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Hierarchical drift-diffusion modelling uncovers differences of valenced self-evaluation

Nan Wang[1,2] | Kun Shi[1,2] | Jiwen Li[1,2] | Haopeng Chen[1,2] | Jianchao Tang[1,2] | Yadong Liu[1,2] | Xiaolin Zhao[1,2] | Juan Yang[1,2]

[1]Faculty of Psychology, Southwest University, Chongqing, China

[2]Key Laboratory of Cognition and Personality, Ministry of Education, Southwest University, Chongqing, China

Correspondence
Juan Yang, Faculty of Psychology, Southwest University, Chongqing, China.
Email: valleyqq@swu.edu.cn

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Abstract
Differences in valenced self-evaluation refer to positive and negative coexistence in the process of self-evaluation, while there is a clear difference in cognitive processes. The present study aimed to uncover the differences in the latent cognitive parameters (e.g., processing speed) in valenced self-evaluation using the hierarchical drift-diffusion model in two independent experiments. A self-referential decision-making task was applied in both experiments, and a self-descriptiveness task plus the rating of related emotions (e.g., pride and shame) were also used but only in Experiment 2. Results of Experiments 1 & 2 showed a faster processing speed for accepting positive attributes and longer times for encoding and response execution in negative self-evaluation. Moreover, Experiment 2 found cognitive parameters had predictive effects on subsequent decisional outcomes such as self-descriptiveness and self-related emotions via Bayesian inference. The current study provided findings that help to understand the cognitive mechanism behind self-positivity and self-accuracy biases.

KEYWORDS
Bayesian inference, hierarchical drift-diffusion model, self-accuracy bias, self-positivity bias, valenced self-evaluation

1 | INTRODUCTION

A growing number of studies have found people generally adopt different ways of evaluating positive and negative self-related attributes (DeMarree et al., 2011; Hu et al., 2020; Riketta & Ziegler, 2006; Yang et al., 2020), which can also be termed as positive–negative asymmetry in valenced self-evaluation (Wang et al., 2022). For example, people often make fast decisions while evaluating positive self-related traits, while they have slower responses to negative self-evaluation (Ke et al., 2020). Accordingly, people would accept their positive traits more willingly and tend to deny negative self-related traits (Frewen & Lundberg, 2012), but recent studies found complex judgements during negative self-evaluation, showing that people don't always refuse negative traits, and sometimes they might accept their negative parts (Heine et al., 2001; Wang et al., 2022; Yang et al., 2020). This phenomenon even exhibits its influence on the neural level, by showing that the neural pattern of positive self-knowledge mainly included the ventral part of anterior cingulate cortex (ACC), while negative self-knowledge mainly included the ventral and dorsal parts of ACC and cognitive control network (dorsolateral prefrontal cortex: dlPFC) (Chen et al., 2021).

In terms of this positive and negative asymmetry of self-evaluation, researchers believed that two biases associated with self-related processes are the main causes: self-positivity bias and self-accuracy bias (Chen et al., 2021; Wang et al., 2022). The self-positivity bias leads people to believe that they are more positive and less negative, consequently, they are faster and more

Nan Wang and Kun Shi are co-first authors of the article.

receptive when evaluating their positive attributes and slower and more rejective toward the negativity. A recent meta-study demonstrated that people have a larger self-positivity bias toward the positive dimension, which suggests people have a larger tendency toward self-enhancing (accepting positive traits) than self-protecting (rejecting negative traits) (Zell et al., 2019). Moreover, influenced by self-accuracy bias, people embrace their true self by rejecting positive and accepting negative attributes. Previous studies also found this bias was more pronounced for negative self-evaluation, that the likelihood of affirming negativity is higher than rejecting positive traits (Heine et al., 2001; Hermann & Arkin, 2013; Yang et al., 2020).

Traditional behavioural studies have largely investigated both reaction times (RTs) and choices during valenced self-evaluation. For example, the mean values of RTs and choices (accepting rate, self-descriptiveness) between the positive and negative self-evaluation were estimated and compared and were further used to speculate the response bias or motivation indirectly (Markus, 1977; Rameson et al., 2010; Zhang et al., 2013). However, for tasks like self-referential task, there are no correct or wrong answers, and people would have different RTs and processing for different choices. Only comparing the mean values of RTs and choices may make it difficult to reveal the whole complexity of valenced self-evaluation. Moreover, it has been pointed out that RTs can be affected by other noise factors during processing (non-decisional factors such as motor response), and simple RT measurements in two-choice tasks may be suboptimal (Dainer-Best, Lee, et al., 2018; White et al., 2010). Therefore, sorely focusing on the difference in the mean value of RTs and choices would reduce the degree of utilization of the available information (Voss et al., 2013). And by considering the mean values of RTs and responses together can we fully understand the valenced self-evaluation.

The drift-diffusion model (DDM) is a computational model that can analyse the whole RT distribution for different responses, isolating noise factors such as motor response. It is a sequential sampling model originally proposed for two-choice cognitive tasks, such as discrimination tasks or study-test paradigms (Ratcliff, 1978, 1979, 1985; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998). It can reveal the underlying cognitive processes that contribute to accuracy and response times (Ratcliff, 1985). In recent years, DDM has been extensively applied in the field of social and personality psychology due to its benefits in directly describing the latent delusional process from the task, rather than relying on questionnaires (Johnson et al., 2017). For example, it has been used in studies on emotion regulation (Warren et al., 2020), moral decision-making (Yu et al., 2021), and self-related processes (Dainer-Best, Disner, et al., 2018; Dainer-Best, Lee, et al., 2018; Golubickis et al., 2017; Hu et al., 2020).

Self-prioritization effects have been found using the DDM through comparisons with friends or others, and previous studies found people processed self-related information faster and more accurately compared to other-related, which was mainly demonstrated by stimulus-related parameter: drift rate (v) (Falbén et al., 2020; Golubickis et al., 2017, 2018; Hu et al., 2020). Moreover, there are also studies exploring valenced self-evaluation using DDM. It has been found that drift rate (v) was faster for self-related positive compared to self-related negative or other-related positive information (Dainer-Best, Disner, et al., 2018; Dainer-Best, Lee, et al., 2018; Golubickis et al., 2021; Hu et al., 2020). However, these studies mainly focused on the cognitive processes of specific groups such as depression with respect to negative self-evaluation. Few studies have considered the cognitive process of valenced self-evaluation and the difference between positive and negative processing.

Self-evaluation could be seen as a decision-making process in which individuals assign judgement and value to themselves (Tesser & Paulhus, 1983). When combined with DDM, it can optimize information by calculating many parameters such as drift rate (v), starting point (z), non-decisional time (t), and threshold separation (a) using choice and RTs data (see Figure S1, Ratcliff et al., 2016; Voss et al., 2013). Firstly, threshold separation (a), also known as the decision boundary or decision criterion, refers to the amount of information required for the decision response or the psychological distance between two options: self-referential (upper boundary) and not self-referential (lower boundary). The larger the threshold separation (a) is, the more cautious people are during decision-making (Clay et al., 2017). Secondly, the starting point (z) reflects an automatic response bias triggered by expectations or cues before stimuli, which exists prior to the decision-making process (Warren et al., 2020). If the initial value (z) is significantly greater than 0.5 (1/2a), there is a notable response bias toward the self-referential response threshold. Otherwise, the response bias toward the non-self-referential response threshold is significant. Furthermore, the drift rate (v) represents the speed of the information processing, and its sign (positive or negative) also indicates the decision tendency at the stimulus-processing level. Whether it is significantly larger than 0 indicates whether the decision is biased to self-referential or not. Different from the starting point (z), drift rate (v) refers to the decision tendency during the process of information accumulation, more related to the perceptual processes (White et al., 2018). Lastly, non-decisional time (t) represents the time taken for encoding and decision execution (i.e., key-pressing) (Weindel et al., 2021). By using this model, parameters like drift rate (v) could be compared for the information processing between positive and negative self-evaluation.

A previous study has suggested that response bias exists early, before the stimuli, and may be evoked by expectation (White et al., 2018). Decisions will be made once the accumulation of information reaches the threshold starting from that, therefore pre-stimulus response bias can affect the following responses (Guan et al., 2021). It has been proposed that not only pre-stimulus expectation but also processing speed or motor response can affect the final choice thereafter (de Lange et al., 2013; Reed, 1973). Therefore, underlying cognitive parameters such as drift rate (v) or non-decisional time (t) during self-evaluation may further influence the final decision, i.e., self-descriptiveness. Interestingly, emotions related to decision-making could reflect people's feelings and attitudes about their choices (Sevdalis et al., 2007). The relationship between cognition and emotion in self-evaluation is complex. However, it has been demonstrated that the context of self-evaluation can evoke emotions such as pride and shame (Sedikides et al., 2006; Tracy & Robins, 2004). A recent study has found that emotional ratings after self-evaluation (e.g., pride and shame) can be predicted by self-descriptiveness (Wang et al., 2022). It has been noted that the subsequent emotions can be influenced by the decision-making process, suggesting that feelings of pride and shame during self-evaluation may be influenced by cognitive factors and self-description (Engel et al., 1986).

Paying attention to the relationships among cognitive parameters, self-descriptiveness, and self-related emotions may help us understand the mechanism of valenced self-evaluation. Self-positivity bias and self-accuracy bias persist throughout the entire process of self-evaluation, influencing every stage and aspect. Given the notion that the decision-making process is continuous, validating the above discussions could help to explore the effects and processing of these biases, and also aid in understanding the valenced difference of self-related processes. Therefore, the current study was designed to thoroughly investigate the process of evaluating oneself with positive or negative emotions. Two independent experiments were designed to validate the findings. Experiment 1 will primarily focus on the underlying cognitive factors of valenced self-evaluation using DDM, and Experiment 2 will replicate the results and subsequently incorporate related emotions to reveal the complete dynamic process of self-evaluation through regression models.

Combined with DDM to reflect the relevant parameters of the cognitive decision-making process: drift rate (v), threshold separation (a), and non-decisional time (t), the following hypotheses are proposed:

Hypothesis 1. People have decision tendency for accepting positive traits ($v>0$) and rejecting negative traits ($v<0$).

Hypothesis 2. Compared to positive self-evaluation, people have longer RTs and stricter decision criteria during negative self-evaluation, which would be revealed by lower drift rate (v), longer non-decisional time (t), and larger threshold separation (a).

Hypothesis 3. Drift rate (v), non-decisional time (t), and threshold separation (a) can predict subsequent decisional outcomes like self-descriptiveness.

Hypothesis 4. Drift rate (v), non-decisional time (t), threshold separation (a), can predict the related emotion afterwards like pride and shame.

2 | EXPERIMENT 1

2.1 | Method

2.1.1 | Participant

According to G*Power 3.1 (Faul et al., 2007), a minimum of 45 people were required to compare the difference between two dependent means (matched pairs, a two-tailed paired-samples t-test), when using 0.95 statistical power to detect a medium effect size (Cohen's $d_z=0.5$) and an alpha of 0.05. In addition, another effect size (Cohen's $d_z=1.47$[1]) from a related previous study (Chen et al., 2021) was also used for calculation, and the suggested sample size was 17. Therefore, 64 college students (35 women, age $=20.67\pm1.43$) were recruited to participate in the current experiment. All the participants were unaware of the true purpose before the experiment and provided written informed consent for participating. They all had normal or corrected normal vision and had no self-reported history of psychiatric or neurological disorders. The experiment was carried out by the code of ethics of the World Medical Association (Declaration of Helsinki) and approved by the ethics review board of the local university (H23010).

2.1.2 | Material

The trait words were chosen from materials from a published study (Wang et al., 2022), which were pre-examined for desirability, meaningfulness, and familiarity. All these words are frequently used by college students in real life, with average word frequency and the same word length (in Chinese). 70 words were used in the current study, half of which were positive valenced and the other half were negative valenced.

2.1.3 | Task and procedure

A two-choice self-referential decision-making task (tc-SRT) was designed in the current experiment. It was programmed using E-prime 2.0 and presented on a 17-inch screen of 1024 pixels × 768 pixels. In the SRT, participants needed to judge as quickly as possible whether the trait was self-referential or not. Each word was displayed on the centre of the screen with an interval of 500 ms fixation "+." Participants were required to respond using key "F" for yes (self-descriptive), and "J" for no (not self-descriptive). The words would always display on the screen until the response was made. To reduce system error, there were 60 words (30 positive and 30 negative) randomly selected from the 70-word pool. Responses and RTs were all collected.

2.1.4 | Data preparation and analysis

Trials with RTs that were more than 3 standard deviations above the average or less than 300 ms were all excluded. Because this experiment was a within-subject design, a paired-sample *t*-test was conducted on RTs to evaluate the distinction between positive and negative items using bruceR (Bao, 2023; R Core Team, 2021; RStudio Team, 2020). The hierarchical drift-diffusion model (HDDM) was used, employing hierarchical Bayesian parameter estimation methods to simultaneously estimate both individual and group parameters. Individual parameter estimations were constrained by group-level distribution, as HDDM operates under the assumption that participants within each group are similar to each other (Wiecki et al., 2013). Responses and clean RTs were fitted into the HDDM (Wiecki et al., 2013) using Python 3.7 to further investigate the cognitive parameters of self-evaluation (Van Rossum & Drake, 2009). Separate drift rate (v), threshold separation (a), and non-decisional time (t) were estimated for valenced stimuli in six models. In tc-SRT, individuals could not know the stimulus valence of the next trial, so the starting point (z) was set to 0.5 by default as there would be no pre-stimuli response bias toward any choices. Model 1, Model 2, and Model 3 only contained v, a, t varying with valence. Model 4, Model 5, and Model 6 correspond to v, a; v, t; a, t varying with valence respectively. Model 7 was also constructed with varied values for v, a, and t (see Table 1). To assess the adequacy of the HDDM model, seven models were tested for comparison.[2] Bayesian posterior distributions were modelled using a Markov Chain Monte Carlo (MCMC) with 10,000 iterations, following 5000 burn-in samples. 5% of the trials were considered as outliers through the HDDM inbuilt function (the outliers were accounted for as guessing responses through a mixture model) using a built-in exclusion function.

2.2 | Results

2.2.1 | Reaction times

Participants' choice ratios for accepting items (%) and RTs were listed in Table S1. A paired samples *t*-test was conducted on the RTs between positive and negative items, and results found RTs for negative items were significantly longer than positive items, $t_{(63)} = -4.890$, $p < 0.001$, 95%CI = [−0.86, −0.36], Cohen's $d = -0.610$.

2.2.2 | DDM

Since Model 5 yielded the best fit (i.e., the smallest DIC value, see Table 1), the parameter of threshold separation (a) would not be included in the following analyses. The assessment of the model convergence was realized by visually inspecting chains (see Figure S2) and R-hat (Gelman-Rubin) statistics. Furthermore, the R-hat (Gelman-Rubin) statistics were accessed with five chains, each with 10,000 iterations and 5000 burn-in samples. The R-hats for each parameter in Model 5 were all close to 1 and not more than 1.1 ($M = 1.000136$, SD = 0.000221), which indicated qualified convergence (Ulrichsen et al., 2020).

Because HDDM was conducted in a Bayesian framework, significance testing for HDDM parameters between positive and negative items was directly estimated on the posterior through Bayesian p values. Drift rate (v) for positive items was significantly higher than 0 [p Bayes$_{(pos>0)} = 1.000$] which meant people had a decision tendency to accept positive items during the decision-making process, and v for negative items was significantly lower than 0 [p Bayes$_{(neg<0)} = 1.000$] that reflected a decision tendency for rejecting negative items. When converted to absolute values, there was a difference between positive items and negative items [p Bayes$_{(pos>neg)} = 0.987$], which can be interpreted as processing speeds for positive items were faster than negative items. In addition, non-decisional time (t) was longer for negative evaluations compared to positive evaluations [p Bayes$_{(pos>neg)} = 0.000$], which reflected the time of encoding and decision execution for negative items was longer (see Figure 1 and Table S1).

TABLE 1 Deviance information criterion (DIC) values for each model in Exp 1.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	v	a	t	v, a	v, t	a, t	v, a, t
DIC	5342.868	7499.791	7378.259	5312.962	5195.673	7390.101	5227.780

Note: A DIC difference of 10 is strong evidence for model comparison (Kass & Raftery, 1995).

2.3 | Discussion

Experiment 1 validated Hypothesis 1 as well as parts of Hypothesis 2. However, threshold separation (*a*) was not considered in the final analyses due to model comparisons all of which would be further replicated in Experiment 2. In addition, Experiment 1 has not yet considered the emotional feedback that follows self-evaluation. This would all be further validated in Experiment 2.

3 | EXPERIMENT 2

3.1 | Method

3.1.1 | Participant

Same as Experiment 1, the required sample size (45) was followed and 50 college students (29 women, age = 19.94 ± 1.67) participated in the current experiment. All the participants were unaware of the true purpose before the experiment and provided written informed consent for participating. All works were carried out by the code of ethics of the World Medical Association (Declaration of Helsinki) and approved by the ethics review board of the local university (H23010).

3.1.2 | Task and procedure

A self-referential decision-making task (tc-SRT) and a self-descriptiveness task (SDT) plus the rating of related emotions (e.g., pride and shame) were adopted, using the same materials as Experiment 1 (see Figure 2). Except in this experiment, they needed to respond to all 70 words, not randomly chosen words. This adaption was made to increase the trial numbers. In SDT, participants also needed to judge how much each trait was

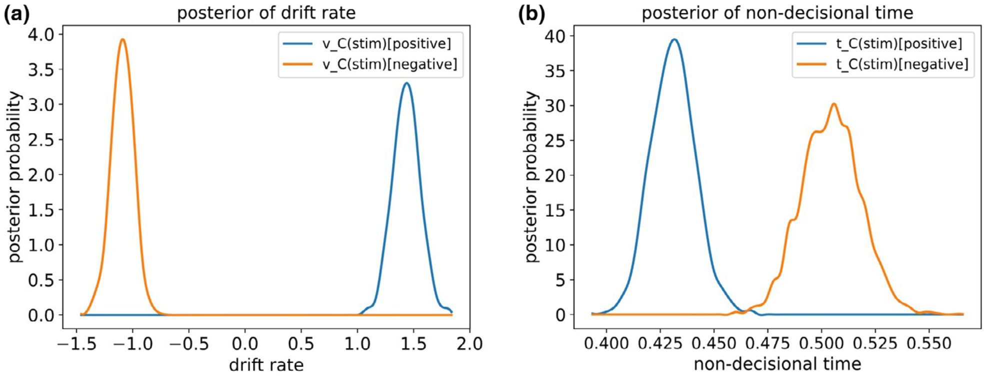

FIGURE 1 The posterior distribution of DDM parameters for different valence in Exp 1. Both parameters (drift rate (v) and non-decisional time (t)) for negative and positive conditions were plotted, including v (a), t (b). [Colour figure can be viewed at wileyonlinelibrary.com]

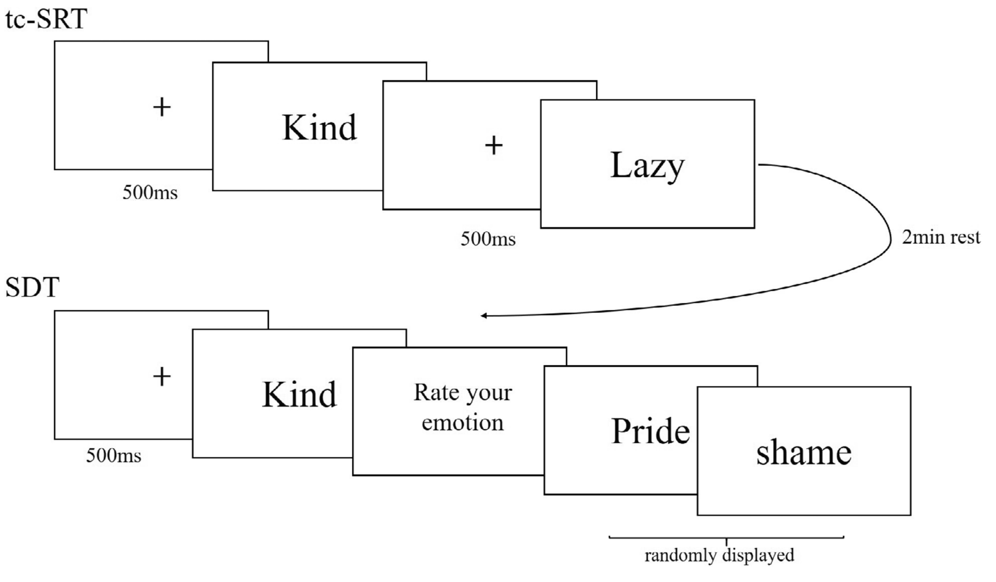

FIGURE 2 Procedure in Exp 2. A self-referential decision-making task (tc-SRT) and a self-descriptiveness task (SDT) plus the rating of related emotions (e.g., pride and shame) were adopted.

self-descriptive, with a seven-point scale representing "not self-descriptive at all" (1) to "very self-descriptive" (7). After evaluating the self-descriptiveness of each trait, participants also needed to answer how much pride and shame they felt about this evaluation using a similar point scale ranging from not at all (1) to very (7). Because the tc-SRT needed a quick response, to avoid the habituation effect, participants always finished tc-SRT first and then did SDT.

3.1.3 | Data preparation and analysis

HDDM was also constructed into seven identical models as Experiment 1 (see Table 2). Besides the analyses in Experiment 1, Bayesian correlation and regression analyses were also conducted to explore the association between the HDDM parameters, self-descriptiveness, pride, and shame. All Bayesian analyses were conducted using JASP (version 0.18.0, developed at the University of Amsterdam, 2022).

3.2 | Results

3.2.1 | Reaction times

Paired samples *t*-test was conducted on the RTs between positive and negative items, and it was found that RTs for negative items were significantly slower than positive items, $t_{(49)}=-3.760$, $p<0.001$, 95%CI=[−0.82, −0.25], Cohen's $d=-0.530$ (see Table S2).

3.2.2 | DDM

Model 5 still yielded the best fit (i.e., the smallest DIC value, see Table 2). The assessment of the model convergence was also realized by visually inspecting chains (see Figure S3) and R-hat (Gelman-Rubin) statistics. Furthermore, the R-hat (Gelman-Rubin) statistics for Model 5 were also achieved with five chains, each with 10,000 iterations and 5000 burn-in samples. The R-hats for each parameter all showed good convergence ($M=1.00013$, SD=0.000184).

Drift rates (v) for positive items were significantly higher than 0 [p $\text{Bayes}_{(pos>0)}=1.000$], and for negative items were significantly lower than 0 [p $\text{Bayes}_{(neg<0)}=1.000$], which meant people had the decision tendency for both accepting positive and rejecting negative. When converting to absolute values, there was a significant difference between positive items and negative items [p $\text{Bayes}_{(pos>neg)}=0.994$], which can be interpreted as processing speeds for positive items being faster compared to negative items. Moreover, non-decisional time (t) was longer for negative items [p $\text{Bayes}_{(pos>neg)}=0.0008$], reflecting a longer time of encoding and decision execution for negative processing (see Figure 3 and Table S2).

3.2.3 | Bayesian Pearson correlations and regression

To explore the relation among all variables and test Hypotheses 3 and 4, the current experiment conducted Bayesian statistics for correlation and regression

TABLE 2 Deviance information criterion (DIC) values for each model in Exp 2.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	v	*a*	*t*	*v, a*	*v, t*	*a, t*	*v, a, t*
DIC	4531.175	5955.65	5787.841	4495.281	4338.161	5796.967	4362.542

Note: A DIC difference of 10 is strong evidence for model comparison (Kass & Raftery, 1995).

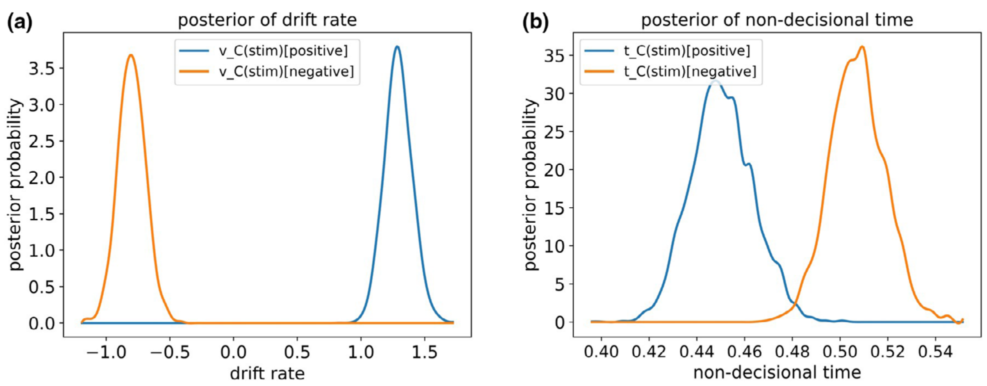

FIGURE 3 The posterior distribution of DDM parameters for different valence in Exp 2. Both parameters (drift rate (v) and non-decisional time (t)) for negative and positive conditions were plotted, including v (a), t (b). [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Results in Bayesian correlation analysis in Exp 2 (N=50).

	Variable		t	v	Self-descriptiveness	Pride	Shame
Positive items	t	r	—				
		BF_{10}	—				
	v	r	—	—			
		BF_{10}	—	—			
	Self-descriptiveness	r	−0.289	0.549	—		
		BF_{10}	1.318	687.449	—		
	Pride	r	−0.132	0.432	0.673	—	
		BF_{10}	0.265	20.64	191189.22	—	
	Shame	r	−0.098	−0.182	−0.156	0.045	—
		BF_{10}	0.22	0.383	0.312	0.185	—
Negative items	t	r	—				
		BF_{10}	—				
	v	r	—	—			
		BF_{10}	—	—			
	Self-descriptiveness	r	−0.091	0.837	—		
		BF_{10}	0.214	$2.099\times10^{+11}$	—		
	Pride	r	−0.021	−0.401	−0.369	—	
		BF_{10}	0.178	10.186	5.213	—	
	Shame	r	0.065	0.485	0.603	0.045	—
		BF_{10}	0.195	84.899	5863.485	0.185	—

Note: t: non-decisional time, v: drift rate.

analyses.[3] The criteria suggested by Jeffreys (1998) were followed to interpret the Bayes factor (BF), i.e., $BF_{01}<1/10$ ($BF_{10}>10$) indicates strong evidence supporting H_0 (H_1), $1/10<BF_{01}<1/3$ ($3<BF_{10}<10$) indicates moderate evidence supporting H_0 (H_1), $1/3<BF_{01}<1$ ($1<BF_{10}<3$) indicates anecdotal evidence supporting H_0 (H_1). The current experiment only accepted results that reached strong evidence ($BF_{10}>10$; Table 3).

For positive self-evaluation, drift rate (v) was positively correlated with self-descriptiveness ($r_{(50)}=0.549$, $BF_{10}=687.449$), and pride ($r_{(50)}=0.432$, $BF_{10}=20.64$). Self-descriptiveness positively correlated with pride ($r_{(50)}=0.673$, $BF_{10}=191189.22$). Moreover, regarding negative self-evaluation, drift rate (v) was positively correlated with self-descriptiveness ($r_{(50)}=0.837$, $BF_{10}=2.099\times10^{+11}$), and shame ($r_{(50)}=0.485$, $BF_{10}=84.899$), while it was negatively correlated with pride ($r_{(50)}=-0.401$, $BF_{10}=10.186$). Self-descriptiveness positively correlated with shame ($r_{(48)}=0.603$, $BF_{10}=5868.435$), but negatively correlated with pride ($r_{(50)}=-0.369$, $BF_{10}=5.213$).

Based on the correlation results, a total of five models were analysed in Bayesian linear regression (see Table 4). For positive self-evaluation, model 1 showed drift rate (v) predicted self-descriptiveness ($R^2_{(50)}=0.301$, $BF_{10}=524.521$), and model 2 showed drift rate (v) predicted pride ($R^2_{(50)}=0.186$, $BF_{10}=19.686$). On the other hand, when evaluating negative traits, model 3 showed drift rate (v) predicted self-descriptiveness ($R^2_{(50)}=0.701$, $BF_{10}=1.198\times10^{+11}$), and model 4 showed not only drift rate (v) itself could predict shame ($R^2_{(50)}=0.235$, $BF_{10}=73.089$), but also drift rate (v) and non-decisional time (t) could together predict shame ($R^2_{(50)}=0.235$, $BF_{10}=20.421$).

3.3 | Discussion

Similar HDDM results were also found in Experiment 2, valence differences in cognitive parameters of self-evaluation were shown on drift rate (v) and non-decisional time (t). Hypothesis 1 and Hypothesis 2 were all validated, except for threshold separation (a), as it was also not included in the final model. It can be found that people have a decision tendency for both accepting positive traits and rejecting negative traits. Furthermore, significant differences in drift rate (v) and non-decisional time (t) revealed that the processing speed was faster and the time for encoding and decision execution was shorter during positive self-evaluation.

Apart from replicating Experiment 1, Experiment 2 also tried to examine two hypotheses: Hypothesis 3 and Hypothesis 4, about the predictive relation among HDDM parameters, self-descriptiveness, and self-conscious emotion (pride and shame). Different mechanisms can be observed between positive and negative evaluation processes. It was found that compared to non-decisional time (t), drift rate (v) had a stronger predictive effect for self-descriptiveness and self-related emotion,

TABLE 4 Results in Bayesian regression analyses in Exp 2 ($N=50$).

	Outcome variable	Models	$P(M)$	$P(M\|\text{data})$	BF_M	BF_{10}	R^2
positive items	Model 1: Self-descriptiveness	Null model	0.5	0.002	0.002	1	0
		v	0.5	0.998	524.521	524.521	0.301
	Model 2: Pride	Null model	0.25	1.429×10^{-5}	4.288×10^{-5}	1	0
		v	0.083	9.379×10^{-5}	0.001	19.686	0.186
		$v+t$	0.083	3.767×10^{-5}	4.144×10^{-4}	7.907	0.198
		t	0.083	1.909×10^{-6}	2.099×10^{-5}	0.401	0.017
negative items	Model 3: Self-descriptiveness	Null model	0.5	8.346×10^{-12}	8.346×10^{-12}	1	0
		v	0.5	1	$1.198\times10^{+11}$	$1.198\times10^{+11}$	0.701
	Model 4: Shame	Null model	0.25	3.613×10^{-4}	0.001	1	0
		v	0.083	0.009	0.098	73.089	0.235
		$t+v$	0.083	0.002	0.027	20.421	0.235
		t	0.083	3.700×10^{-5}	4.070×10^{-4}	0.307	0.004

Note: t: non-decisional time, v: drift rate.
The models that did not have enough evidence to support any regressions were not included in the current manuscript.

especially for positive self-evaluation. Moreover, the predictable emotions were also different between positive and negative processes. Pride can be more easily predicted for positive self-evaluation, while it was shame during negative self-evaluation. On the one hand, for positive self-evaluation, participants had a strong tendency to quickly accept positive traits, which further predicted a higher level of affirmance and pride afterward. On the other hand, when evaluating negative traits, they tended to reject them at a slower speed (compared to accepting positive traits) and longer time for non-decisional processes, which predicted stronger refusal and shame afterward.

4 | GENERAL DISCUSSION

The present study investigated the underlying cognitive factors during valenced self-evaluation through two experiments. The valence differences can be observed in the cognitive aspects of self-evaluation. Slower decision-making in negative self-evaluation was attributed to both slower processing speed and longer encoding and decision execution times, indicating a valence difference in self-evaluation that encompasses both decisional and non-decisional processes. Furthermore, drift rate (v) was higher (faster and all above 0) during the positive compared to the negative process, indicating a stronger self-positivity bias in positive self-evaluation, in line with the previous study (Zell et al., 2019). Therefore, it can be indicated that the biased behaviours toward positivity in self-evaluation could be reflected in the decision tendency during the processing of perceptual information (Derreumaux et al., 2023; Voss et al., 2010; White & Poldrack, 2014).

According to the regression models, for both positive (Model 1) and negative traits (Model 3), drift rates (v) could positively predict self-descriptiveness. However, when considering the sign of drift rate (v), current results revealed a clear valence difference. For negative self-evaluation, as drift rates (v) were all negative values, positive prediction suggested that when people processed negative information slowly, they were more likely to consider it as self-descriptive. Therefore, the current results provided direct evidence for self-accuracy bias especially during the negative process, that if people take a longer time to process negative traits, they are more likely to accept them later, suggesting that the negative process for self-evaluation is indeed more complex (Heine et al., 2001; Wang et al., 2022; Yang et al., 2020).

The current study shed light on the field of self-related processes, such as self-evaluation, through the application of DDM and the regression models. Focusing on the underlying dynamics can help understand the cognitive mechanisms involved in self-evaluation. Furthermore, DDM can provide a new perspective for examining self-related response bias or motive. The findings of the current study examine the effects of HDDM parameters, focusing on self-related biases and expanding their representations. It can be inferred that a self-positivity bias was evident in both accepting positive traits and rejecting negative traits. This bias may originate from drift rate (v): a parameter that relates to the processing for the traits, then further continue to influence related decisions and emotions afterwards. Moreover, previous studies have found that people sometimes readily accept their negative characteristics, reflecting self-accuracy bias (Heine et al., 2001; Hermann & Arkin, 2013; Yang et al., 2020). The current finding supported this by showing the key role of drift rate (v).

However, the current study had a few limitations: (1) In Experiment 1, trait words were randomly selected to reduce system error. However, the trial number was relatively not enough for DDM (Lerche et al., 2017), therefore all 70 words were used in Experiment 2, rather than randomly selecting. Even though the trial number was still below standard in Experiment 2, consistent results can still be found regardless of this different task setting, which still suggested the robustness of the current finding. (2) The present study did not find consistent results regarding pride in negative self-evaluation, unlike the previous study that used the same task and materials (Wang et al., 2022). The correlation between self-descriptiveness and pride was negative in negative self-evaluation ($r_{(50)}=-0.369$, $BF_{10}=5.213$). However, the previous study found that self-descriptiveness for negative traits can positively predict pride. Previous studies have suggested that perfectionism can influence feelings of pride and shame in unpleasant self-related situations (Sagar & Stoeber, 2009; Stoeber et al., 2008). Therefore, extraneous variables such as perfectionism may have an impact on the current results, given the relatively smaller sample sizes in the current study. More extraneous variables need to be considered in the future studies when exploring pride and shame in the context of self-related processes. (3) Since the design was without any cues to remind participants of the preceding stimuli, the starting point (z) cannot be included in the DDM models to study the pre-stimulus response bias. In future studies, adding cues to show the valence of the stimuli would be better to fully explore the response bias in self-evaluation at different levels.

5 | CONCLUSIONS

The current study found the following: (1) People had faster processing speed for positive self-evaluation; moreover, they had longer non-decisional time during negative self-evaluation; (2) self-positivity bias can be revealed through processing speed for accepting positivity and denying negativity; (3) cognitive parameters including processing speed had various predictive effects on self-descriptiveness, which could both reflect self-positivity bias and self-accuracy bias.

AUTHOR CONTRIBUTIONS

Nan Wang: Conceptualization; Investigation; Formal analysis; Writing – original draft. **Kun Shi:** Formal analysis; Writing – review and editing. **Jiwen Li:** Conceptualization; Writing – review and editing. **Haopeng Chen:** Formal analysis; Writing – review and editing. **Jianchao Tang:** Investigation. **Yadong Liu:** Writing – review and editing. **Xiaolin Zhao:** Writing – review and editing. **Juan Yang:** Funding acquisition; Supervision; Writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Following the suggestion of Wilkinson et al. (2016), we uploaded the raw data (collected in 2021 and 2022), the analysis code, and the README file to the third-party archive (Open Science Framework, DOI 10.17605/OSF.IO/PEK34).

ETHICS STATEMENT

The experiment was carried out by the code of ethics of the World Medical Association (Declaration of Helsinki) and approved by the ethics review board of the local university (H23010). The ethics statement was also added in the manuscript (see Sections 2.1.1 and 3.1.1).

RESEARCH MATERIALS STATEMENT

Research sharing not applicable to this article as no datasets were generated or analysed during the current study.

PRE-REGISTRATION STATEMENT

The current study was not pre-registered.

ORCID

Juan Yang https://orcid.org/0000-0002-0739-6998

ENDNOTES

[1] This effect size was calculated based on t value and sample number (N) from previous study through $\text{Cohen}'d_z = \frac{t}{\sqrt{N}}$ (Lakens, 2013).

[2] We used *hddm.HDDMRegressor( )* to fit the models as it is a within-subject design, and adapted two choices (self-descriptive and not self-descriptive) as two boundaries.

[3] Drift rate (v) was original values when entering the correlation and regression analyses.

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SUPPORTING INFORMATION

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