than Bad-Person condition (t(32) = -3.282, p = 0.0085).

BGLM.

Signal detection theory analysis of accuracy.

Reaction time.

Part 2: interaction between valence and identity

In this part, we report four experiments that aimed at testing whether the positivity effect found in the previous experiment can be modulated by the self-referential processing.

Experiment 3a

To examine the modulation effect of positive valence was an intrinsic, self-referential process, we designed study 3. In this study, moral valence was assigned to both self and a stranger. We hypothesized that the modulation effect of moral valence will be stronger for the self than for a stranger.

Method.

Participants.

38 college students (15 female, age = 21.92 ± 2.16) participated in experiment 3a. All of them were right-handed, and all had normal or correted-to-normal vision. Informed consent was obtained from all participants prior to the experiment according to procedures approved by a local ethics committee. One female and one male student did not finish the experiment, and 1 participants' data were excluded from analysis because less than 60% overall accuracy, remains 35 participants (13 female, age = 22.11 ± 2.13).

Design.

Study 3a combined moral valence with self-relevance, hence the experiment has a $2 \times 3 \times 2$ within-subject design. The first variable was self-relevance, include two levels: self-relevance vs. stranger-relevance; the second variable was moral valence, include good, neutral and bad; the third variable was the matching between shape and label: match vs. nonmatch.

Stimuli.

The stimuli used in study 3a share the same parameters with experiment 1 & 2. The differences was that we used six shapes: triangle, square, circle, trapezoid, diamond, regular pentagon, and six labels: good self, neutral self, bad self, good person, bad person, and neutral person. To match the concreteness of the label, we asked participant to chosen an unfamiliar name of their own gender to be the stranger.

Procedure.

After being fully explained and signed the informed consent, participants were instructed to chose a name that can represent a stranger with same gender as the participant themselves, from a common Chinese name pool. Before experiment, the experimenter explained the meaning of each label to participants. For example, the "good self" mean the morally good side of themselves, them could imagine the moment when they do something's morally applauded, "bad self" means the morally bad side of themselves, they could also imagine the moment when they doing something morally wrong, and "neutral self" means the aspect of self that does not related to morality, they could imagine the moment when they doing something irrelevant to morality. In the same sense, the "good other", "bad other", and "neutral other" means the three different aspects of the stranger, whose name was chosen before the experiment. Then, the experiment proceeded as study 1a. Each participant finished 6 blocks, each have 120 trials. The sequence of trials was pseudo-randomized so that there are 10 matched trials for each condition and 10 non-matched trials for each condition (good self, neutral self, bad self, good other, neutral other, bad other) for each block.

Data Analysis.

Data analysis followed strategies described in the general method section. Reaction times and *d* prime data were analyzed as in study 1 and study 2, except that one more within-subject variable (i.e., self-relevance) was included in the analysis.

Results.

NHST.

Figure 15 shows *d* prime and reaction times of experiment 3a. Less than 5% correct trials with less than 200ms reaction times were excluded.

d prime.

There was evidence for the main effect of valence, $F(1.89, 64.37) = 11.09$, $MSE = 0.23$, $p < .001$, $\hat{\eta}^2_G = .039$, and main effect of self-relevance, $F(1, 34) = 3.22$, $MSE = 0.54$, $p = .082$, $\hat{\eta}^2_G = .015$, as well as the interaction, $F(1.79, 60.79) = 3.39$, $MSE = 0.43$, $p = .045$, $\hat{\eta}^2_G = .022$.

We then conducted separated ANOVA for self-referential and other-referential trials. The valence effect was shown for the self-referential conditions, $F(1.65, 56.25) = 13.98$, $MSE = 0.31$, $p < .001$, $\hat{\eta}^2_G = .119$. Post-hoc test revealed that the Good-Self condition (1.97 ± 0.14) was with greater d prime than Netural condition (1.41 ± 0.12, $t(34) = 4.505$, $p = 0.0002$), and Bad-self condition (1.43 ± 0.102), $t(34) = 3.856$, $p = 0.0014$. There was difference between neutral and bad condition, $t(34) = -0.238$, $p = 0.9694$. However, no effect of valence was found for the other-referential condition $F(1.98, 67.36) = 0.38$, $MSE = 0.35$, $p = .681$, $\hat{\eta}^2_G = .004$.

Reaction time.

We found interaction between Matchness and Valence ($F(1.98, 67.44) = 26.29$, $MSE = 730.09$, $p < .001$, $\hat{\eta}^2_G = .025$) and then analyzed the matched trials and nonmatch trials separately, as in previous experiments.

For the match trials, we found that the interaction between identity and valence, $F(1.72, 58.61) = 3.89$, $MSE = 2,750.19$, $p = .032$, $\hat{\eta}^2_G = .019$, as well as the main effect of valence $F(1.98, 67.34) = 35.76$, $MSE = 1,127.25$, $p < .001$, $\hat{\eta}^2_G = .079$, but not the effect of identity $F(1, 34) = 0.20$, $MSE = 3,507.14$, $p = .660$, $\hat{\eta}^2_G = .001$. As for the d prime, we separated analyzed the self-referential and other-referential trials. For the Self-referential trials, we found the main effect of valence, $F(1.80, 61.09) = 30.39$, $MSE = 1,584.53$, $p < .001$, $\hat{\eta}^2_G = .159$; for the other-referential trials, the effect of valence is weaker, $F(1.86, 63.08) = 2.85$, $MSE = 2,224.30$, $p = .069$, $\hat{\eta}^2_G = .024$. We then focused on the self conditions: the good-self condition (713 ± 12) is faster than neutral- (776 ± 11.8), $t(34) =$ -7.396, $p < .0001$, and bad-self (772 ± 10.1) conditions, $t(34) =$ -5.66, $p < .0001$. But there is not difference between neutral- and bad-self conditions, $t(34) = 0.481$, $p = 0.881$.

For the nonmatch trials, we didn't found any strong effect: identity, $F(1, 34) = 3.43$, $MSE = 660.02$, $p = .073$, $\hat{\eta}^2_G = .004$, valence $F(1.89, 64.33) = 0.40$, $MSE = 444.10$, $p = .661$, $\hat{\eta}^2_G = .001$, or interaction between the two $F(1.94, 66.02) = 2.42$, $MSE = 817.35$, $p = .099$, $\hat{\eta}^2_G = .007$.

BGLM.

Signal detection theory analysis of accuracy.

We found that the d prime is greater when shapes were associated with good self condition than with neutral self or bad self, but shapes associated with bad self and neutral self didn't show differences. comparing the self vs other under three condition revealed that shapes associated with good self is greater than with good other, but with a weak evidence. In contrast, for both neutral and bad valence condition, shapes associated with other had greater d prime than with self.

Reaction time.

In reaction times, we found that same trends in the match trials as in the d prime: while the shapes associated with good self was greater than with good other (log mean diff = -0.02858, 95%HPD[-0.070898, 0.0154]), the direction is reversed for neutral and negative condition. see Figure 16

HDDM. We fitted our data with HDDM, using the response-coding (also see Hu et al., 2020). We estimated separate drift rate (v), non-decision time (T_0), and boundary separation (a) for each condition. We found that the shapes tagged with good person has higher drift rate and higher boundary separation than shapes tagged with both neutral and bad person. Also, the shapes tagged with neutral person has a higher drift rate than shapes tagged with bad person, but not for the boundary separation. Finally, we found that shapes tagged with bad person had longer non-decision time (see figure 17)).

Results

Effect of moral valence

In this part, we synthesized results from experiment 1a, 1b, 1c, 2, 5 and 6a. Data from 192 participants were included in these analyses. We found differences between positive and negative conditions on RT was Cohen's d = -0.58 ± 0.06, 95% CI [-0.70 -0.47]; on *d'* was Cohen's d = 0.24 ± 0.05, 95% CI [0.15 0.34]. The effect was also observed between positive and neutral condition, RT: Cohen's d = -0.44 ± 0.10, 95% CI [-0.63 -0.25]; *d'*: Cohen's d = 0.31 ± 0.07, 95% CI [0.16 0.45]. And the difference between neutral and bad conditions are not significant, RT: Cohen's d = 0.15 ± 0.07, 95% CI [0.00 0.30]; *d'*: Cohen's d = 0.07 ± 0.07, 95% CI [-0.08 0.21]. See Figure 18 left panel.

Interaction between valence and self-reference

In this part, we combined the experiments that explicitly manipulated the self-reference and valence, which includes 3a, 3b, 6b, 7a, and 7b. For the positive versus negative contrast, data were from five experiments with 178 participants; for positive versus neutral and neutral versus negative contrasts, data were from three experiments (3a, 3b, and 6b) with 108 participants.

In most of these experiments, the interaction between self-reference and valence was significant (see results of each experiment in supplementary materials). In the mini-meta-analysis, we analyzed the valence effect for self-referential condition and other-referential condition separately.

For the self-referential condition, we found the same pattern as in the first part of results. That is we found significant differences between positive and neutral as well as positive and negative, but not neutral and negative. The effect size of RT between positive and negative is Cohen's d = -0.89 ± 0.12, 95% CI [-1.11 -0.66]; on *d'* was Cohen's d = 0.61

$\pm$ 0.09, 95% CI [0.44 0.78]. The effect was also observed between positive and neutral condition, RT: Cohen's d = -0.76 $\pm$ 0.13, 95% CI [-1.01 -0.50]; d': Cohen's d = 0.69 $\pm$ 0.14, 95% CI [0.42 0.96]. And the difference between neutral and bad conditions are not significant, RT: Cohen's d = 0.03 $\pm$ 0.13, 95% CI [-0.22 0.29]; d': Cohen's d = 0.08 $\pm$ 0.08, 95% CI [-0.07 0.24]. See Figure 18 the middle panel.

For the other-referential condition, we found that only the difference between positive and negative on RT was significant, all the other conditions were not. The effect size of RT between positive and negative is Cohen's d = -0.28 $\pm$ 0.05, 95% CI [-0.38 -0.17]; on d' was Cohen's d = -0.02 $\pm$ 0.08, 95% CI [-0.17 0.13]. The effect was not observed between positive and neutral condition, RT: Cohen's d = -0.12 $\pm$ 0.10, 95% CI [-0.31 0.06]; d': Cohen's d = 0.01 $\pm$ 0.08, 95% CI [-0.16 0.17]. And the difference between neutral and bad conditions are not significant, RT: Cohen's d = 0.14 $\pm$ 0.09, 95% CI [-0.03 0.31]; d': Cohen's d = 0.05 $\pm$ 0.07, 95% CI [-0.08 0.18]. See Figure 18 right panel.

Generalizibility of the valence effect

In this part, we reported the results from experiment 4 in which either moral valence or self-reference were manipulated as task-irrelevant stimuli.

For experiment 4a, when self-reference was the target and moral valence was task-irrelevant, we found that only under the implicit self-referential condition, i.e., when the moral words were presented as task irrelevant stimuli, there was the main effect of valence and interaction between valence and reference for both d prime and RT (See supplementary results for the detailed statistics). For d prime, we found good-self condition (2.55 $\pm$ 0.86) had higher d prime than bad-self condition (2.38 $\pm$ 0.80); good self condition was also higher than neutral self (2.45 $\pm$ 0.78) but there was not statistically significant, while the neutral-self condition was higher than bad self condition and not significant neither. For reaction times, good-self condition (654.26 $\pm$ 67.09) were faster relative to bad-self condition (665.64 $\pm$ 64.59), and over neutral-self condition (664.26 $\pm$ 64.71). The difference between neutral-self and bad-self conditions were not significant. However, for the other-referential condition, there was no significant differences between different valence conditions. See Figure 19.

For experiment 4b, when valence was the target and the identity was task-irrelevant, we found a strong valence effect (see supplementary results and Figure 20, Figure 21).

In this experiment, the advantage of good-self condition can only be disentangled by comparing the self-referential and other-referential conditions. Therefore, we calculated the differences between the valence effect under self-referential and other referential conditions and used the weighted variance as the variance of this differences. We found this modulation effect on RT. The valence effect of RT was stronger in self-referential than other-referential for the Good vs. Neutral condition (-0.33 $\pm$ 0.01), and to a less extent the Good vs. Bad condition (-0.17 $\pm$ 0.01). While the size of the other effect's CI included zero, suggestion those effects didn't differ from zero. See Figure 22.

Specificity of valence effect

In this part, we analyzed the results from experiment 5, which included positive, neutral, and negative valence from four different domains: morality, emotion, aesthetics of human, and aesthetics of scene. We found interaction between valence and domain for both d prime and RT (match trials). A common pattern appeared in all four domains: each domain showed a binary results instead of gradient on both d prime and RT. For morality, aesthetics of human, and aesthetics of scene, the positive conditions had advantages over both neutral and negative conditions (greater d prime and faster RT), and neutral and negative conditions didn't differ from each other. But for the emotional stimuli, it was the positive and neutral had advantage over negative conditions, while positive and neutral conditions were not significantly different. See supplementary materials for detailed statistics. Also note that the effect size in moral domain is smaller than the aesthetic domains (beauty of people and beauty of scene). See Figure 23.

Self-reported personal distance

See Figure 24.

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.

We focused on the task-questionnaire correlation, the results revealed that the score from three questionnaire are related to behavioral responses data. First, the external moral identity is positively correlated with boundary separation of moral good condition, $r = 0.194$, 95% CI [0.023 0.350]); the moral self image is positively correlated with the drift rate ($r = 0.191$, 95% CI [-0.016 0.354]) of the morally good condition. See Figure 25.

Second, we found the personal distance between self and good is positively correlated with the boundary separation of neutral condition and the self-neutral distance is negatively correlated with the boundary separation of neutral condition. See figure 26

Third, we found the self esteem score was negative correlated with the d' of bad conditions ($r = -0.16$, 95% CI [-0.277 -0.038]) and the neutral conditions ($r = -.197$, 95% CI [-0.348 -0.026]). See Figure 27.

We also explored the correlation between behavioral data and questionnaire scores separately for experiments with and without self-referential. For experiments without self-referential (Valence effect), we found the personal distance between Good-person and self is positively correlated with boundary separation of good conditions, r = 0.292, 95% [0.071 0.485]. also personal distance between the bad and neutral person is positively correlated with non-responding time of bad and neutral conditions, r = 0.249, 0.233, respectively.

For experiments with self-referential (Valence effect for the self), we found self-esteem is negatively correlated with d prime of neutral condition, r = -0.272, [-0.468 -0.052], the self-good distance is positively correlated with d prime for Bad condition, r = 0.185, 95%CI[0.004 0.354].

Discussion

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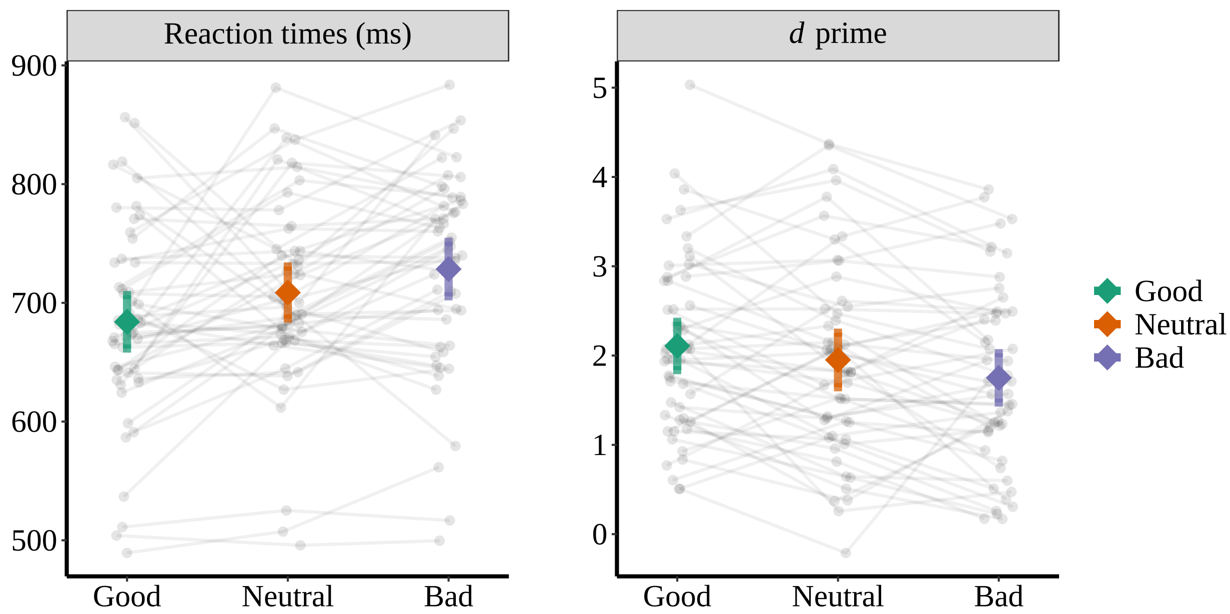

Figure 1. RT and *d* prime of Experiment 1a.

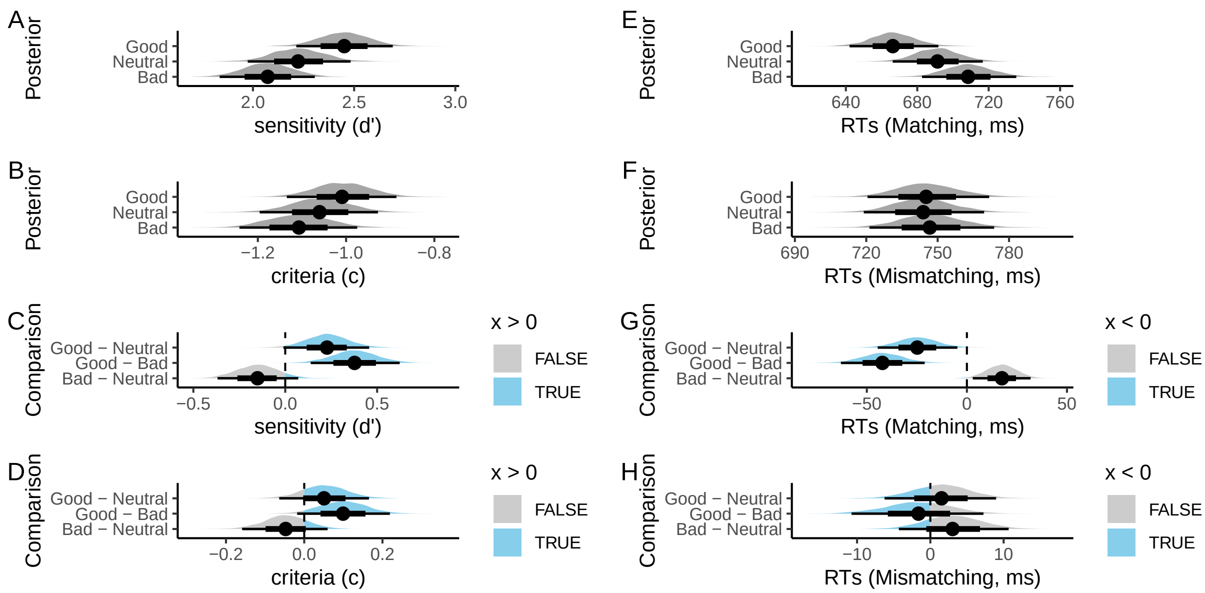

Figure 2. Exp1a: Results of Bayesian GLM analysis.

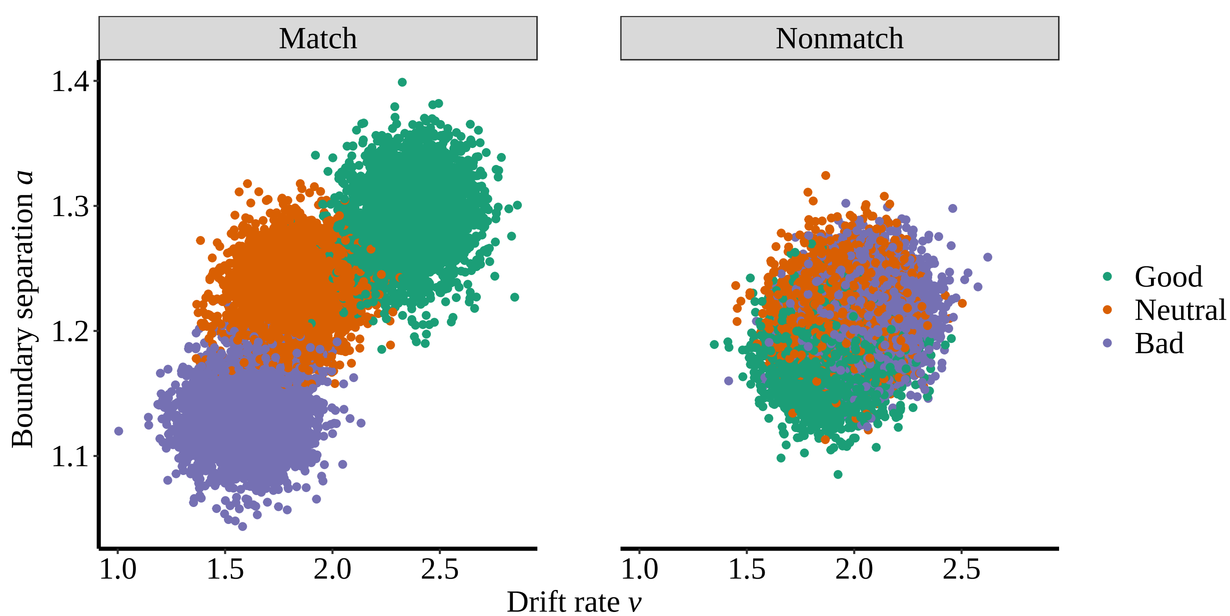

Figure 3. Exp1a: Results of HDDM.

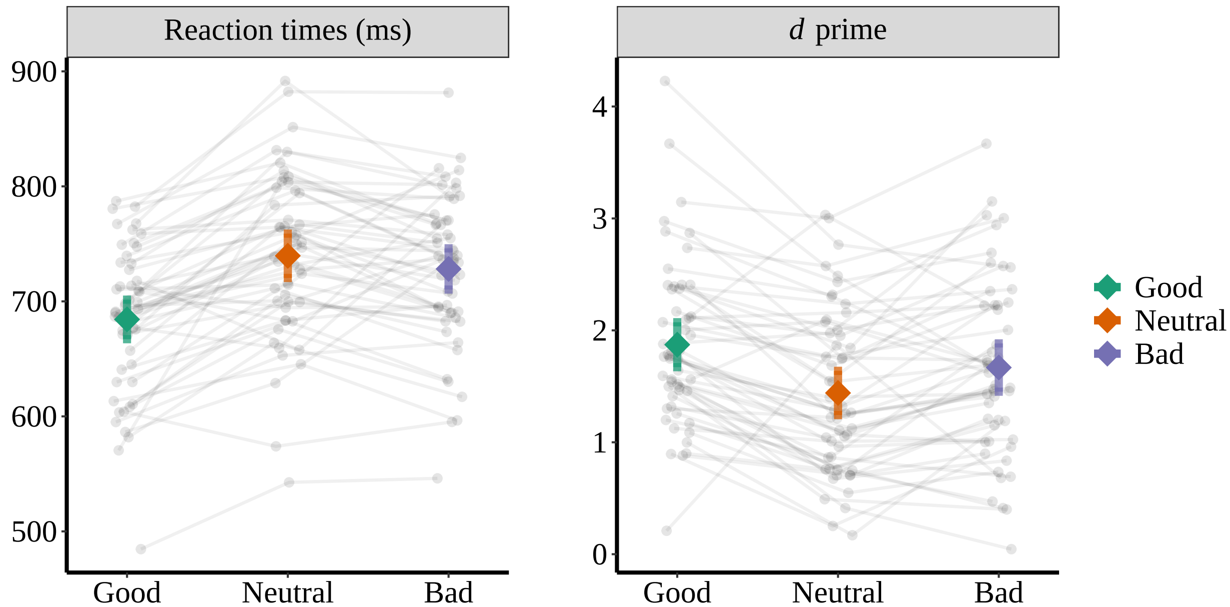

Figure 4. RT and d prime of Experiment 1b.

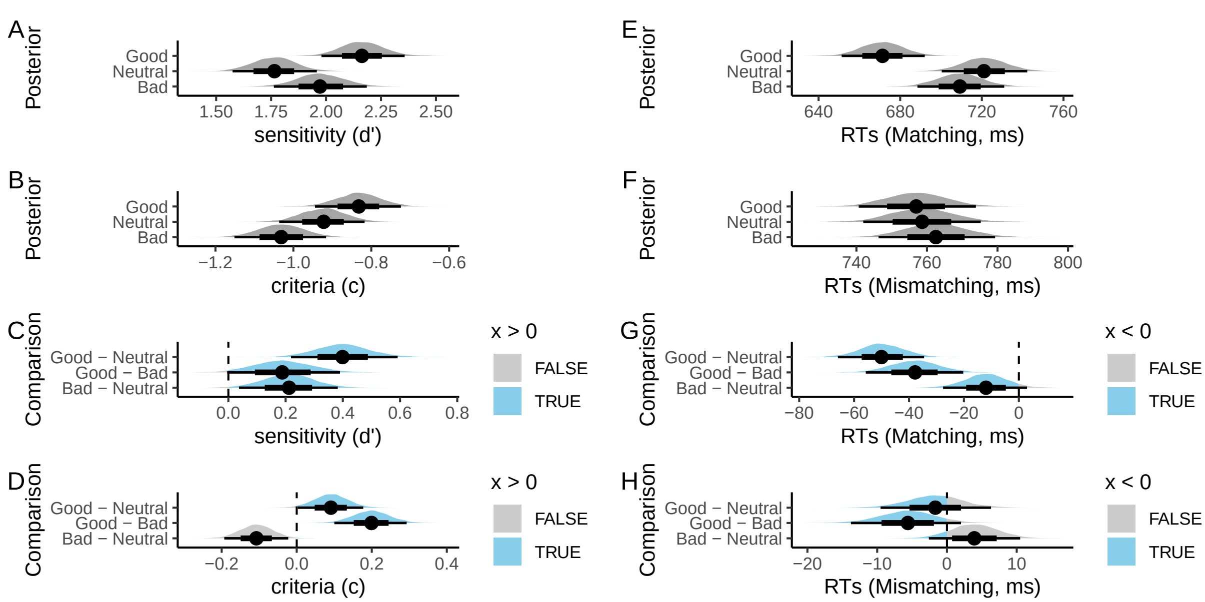

Figure 5. Exp1b: Results of Bayesian GLM analysis.

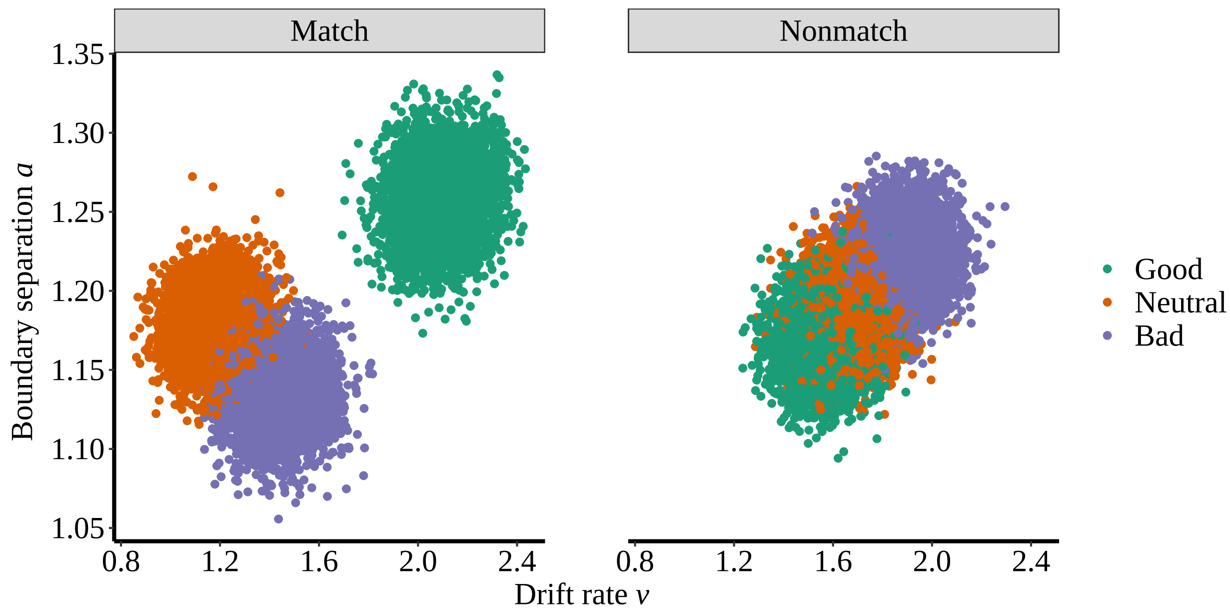

Figure 6. Exp1b: Results of HDDM.

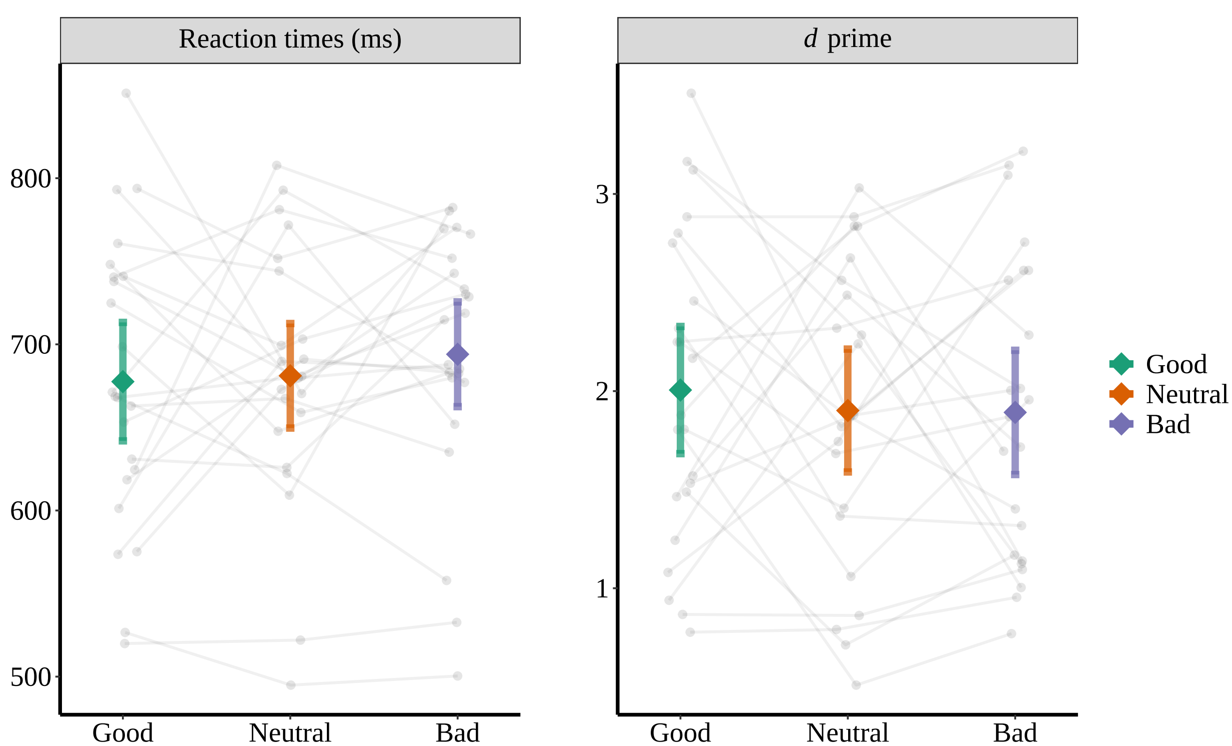

Figure 7. RT and d prime of Experiment 1c.

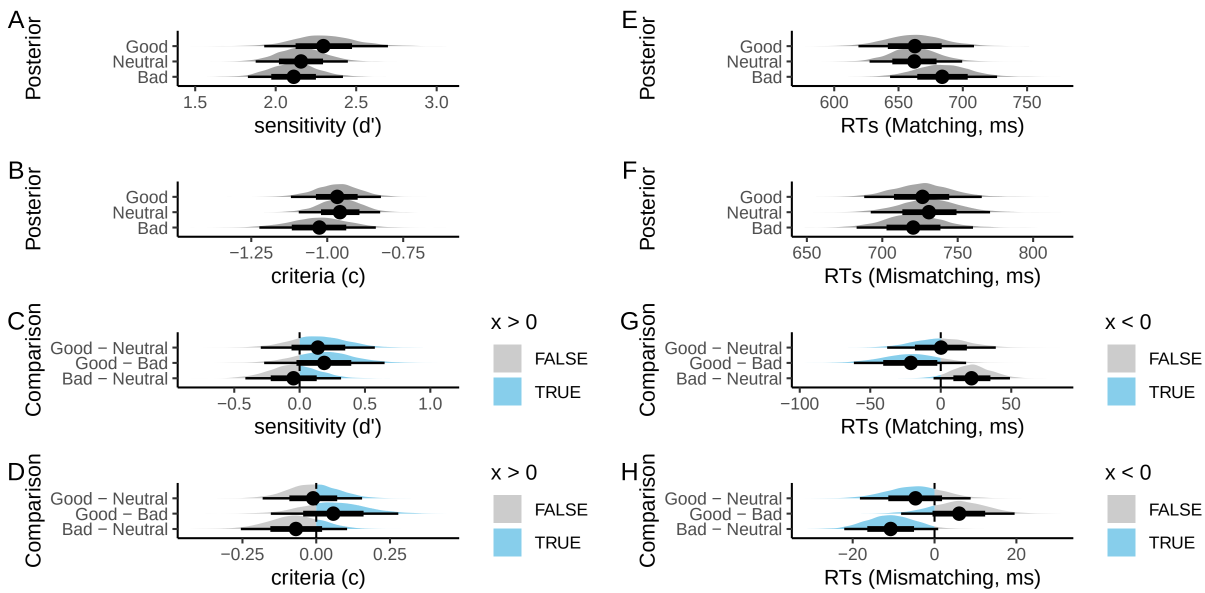

Figure 8. Exp1c: Results of Bayesian GLM analysis.

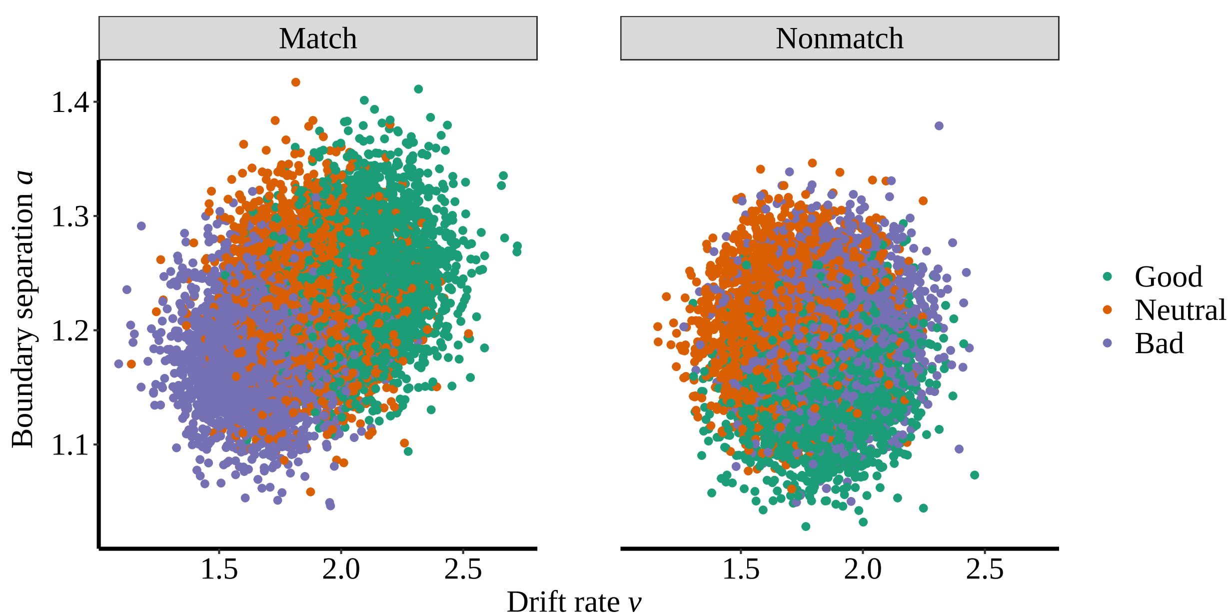

Figure 9. Exp1c: Results of HDDM.

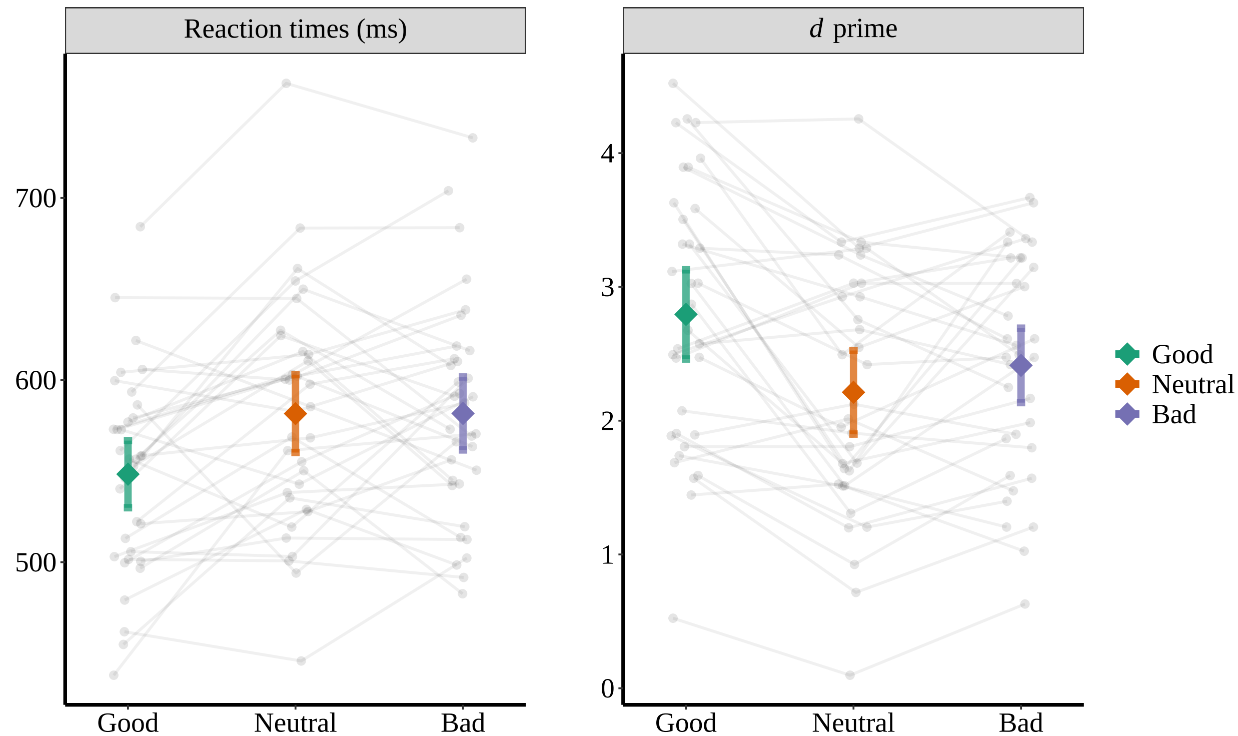

Figure 10. RT and *d* prime of Experiment 2.

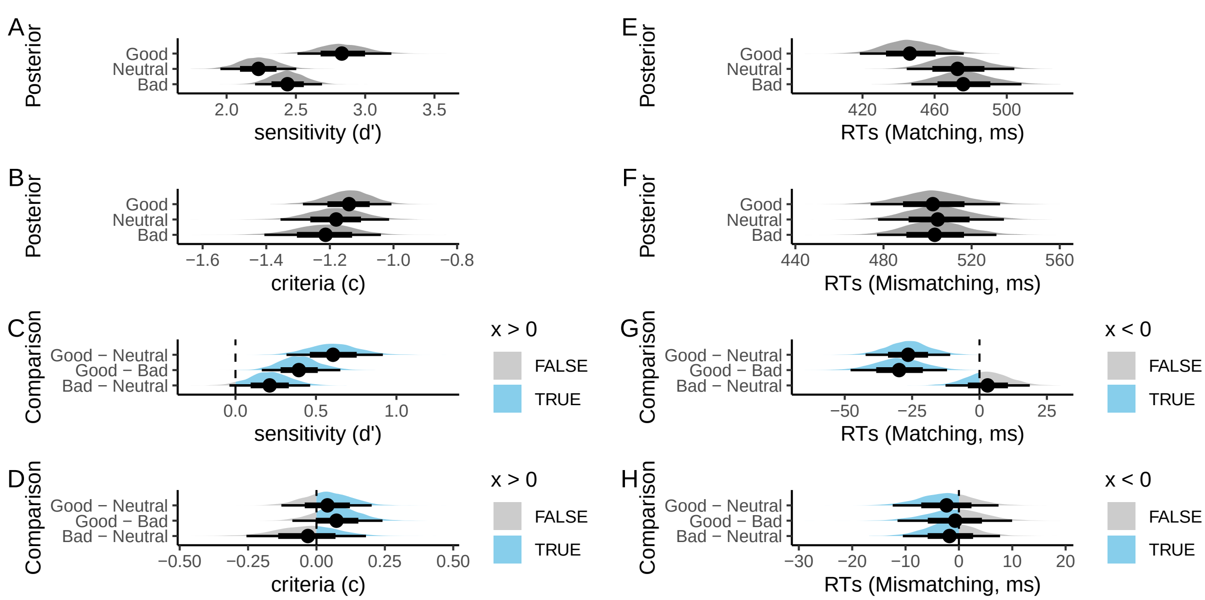

Figure 11. Exp2: Results of Bayesian GLM analysis.

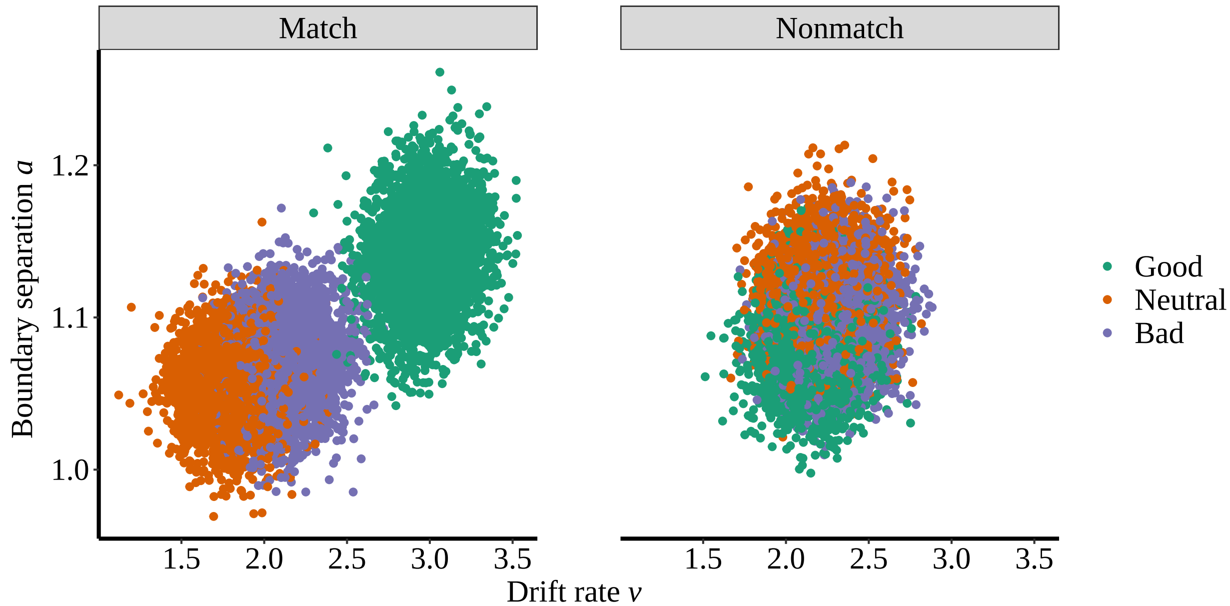

Figure 12. Exp2: Results of HDDM.

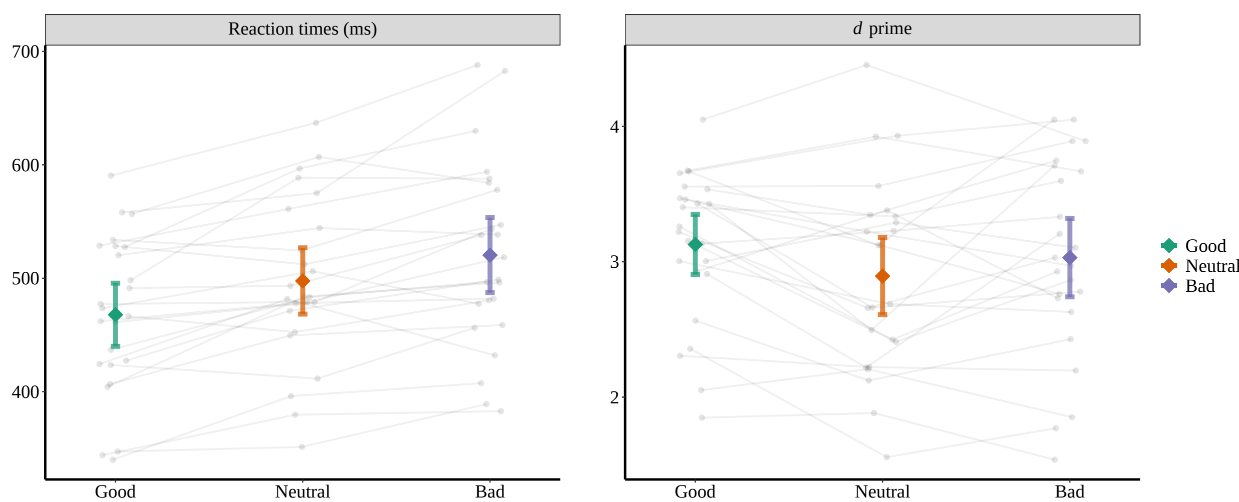

Figure 13. RT and *d* prime of Experiment 6a.

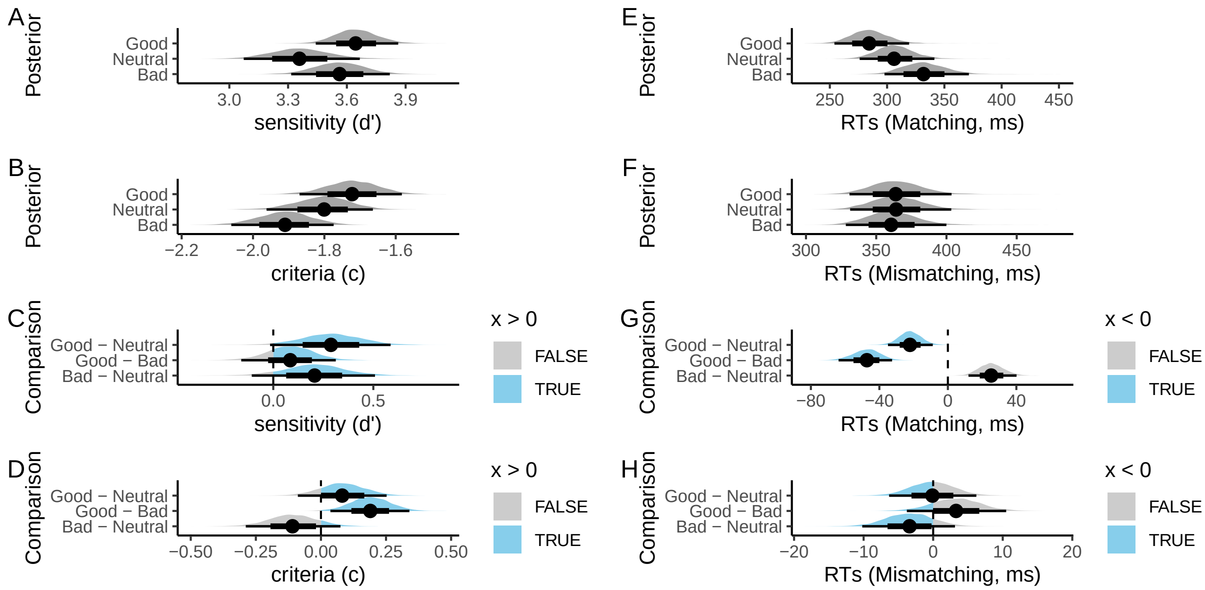

Figure 14. Exp1b: Results of Bayesian GLM analysis.

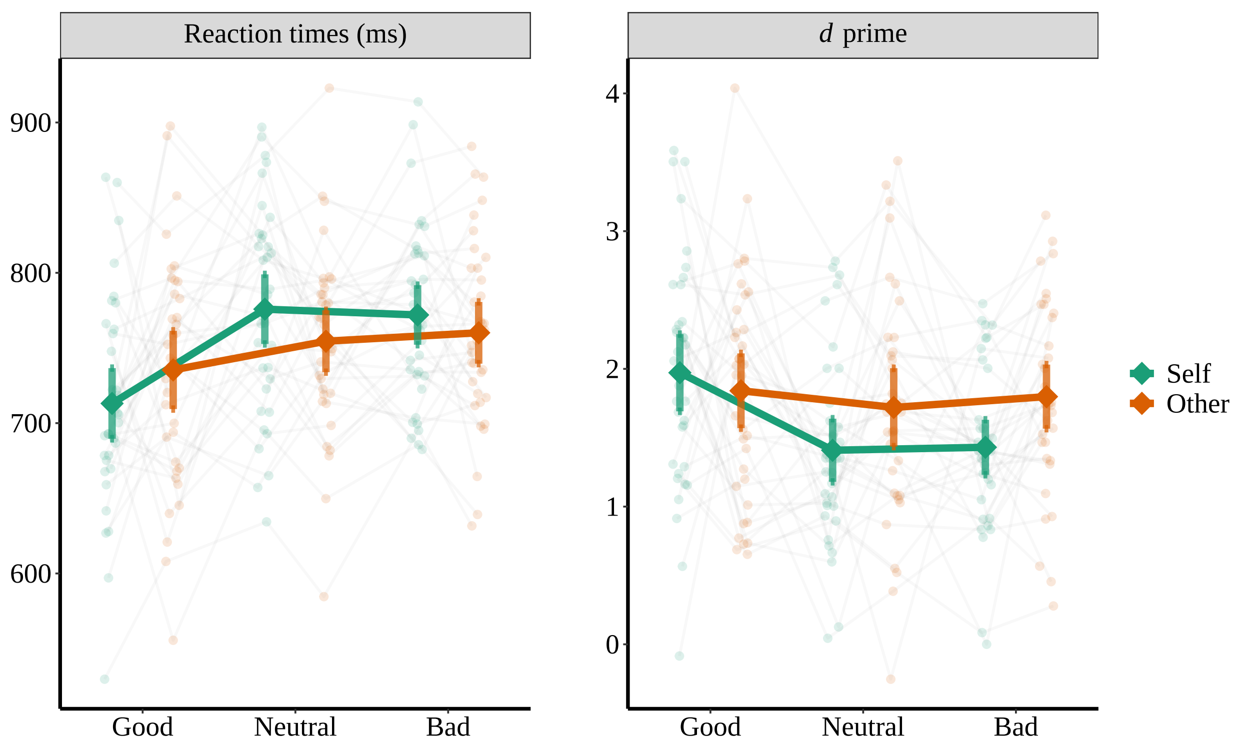

Figure 15. RT and *d* prime of Experiment 3a.

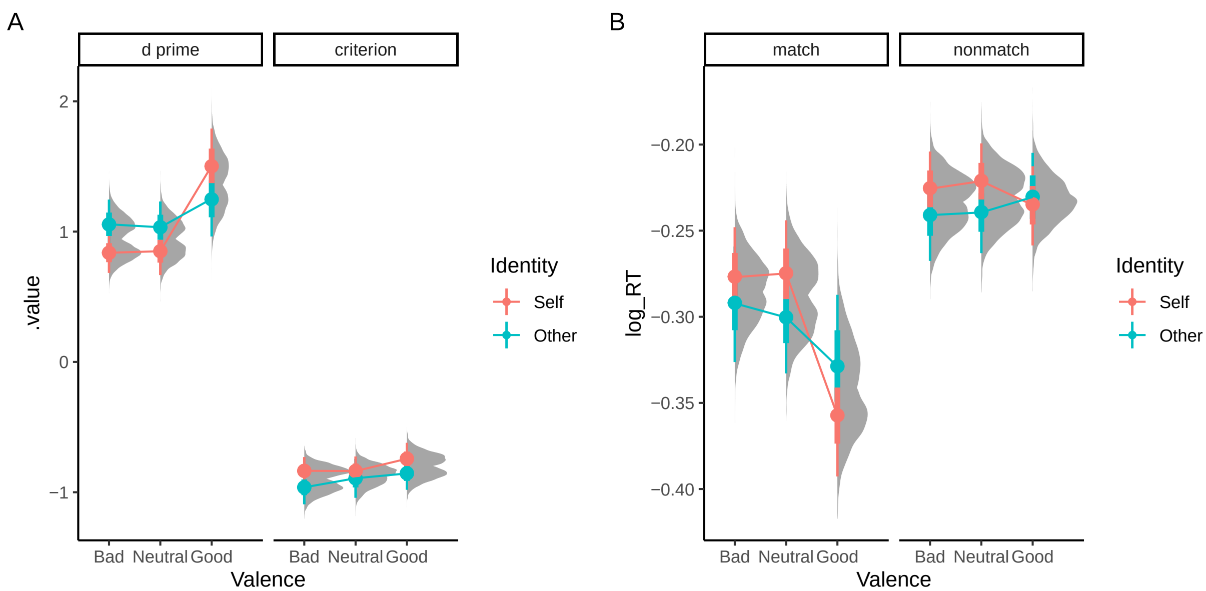

Figure 16. Exp3a: Results of Bayesian GLM analysis.

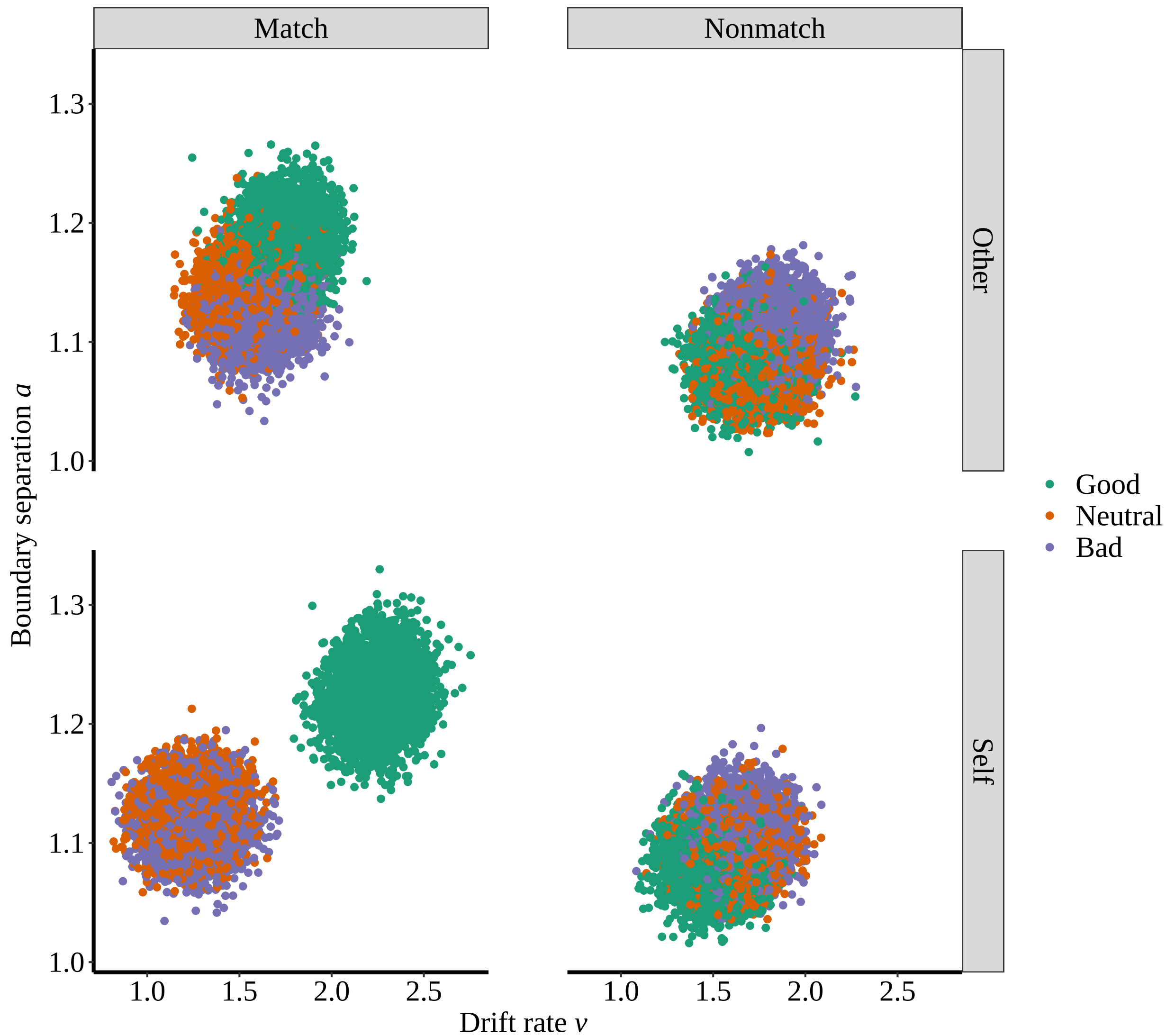

Figure 17. Exp3a: Results of HDDM.

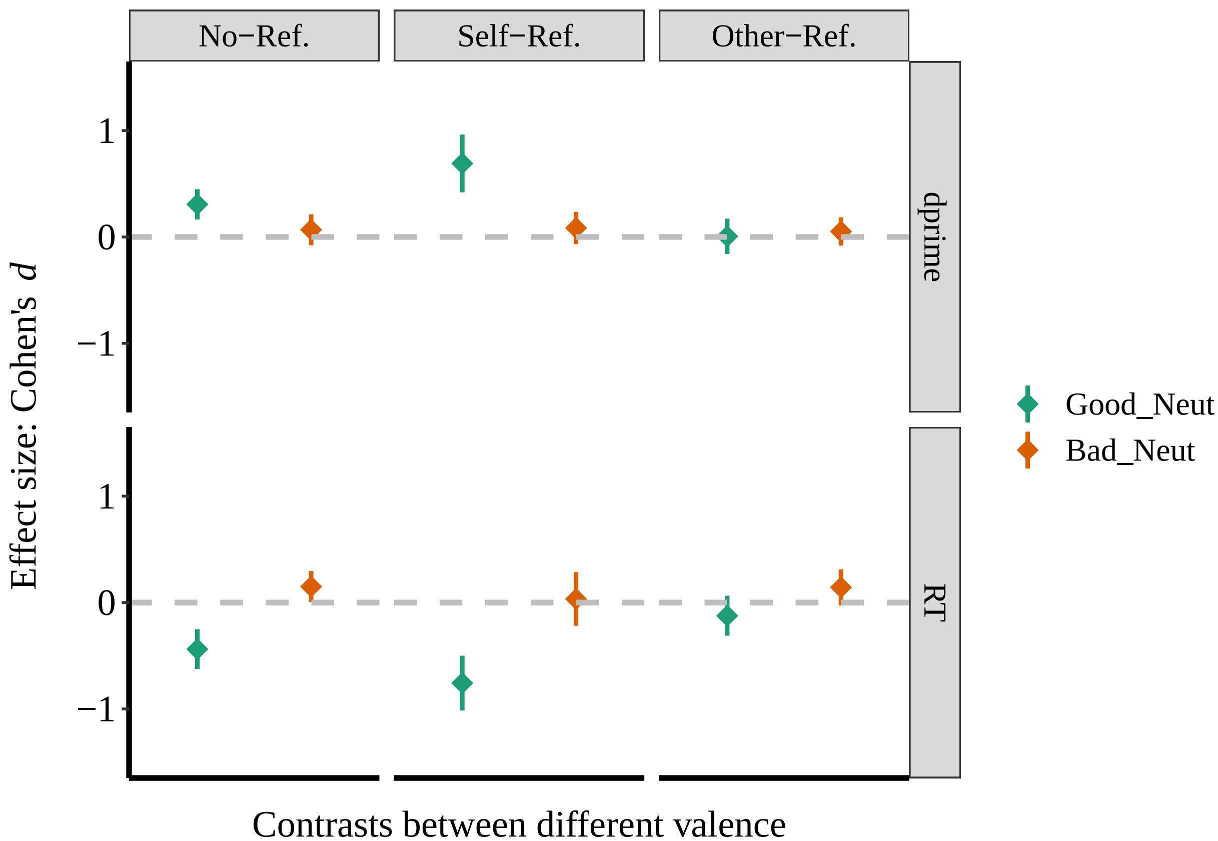

Figure 18. Effect size (Cohen's d) of Valence.

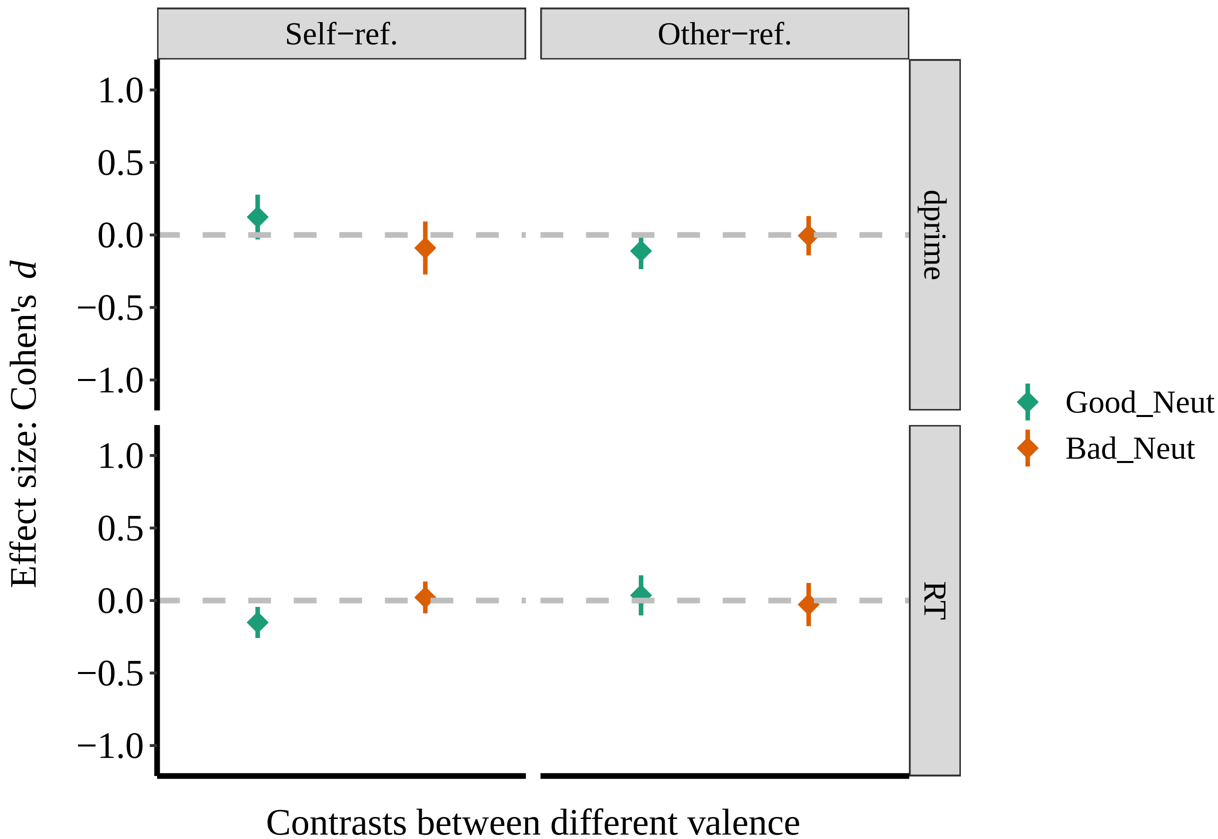

Figure 19. Effect size (Cohen's d) of Valence in Exp4a.

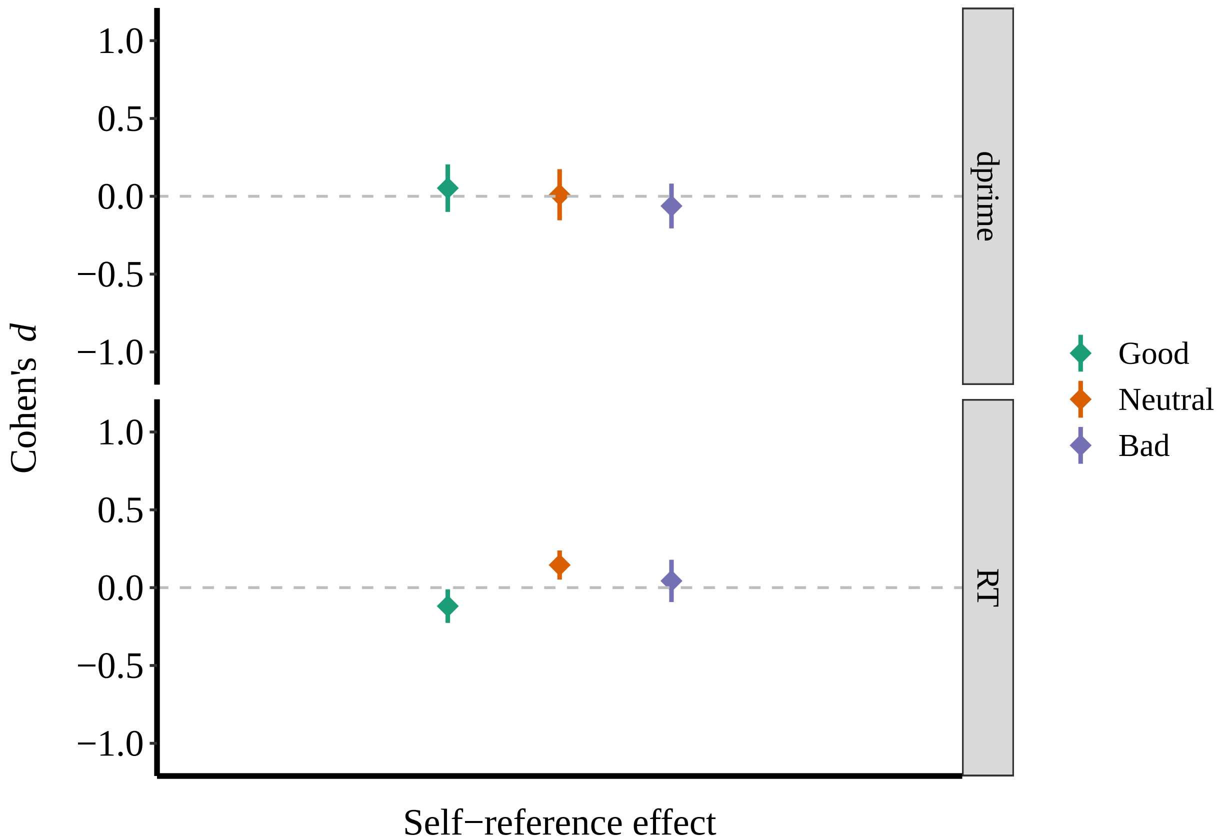

Figure 20. Effect size (Cohen's d) of Valence in Exp4b.

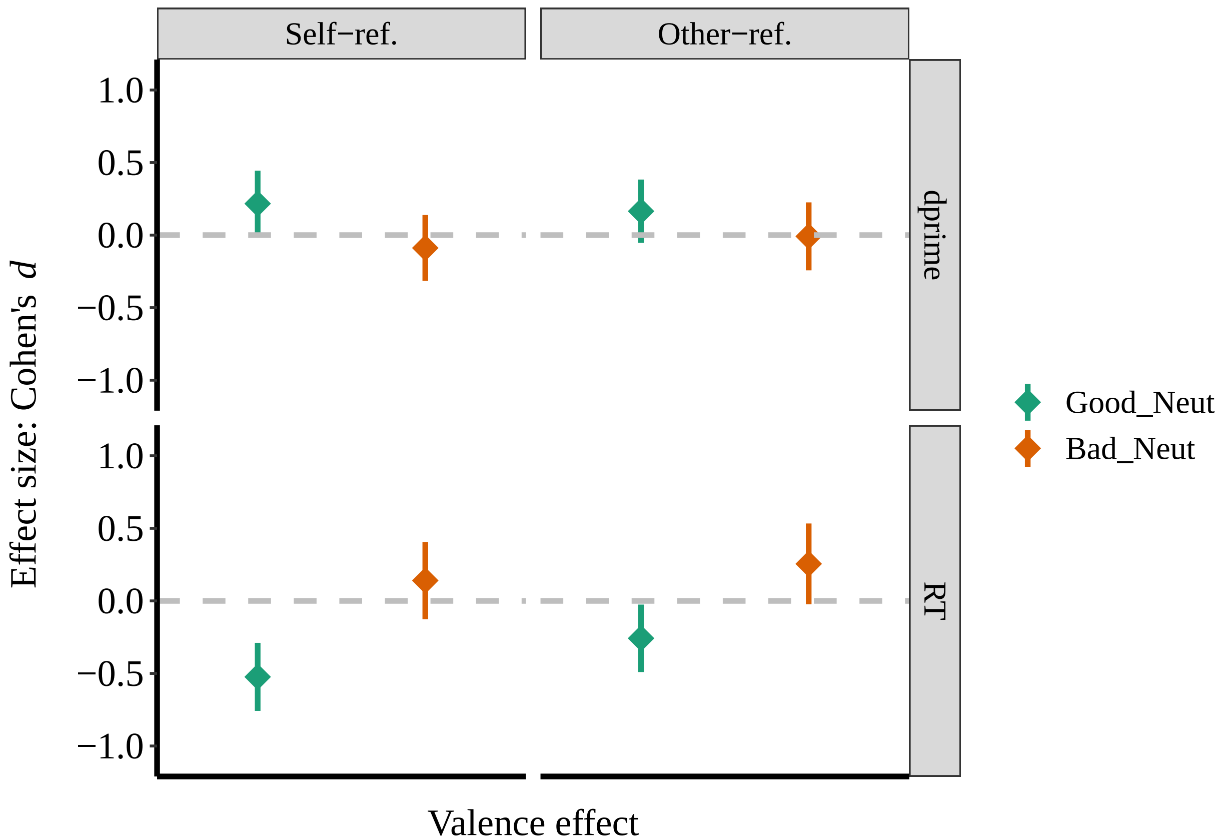

Figure 21. Effect size (Cohen's d) of Valence in Exp4b.

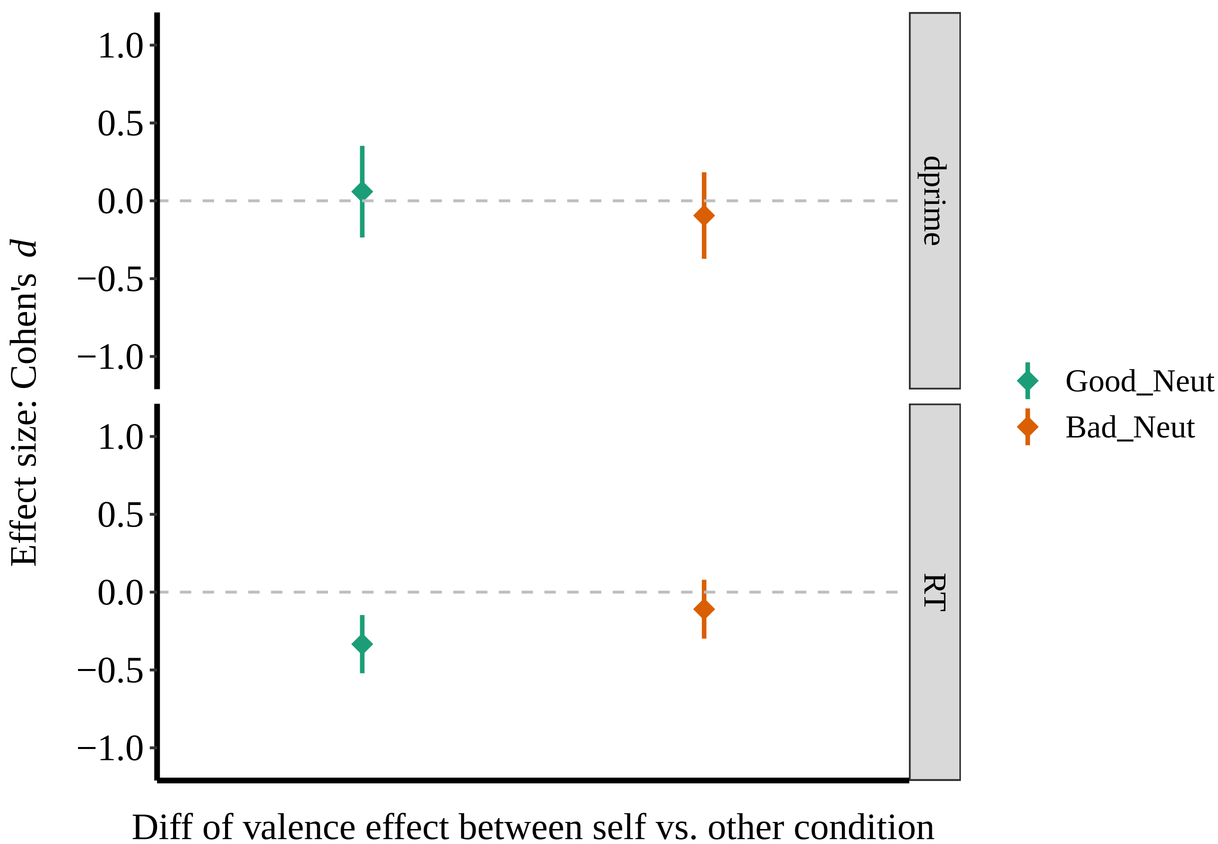

Figure 22. Effect size (Cohen's d) of Valence in Exp4b.

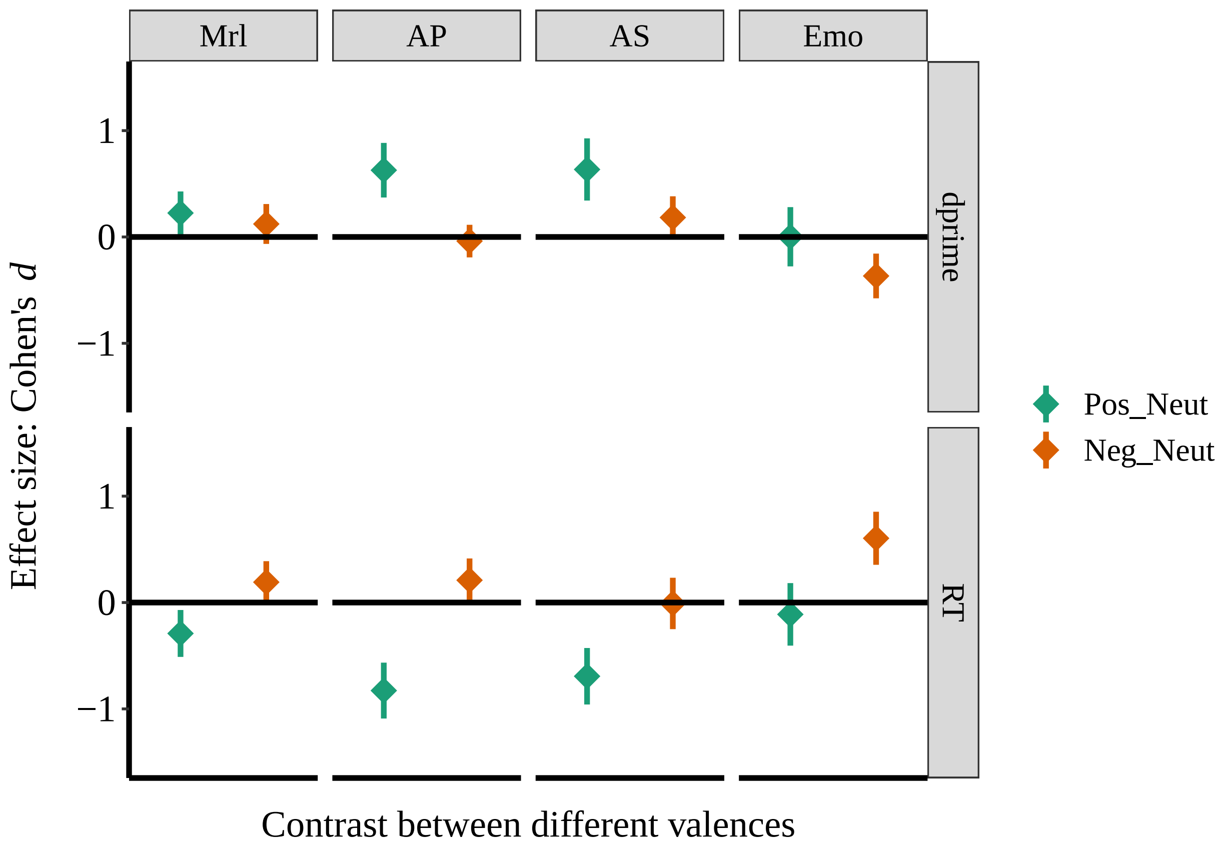

Figure 23. Effect size (Cohen's d) of Valence in Exp5.

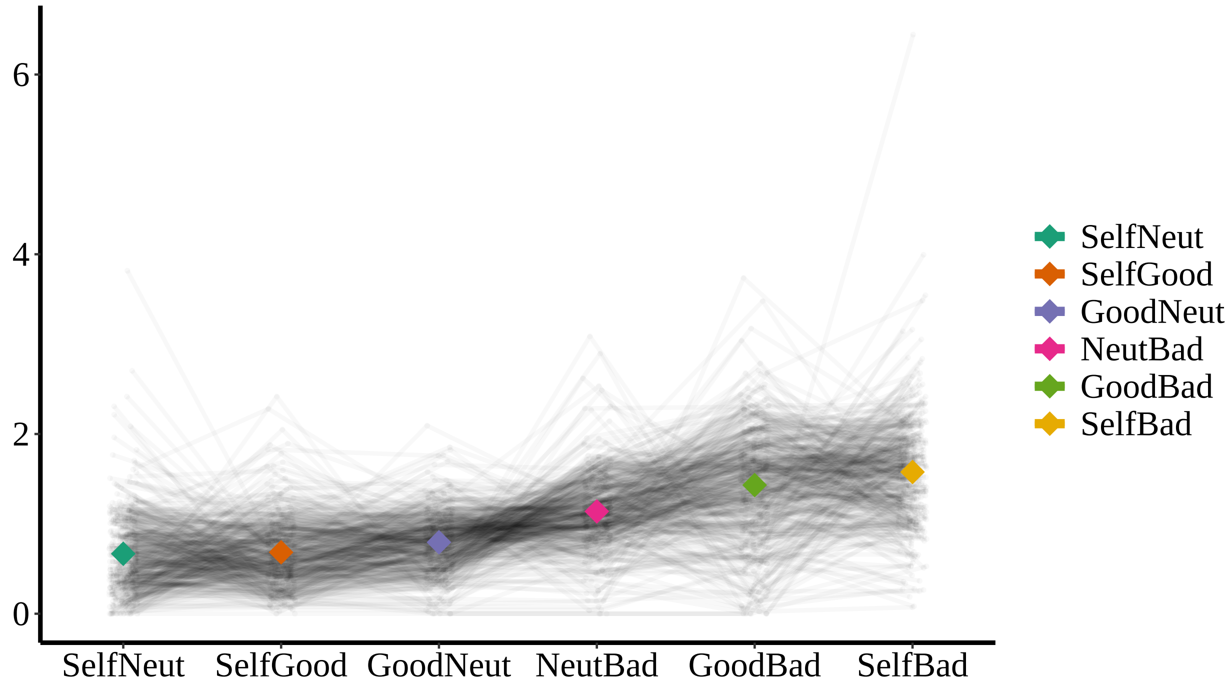

Figure 24. Self-rated personal distance

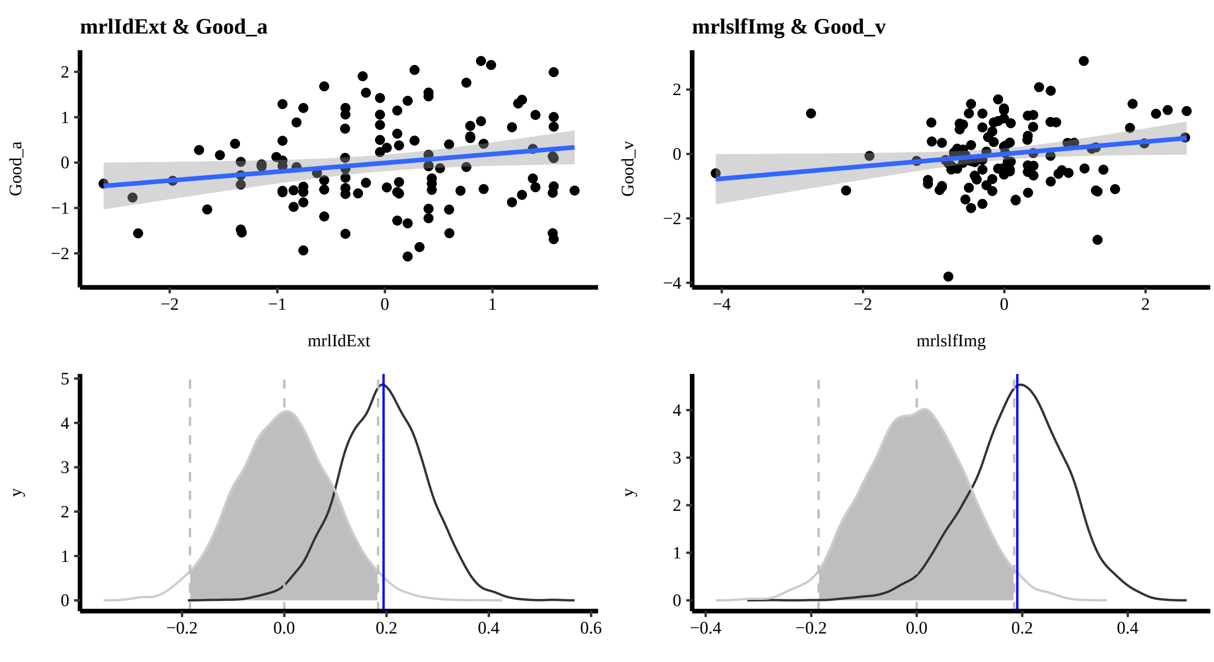

Figure 25. Correlation between moral identity and boundary separation of good condition; moral self-image and drift rate of good condition

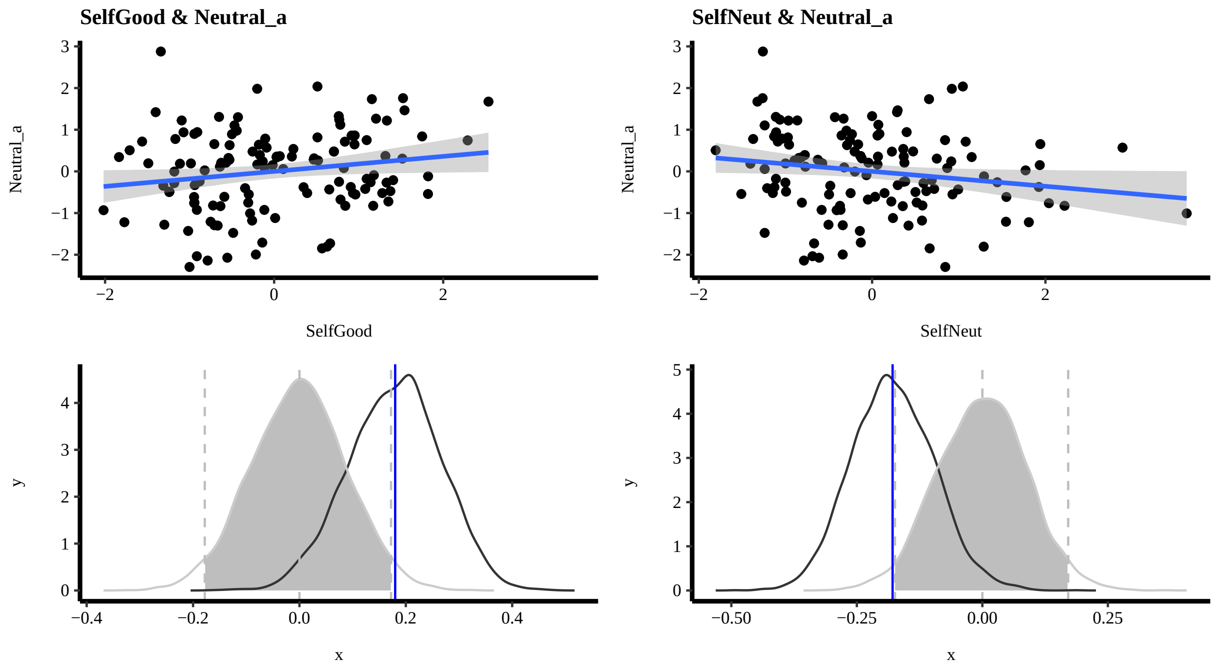

Figure 26. Correlation between personal distance and boundary separation of neutral condition

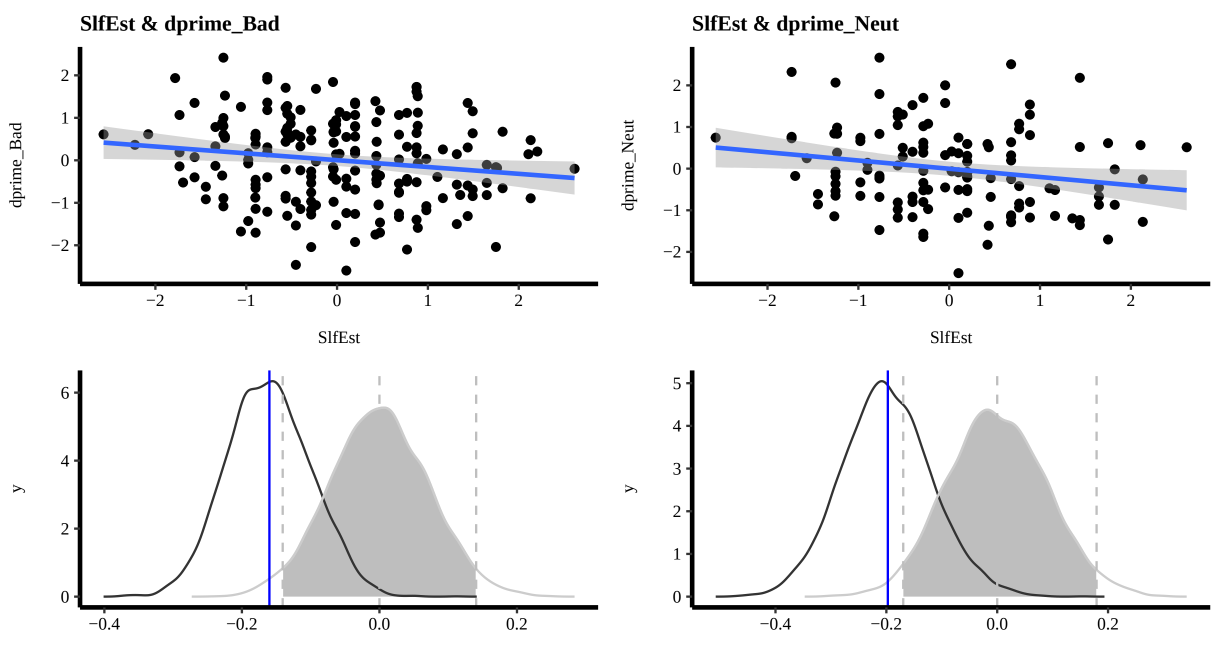

Figure 27. Correlation between self esteem and d prime of bad and neutral conditions