



# Learning about me and you: Only deterministic stimulus associations elicit self-prioritization

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## ABSTRACT

Self-relevant material has been shown to be prioritized over stimuli relating to others (e.g., friend, stranger), generating benefits in attention, memory, and decision-making. What is not yet understood, however, is whether the conditions under which self-related knowledge is acquired impacts the emergence of self-bias. To address this matter, here we used an associative-learning paradigm in combination with a stimulus-classification task to explore the effects of different learning experiences (i.e., deterministic vs. probabilistic) on self-prioritization. The results revealed an effect of prior learning on task performance, with self-prioritization only emerging when participants acquired target-related associations (i.e., self vs. friend) under conditions of certainty (vs. uncertainty). A further computational (i.e., drift diffusion model) analysis indicated that differences in the efficiency of stimulus processing (i.e., rate of information uptake) underpinned this self-prioritization effect. The implications of these findings for accounts of self-function are considered.

## 1. Introduction

Despite longstanding debate about the nature of self and the psychological status of self-function (see Gallagher, 2000; James, 1890; Oakley & Halligan, 2017), work has repeatedly demonstrated the pervasive effects that self-relevance exerts on thinking and doing (Baumeister, 1998; Conway, 2005; Markus & Nurius, 1986; Markus & Wurf, 1987). For example, underpinned by the assumption that self operates as a basic social-cognitive processing hub (Baars, 1988; Conway & Pleydell-Pearce, 2000; Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017), an extensive literature has revealed that personal relevance biases information-processing and response selection in decidedly self-prioritizing and self-enhancing ways (Alexopoulos et al., 2012; Bargh & Pratto, 1986; Constable et al., 2019; Cunningham et al., 2008; Golubickis et al., 2018; Gray et al., 2004; Shapiro et al., 1997; Sui et al., 2012, 2015; Symons & Johnson, 1997). Indeed, such is the power of self-relevance, facilitatory effects arise even when entirely inconsequential stimuli (e.g., shapes, symbols, colors, sounds, avatars) are linked with the self (Falbén et al., 2020a, 2020b; Golubickis et al., 2017, 2020; Schäfer et al., 2015, 2016; Sui et al., 2012; Wang et al., 2016; Woźniak & Knoblich, 2019; Yin et al., 2019). For some, this has suggested that self-prioritization is a mandatory facet of mental life (Sui & Humphreys, 2017; but see Golubickis & Macrae, 2023).

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### 1.1. Self and learning

Extending work on this core topic, recent empirical efforts have investigated the effects of self-relevance on another fundamental psychological process; instrumental learning (Golubickis & Macrae, 2022; Liao et al., 2021; Lockwood et al., 2018). Just as personal significance influences the detection, evaluation, and memorability of stimuli (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017; Symons & Johnson, 1997), so too it impacts how effectively material can be learned. In the first study to explore this issue — in the context of object ownership — Lockwood et al. (2018) adopted an associative-learning task in which participants were required to learn, from a pool of fractals (i.e., unfamiliar stimuli), which items belonged to various individuals (Brovelli et al., 2008; Schultz et al., 1997).<sup>1</sup> A single fractal appeared on each experimental trial and participants had to figure out whether the stimulus was owned by self, a friend, or a stranger (each person owned 4 fractals). Feedback was provided following each response and learning was deterministic in that targets always possessed the same fractals. In this way, instrumental learning was probed under conditions of certainty.

Lockwood et al.'s (2018) findings were informative. Tapping into the operation of an egocentric decision-making strategy (Epley & Gilovich, 2004; Golubickis et al., 2018, 2019), participants tended to report that the fractal presented on the first trial was self-owned, when in fact it was just as likely to belong to either of the other targets. Additionally, responses were faster and more accurate when learning pertained to stimuli owned-by-self compared to items that belonged to a friend or stranger. Finally, learning rates were higher when participants obtained knowledge about the self, although this effect was only reliable when stranger comprised the target of comparison. This latter result is interesting as previous research has indicated that the benefits of self-relevance can be reduced or abolished when the comparison other is a highly familiar individual (Bower & Gilligan, 1979; Kuiper & Rogers, 1979; Symons & Johnson, 1997). Collectively, these findings supplied initial evidence for the biasing effects of self-relevance on associative learning in a deterministic task setting.

Building upon Lockwood et al. (2018), Golubickis and Macrae (2022) broadened this line of inquiry by exploring the effects of self-relevance in a related but more challenging information-processing context; probabilistic learning (i.e., learning under conditions of uncertainty; Frank et al., 2004, 2007). Using a probabilistic selection task (PST), participants viewed three different pairs of Japanese Hiragana characters (i.e., AB, CD, EF), with an item in each pairing representing either self or a friend. The objective was to determine (i.e., learn) which of the symbols was most likely to denote each target based on feedback that indicated the accuracy (or inaccuracy) of their choice selections. Crucially, this trial-by-trial feedback was probabilistic and varied for each stimulus pair (i.e., AB = 80 % – 20 %, CD = 70 % – 30 %, EF = 60 % – 40 %). For example, in AB trials, selecting stimulus A led to positive feedback on 80 % of the trials, whereas selecting stimulus B resulted in positive reinforcement on 20 % of the trials. Thus, over the course of numerous choice selections, learning could be accomplished via positive (e.g., A is correct), negative (e.g., B is incorrect) or both types of feedback (Frank et al., 2007).

Contrasting Lockwood et al. (2018), Golubickis and Macrae (2023) observed that learning rates were slower for self-related compared to friend-related symbols, with self-relevant (vs. friend-relevant) learning characterized by the tendency to exploit rather than explore the choice selections. In task contexts in which rival options are available, a commonplace decision-making dilemma arises. Is it better to make choices that have been rewarding in the past (i.e., exploitation) or instead choose novel selections of uncertain value (i.e., exploration)? For example, when deciding which pizza to order, is it better to select an option that has previously been delicious (e.g., pepperoni) or take a chance on an unknown (i.e., riskier) pie (e.g., anchovy & black olives) which may be wonderful or disappointing (Cohen et al., 2007)? Although optimal learning calls for a balance between these competing strategies, in the long run exploration tends to enhance the acquisition of knowledge (Sutton & Barto, 1998). By revealing participants' tendency to exploit rather than explore choice selections during the PST, Golubickis and Macrae's (2023) findings are interesting as they indicate that self-relevance increased sensitivity to immediate rewards during decision-making (Cohen et al., 2007; Pedersen et al., 2017; Sutton & Barto, 1998).

### 1.2. Learning and self-prioritization

Demonstrating the divergent effects of self-relevance in deterministic and probabilistic task settings, research to date has been instructive (Golubickis & Macrae, 2022; Lockwood et al., 2018). What has not yet been established, however, are the behavioral consequences of these learning experiences. Specifically, once learned, does material about self and others acquired under varying degrees of certainty influence decisional processing? Given the tasks that reliably yield self-prioritization, this turns out to be a noteworthy question. Take, for example, the facilitatory effects of personal possession on object classification (Falbén et al., 2019, 2020b; Golubickis et al., 2018, 2019, 2021). In a typical experiment, participants are initially informed that objects (e.g., pencils & pens) belong either to self or a friend (e.g., self owns pencils, friend owns pens). Next, exemplars of each item are presented in a stimulus-classification task and participants are required to report to whom the object belongs (Golubickis et al., 2018). The frequently reported finding is that responses are faster to self-owned compared to friend-owned objects (i.e., self-ownership effect). Importantly, comparable effects also emerge in matching tasks in which participants judge the accuracy of previously learned shape-label associations, such that self-association enhances performance (Sui et al., 2012, 2013).

Despite target-stimulus associations serving as the foundation of self-prioritization effects in both ownership and shape-label matching tasks (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017; Golubickis & Macrae, 2023), minimal consideration has

<sup>1</sup> Forming and assessing self-object associations through ownership is a common way to explore the dynamics of self-bias (Constable et al., 2014, 2019; Falbén et al., 2020b; Golubickis et al., 2018, 2019, 2021).

been given to the manner in which these linkages are established and how this may potentially influence self-bias. Instead, through instruction followed by a brief period of consolidation, participants are simply required to commit a few target-stimulus relations to memory; specifically, shape-label associations (or variants thereof) in the case of matching tasks (Sui et al., 2012, 2013; Woźniak & Knoblich, 2019), and target-object associations in the case of ownership tasks (Golubickis et al., 2018, 2021). Furthermore, only deterministic target-stimulus associations have been explored in these studies since individuals are always denoted by the same shape or own the same object (Golubickis et al., 2018; Sui et al., 2012). As such, this leaves open the question of whether different learning experiences influence self-prioritization. Notably, does the certainty (vs. uncertainty) with which information has been associated with the self (vs. others) impact the magnitude of self-bias? Usefully, associative-learning paradigms provide a means to address this matter.

In a PST, by manipulating the feedback provided following choice selections, it is possible to explore instrumental learning under conditions of both certainty and uncertainty (Luman et al., 2015, 2021). Using pairs of Hiragana characters (i.e., AB, CD, EF), choice selections can be accompanied by a combination of deterministic and probabilistic feedback. Specifically, one stimulus pair (AB) can elicit consistent (i.e., deterministic) performance feedback (i.e., 100 % reward probability), whereas the other pairs (CD & EF) can be followed by probabilistic feedback that varies in certainty (e.g., 80 % or 60 % reward probability, respectively). In this way, a PST can be used to elucidate whether the way knowledge (i.e., target-stimulus associations) about the self and others is acquired influences subsequent self-prioritization.

### 1.3. The current research

Using a PST together with a stimulus-classification task, here we considered the extent to which different learning experiences impact self-bias. Following Golubickis and Macrae (2022), participants were presented with different pairs of Hiragana characters (denoted as AB, CD, EF) in an associative learning paradigm, with an item in each pairing representing either self or a friend.<sup>2</sup> Based on multiple choice selections, their task was to learn which characters were most likely to represent each of the targets. Crucially, a combination of deterministic and probabilistic feedback was provided following the choice selections (i.e., AB = 100 % – 0 %, CD = 80 % – 20 %, EF = 60 % – 40 %) and learning was established when participants achieved sufficient levels of accuracy for each stimulus pair (Frank et al., 2004, 2007). On successful completion of the PST, to probe the emergence of self-prioritization, participants were presented with the previously learned target-related characters and required to report (i.e., stimulus-classification task) to whom each item referred (Caughy et al., 2021; Falbén et al., 2019; Golubickis et al., 2018, 2019).

Based on previous work, we hypothesized that learning under conditions of certainty versus uncertainty could potentially influence self-bias in two different ways. Given the observation that target-stimulus associations in working memory (i.e., search templates) drive self-prioritization (Golubickis & Macrae, 2023; Reuther & Chakravarthi, 2017; Yin et al., 2019, 2021), it is possible that self-bias may be elicited by all three stimulus pairs, an effect that diminishes in magnitude as a function of increased uncertainty during learning (i.e., AB > CD > EF). That is, outcome ambiguity weakens the strength of target-stimulus relations, hence the extent of self-prioritization. Alternatively, Lockwood et al. (2018) have suggested that only deterministic target-stimulus associations capture how learning unfolds outside the laboratory as possessions are usually (but not always) either owned-by-self or owned-by-others. Accordingly, given extensive experience forming such deterministic self-object connections, self-prioritization may only emerge when learning takes place under conditions of certainty (i.e., AB > CD = EF). We considered these possibilities in the current investigation.

To identify the processes underpinning task performance, a Drift Diffusion Model (DDM) analysis was conducted on the data as this approach has been applied successfully in previous research exploring the cognitive origins of self-prioritization (Falbén et al., 2020a, 2020b; Golubickis et al., 2018, 2020, 2021; Sui et al., 2023; Svensson et al., 2022). In object-classification tasks, depending on the characteristics of the experimental paradigm under investigation (e.g., differences in item probability, strength of memorial traces, quality of sensory inputs; De Loof et al., 2016; Falbén et al., 2020b; Leite & Ratcliff, 2011; Mulder et al., 2012; Ratcliff, 2014; Svensson et al., 2022; Voss et al., 2004), decision-making can be driven by stimulus and/or response-selection biases. That is, performance can be impacted by the ease with which stimuli are processed (i.e., stimulus bias), the evidential requirements of response selection (i.e., response-selection bias), or both biases in combination (White & Poldrack, 2014).

To date, response-based accounts of self-bias have been derived from studies in which pre-existing or experimentally induced beliefs suggest that either self-related or friend-related stimuli are likely to predominate during a task (e.g., Constable et al., 2019; Falbén et al., 2020b; Golubickis et al., 2018; Svensson et al., 2022). In other words, bias precedes stimulus presentation (Dunovan et al., 2014; White & Poldrack, 2014). In contrast, stimulus-based accounts of self-prioritization have emerged from studies in which the quality of sensory inputs have been manipulated, for example through degradation or differences in presentation times (e.g., Falbén et al., 2020b; Sui et al., 2012, 2015). As the strength of memorial representations (i.e., target-stimulus associations) is known to moderate processing efficiency (i.e., match between a test stimulus and a corresponding representation in working memory; Golubickis & Macrae, 2023; Oberauer, 2019; Olivers et al., 2011; Reuther & Chakravarthi, 2017; Soto et al., 2008; Yin et al., 2019), this suggests that personal relevance may facilitate responding via a stimulus bias (Ratcliff et al., 2016). Specifically, differences in the rate

<sup>2</sup> As in previous research (e.g., Caughy et al., 2021; Golubickis & Macrae, 2021), but contrasting other work (e.g., Lockwood et al., 2018; Sui et al., 2012), best friend was selected as the sole target of comparison for a couple of reasons. First, like self, best friend has an established representation in memory, something that is not the case for stranger. Second, prior work has demonstrated that self-bias is attenuated — or even eliminated — when intimate others comprise the target of comparison (Symons & Johnson, 1997). As such, best friend serves as an optimal target of comparison when exploring the emergence of self-prioritization.

at which evidence is gathered from self-related compared to friend-related Hiragana characters during decision-making.

## 2. Method

### 2.1. Participants and design

Fifty-six participants (31 females, 22 males, 3 others:  $M_{age} = 25.68$ ,  $SD = 2.48$ ), with normal or corrected-to-normal visual acuity completed the experiment. Data collection was conducted online using Prolific Academic (<http://www.prolific.co>), with each participant receiving compensation at the rate of £10 (~\$12.50) per hour. Three participants were excluded due to their inability to respond correctly to nonsensical questions which were employed as an attention check (Oppenheimer et al., 2009). Informed consent was obtained from participants prior to the commencement of the experiment and the protocol was reviewed and approved by the Ethics Committee at the School of Psychology, University of Aberdeen. The experiment had a 2 (Correct Character: self or friend) X 3 (Reward Probability: 100 % or 80 % or 60 %) repeated measures design.

The determination of sample size was predicated on a power analysis conducted prior to data collection. Based on the existing literature (Golubickis et al., 2018, 2021), an a priori power analysis — conducted using the statistical software PANGAEA, v0.2 — indicated that a sample size of 56 participants yielded 82 % power to detect a significant interaction with an effect size of  $d = 0.50$ . As per the predefined stopping rule, data collection ceased upon reaching this target number, thereby precluding incremental sampling that may inflate Type I error rates. The data were not subjected to interim analyses, all statistical evaluations were performed once data collection had been completed.

### 2.2. Stimulus materials and procedure

The experiment, consisting of two phases, was conducted online using Inquisit software which participants accessed via a web link. Phase 1 comprised a PST and phase 2 a stimulus-classification task. First, as in Golubickis and Macrae (2022; Expt. 2), participants performed a PST in which six different pairs of Japanese Hiragana characters (denoted as AB, CD, & EF, see Fig. 1) were presented.<sup>3</sup> Participants were informed they were required to learn, based on feedback provided, which symbol in each pair was most likely to represent them (i.e., self) or a friend. As in previous research, participants were requested to bring their best friend to mind prior to performing the task (Golubickis et al., 2018). After each choice selection, participants were told that onscreen information would indicate whether the response was correct or incorrect. Feedback was either fully informative (i.e., AB pair: A = 100 % correct, B = 0 % correct) or probabilistic (i.e., CD pair: C = 80 % correct, D = 20 % correct; EF pair: E = 60 % correct, F = 40 % correct). Thus, over numerous choice selections, participants learned which character in each pairing was more likely to be correct (i.e., A, C, E rather than B, D, F). The task was completed when sufficient levels of accuracy had been achieved for each stimulus pairing (AB – 60 % or above; CD – 55 % or above; EF – 50 % or above; Frank et al., 2004, 2007).

Each trial began with the presentation of a cue (i.e., the labels “YOU” or “FRIEND”) that indicated the target to which the characters pertained (see Fig. 2, Golubickis & Macrae, 2022). The cue appeared 500 ms before the characters were presented and remained on the screen, above the stimuli, until a response was made. After the participant selected one of the characters, feedback (i.e., the word ‘Correct’ in green or ‘Incorrect’ in red) was presented for 1000 ms, followed by a blank screen for 500 ms, after which the next trial commenced. Responses were made by pressing the appropriate button on the keyboard (i.e., ‘A’ for the character on the left, ‘L’ for the character on the right). The characters in each pairing were equally likely to be presented on the left or right side of the screen and the assignment of the characters to self and friend was counterbalanced across the sample. Participants completed blocks of 120 trials (i.e., 60 self & 60 friend) in which each stimulus pair appeared randomly, equally often, until accuracy reached a satisfactory level. The maximum number of learning blocks was set to three, if participants failed to reach satisfactory levels of performance earlier in the task (Frank et al., 2004, 2007).

Following the learning phase, participants completed a stimulus-classification task (Golubickis et al., 2018), the purpose of which was to test their knowledge of the target-related characters (see Fig. 2). Unlike the PST, only a single character was presented, and feedback was not provided following each response. The task was simply to report, as quickly and accurately as possible, to whom each character referred (i.e., self or friend). Each trial commenced with the presentation of a central fixation cross for 1000 ms, followed by a Hiragana character (200 x 200 pixels) for 100 ms, after which the screen turned blank until a response was made. Following each response, the fixation cross reappeared and the next trial began. Participants completed 12 practice trials, followed by 240 experimental trials split into 3 blocks of 80 trials. Characters representing self or friend appeared 120 times (i.e., 2 x 120 trials), with 40 trials per target for each Reward Probability (i.e., 100 % or 80 % or 60 %). The order of presentation of the trials was randomized. Responses were made using the ‘N’ and ‘M’ buttons on the keyboard and the meaning of the response keys (i.e., self or friend) was counterbalanced across the sample. Upon completion of the task, participants were debriefed and thanked.

<sup>3</sup> As in previous research (Frank et al., 2004, 2007), participants’ knowledge of Hiragana characters was not assessed. Given, however, that familiarity is a powerful determinant of self-bias (Humphreys & Sui, 2016; Sui & Humphreys, 2015), a useful task for future research will be to explore whether prior stimulus exposure moderates the process and products of instrumental learning using a PST.

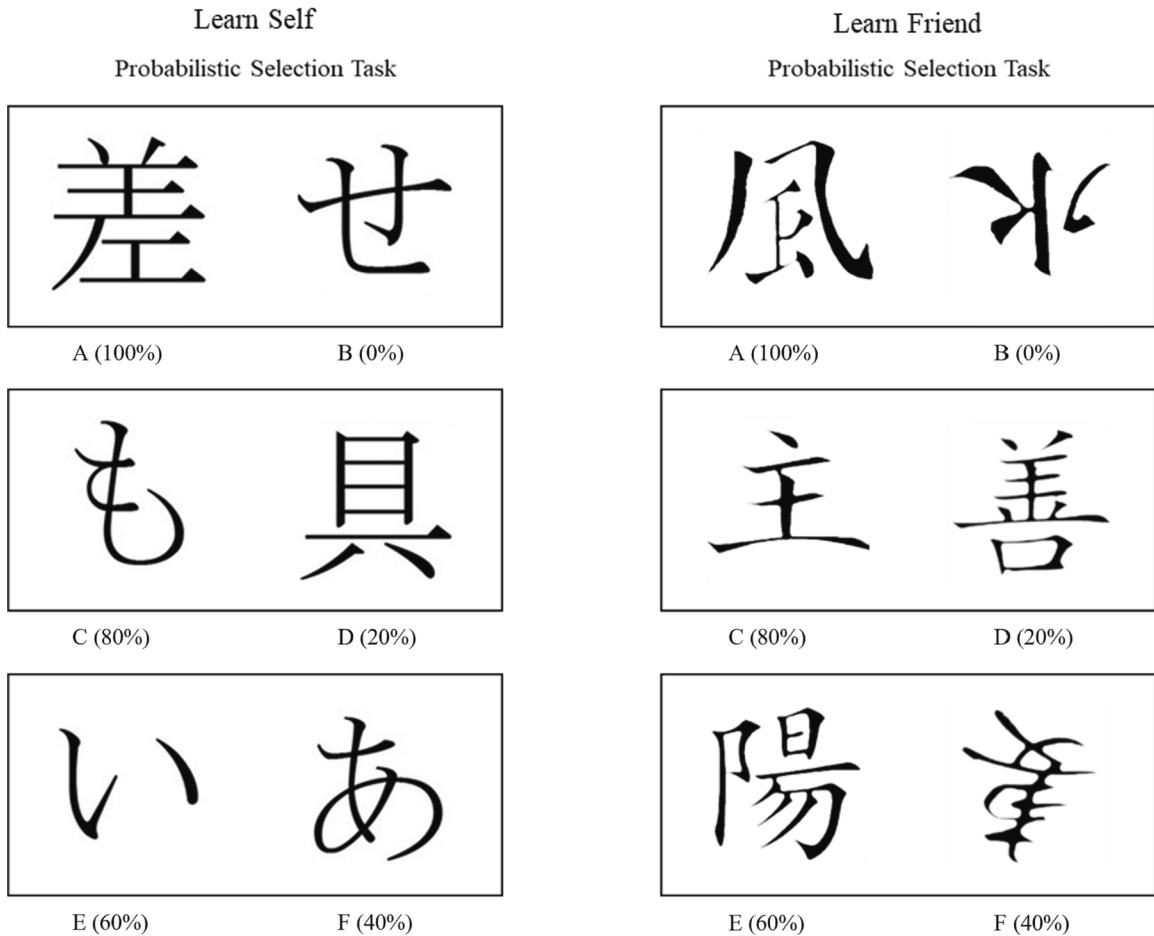


Fig. 1. Experimental stimuli (i.e., Japanese Hiragana characters) and the probability of correct responses during the PST.

### 3. Results

#### 3.1. Learning phase

A trial-by-trial analysis was conducted using generalized estimating equations (GEE) to explore the effects of Trial, Correct Character, and Reward Probability on learning performance. Main effects of Trial (Wald  $\chi^2(1) = 43.82, p < .001$ ), Reward Probability (Wald  $\chi^2(1) = 89.66, p < .001$ ), and a significant Trial X Reward Probability interaction (Wald  $\chi^2(1) = 17.25, p < .001$ ) were observed. Across the stimulus pairs, learning rates decreased as a function of increasing response uncertainty (see Fig. 3). Neither the main effect of Correct Character nor significant interactions involving this factor emerged, indicating that learning performance was equivalent for self and friend.

#### 3.2. Stimulus-classification task

**Reaction Time.** Responses faster than 200 ms and slower than 1100 ms were excluded from the analysis, eliminating less than 1 % of the data (Golubickis et al., 2018). A linear mixed model (LMM) analysis was used to examine the correct reaction times (RTs). Analyses were conducted using JASP (Version 0.16.1, JASP Team, 2022). Correct Character (self or friend) and Reward Probability (100 % or 80 % or 60 %) were treated as categorical fixed effects, and participants as a random effect (Judd et al., 2012). The analysis yielded a significant main effect of Correct Character ( $F = 16.77, p < .001, R^2 = 0.20$ ) and a significant Correct Character X Reward Probability interaction ( $F = 9.85, p < .001, R^2 = 0.20$ ). To further explore the interaction, responses to self-related and friend-related stimuli were compared for each stimulus pair (i.e., AB, CD, EF; see Fig. 4). When the reward probability was 100 %, responses were significantly faster to self-related (vs. friend-related) characters, indicating a self-prioritization effect ( $b = 24.32, SE = 4.08, z = 5.96, p < .001, R^2 = 0.23$ ). No such effect was observed in either the 80 % ( $b = -0.04, SE = 4.16, z = -0.01, p = .992$ ) or 60 % ( $b = 4.88, SE = 4.10, z = 1.19, p = .468$ ) reward probability conditions. All reported  $p$ -values were adjusted for multiple comparisons using the Holm correction method.

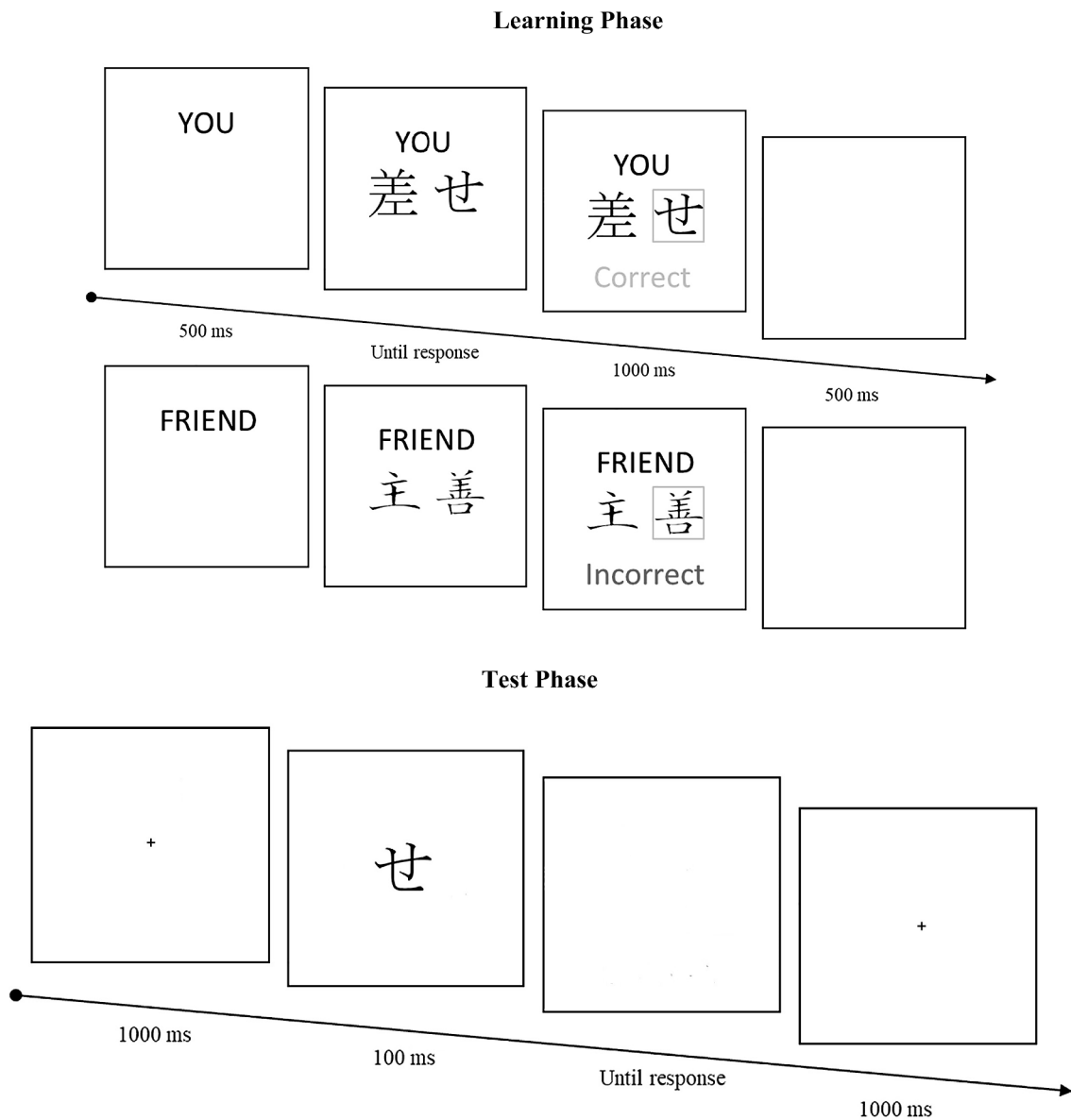


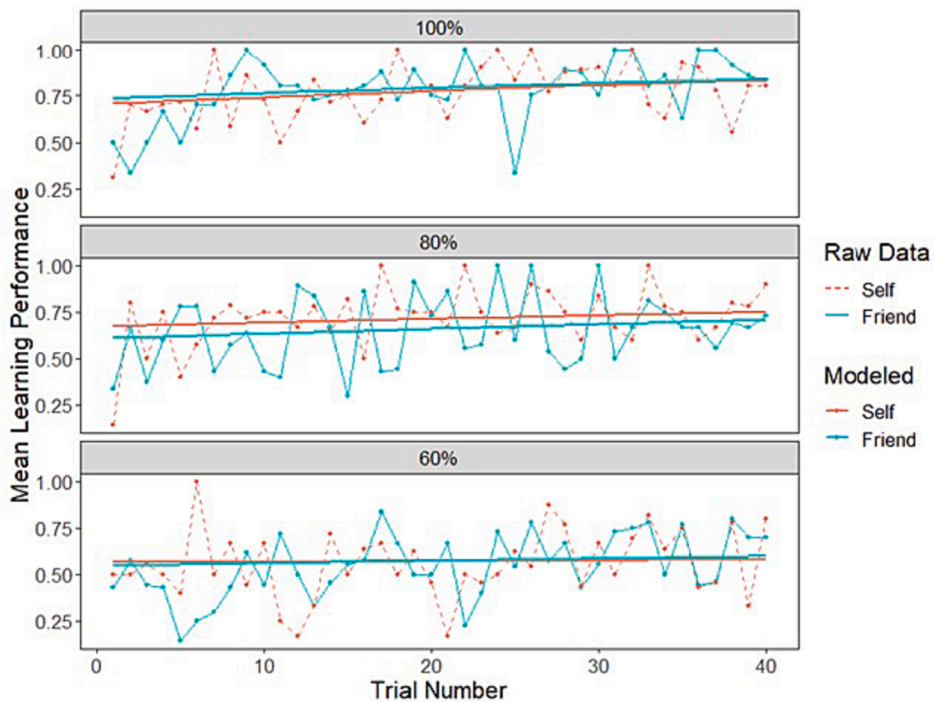
Fig. 2. Schematic illustration of experimental trials in the learning (upper panel) and test (lower panel) phases.

**Accuracy.** A binomial generalized linear mixed model (GLMM) analysis was used to examine response accuracy. This yielded only a significant main effect of Reward Probability ( $\chi^2 = 18.41, p < .001, R^2 = 0.11$ ). Additional contrasts revealed that, compared to the 60 % reward probability condition ( $M = 90\%$ ), accuracy was greater in both the 100 % ( $b = -0.02, SE = 0.01, z =$

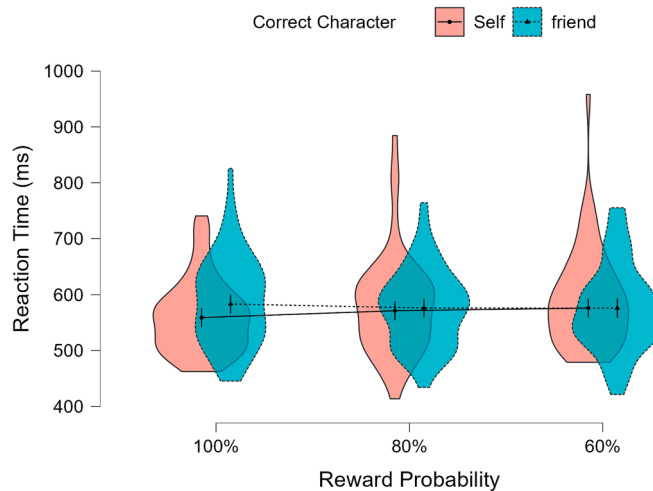
$-3.64, p < .001, R^2 = 0.13$ ) and 80 % ( $b = -0.02, SE = 0.01, z = -2.93, p = .007, R^2 = 0.17$ ) conditions (respective  $M$ s = 92 % & 92 %). No significant difference was observed between the 100 % and 80 % conditions ( $b = 0.01, SE = 0.01, z = 0.95, p = .340$ ). All reported  $p$ -values were adjusted for multiple comparisons using the Holm correction method.

### 3.3. Computational modeling

To identify the processes underpinning task performance, a DDM analysis was conducted on the data. The DDM has several advantages over traditional analytical methods, most notably its ability to explore all the data (i.e., full distributions of RT and accuracy) simultaneously and provide a process-based account of decision-making (Ratcliff et al., 2016). As a sequential sampling model of binary decision-making, the DDM assumes that information is continuously gathered from a stimulus until sufficient evidence has been acquired to make a response. The model describes decisional processing unfolding over time through several conceptually distinct latent parameters, each with unique underlying origins and theoretical interpretations (Ratcliff et al., 2016; White & Poldrack, 2014).



**Fig. 3.** Learning curves over the first 40 trials as a function of Correct Character and Reward Probability. The raw data points represent the observed learning outcomes, and the modeled curves reflect the results of the generalized estimating equations (GEE) analysis. The GEE analysis examines differences in learning trajectories across trials and experimental conditions.



**Fig. 4.** Reaction time as a function of Correct Character and Reward Probability.

The drift rate ( $v$ ) estimates the speed and quality of information acquisition (i.e., larger drift rate = faster information uptake) and is interpreted as a measure of processing efficiency during decision-making. Boundary separation ( $a$ ) estimates the distance between the two response thresholds (i.e., the amount of information required before a decision is made) and is considered a measure of response caution (i.e., larger separation = more cautious decision-making style). The starting point ( $z$ ) specifies the position between the response thresholds where evidence accumulation begins. A non-centered starting point indicates a bias favoring the response closer to the starting point (i.e., less evidence needed to reach the preferred threshold). Finally, the parameter  $t_0$  represents the duration of all non-decisional processes (e.g., stimulus encoding, response execution).

To estimate model parameters, data were submitted to a Bayesian hierarchical drift diffusion modeling toolbox utilizing likelihood approximation networks (i.e., HDDMnn; Fengler et al., 2021; Wiecki et al., 2013). Models were response coded, such that the upper

threshold corresponded to self-related responses and the lower threshold to friend-related responses (Golubickis et al., 2018). Bayesian posterior distributions were modeled using a Markov Chain Monte Carlo (MCMC) with 10,000 samples (including 1,000 burn), with outliers (5 % of the trials) removed by the HDDM software (Ratcliff & Tuerlinckx, 2002; Wiecki et al., 2013). Although the DDM is a widely established computational approach for exploring binary decision-making (Ratcliff et al., 2016), newer variants may better capture the dynamics of decision-making. Specifically, some models extend the standard DDM to account for reductions in decisional caution over time using collapsing bounds via a linear (Angle) or Weibull function (Fengler et al., 2021). Accordingly, three separate classes of the DDM were estimated (i.e., standard DDM, Angle, Weibull) to determine which process specification best captured task performance (Fengler et al., 2021). Model comparison was assessed using the Deviance Information Criterion (DIC), a widely adopted method for comparing hierarchical Bayesian models (Spiegelhalter et al., 1998, 2002). Lower DIC values favor models with the highest likelihood and least number of parameters.

First, a standard DDM was estimated. Based on prior research (Golubickis et al., 2018), drift rate ( $v$ ) varied as a function of Correct Character and Reward Probability and a single starting point ( $z$ ) was estimated to capture the operation of a response selection bias toward self-relevant (vs. friend-relevant) outcomes (DIC = -1734). All subsequent models included this default parameterization. Next, two models (Angle & Weibull) were examined that considered collapsing decisional boundaries (i.e., moving toward the starting

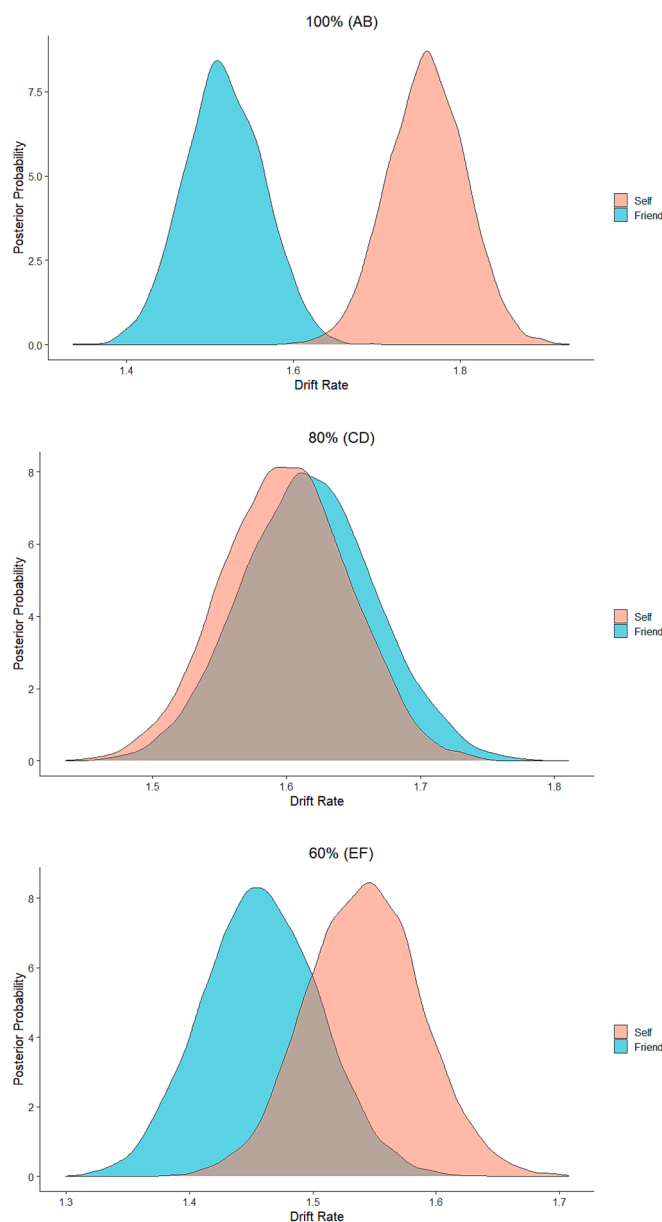


Fig. 5. Mean posterior parameter distributions of drift rate ( $v$ ) as a function of Correct Character and Reward Probability.



point) over time, as opposed to the fixed thresholds in the standard DDM (Shadlen and Kiani, 2013). Whereas the Angle model assumed a linear collapse of the slope parameter ( $\alpha$ , DIC = -3436), the Weibull model allowed for a more gradual collapse, incorporating both scale ( $\alpha$ ) and shape ( $\beta$ ) parameters. This model yielded the best fit (DIC = -3467). To further confirm the Weibull model's validity, three additional models were estimated, allowing: (i)  $\alpha$  (DIC = -3464), (ii)  $\beta$  (DIC = -3462), and (iii) both  $\alpha$  and  $\beta$  (DIC = -3459) to vary as a function of Reward Probability. None of these alternatives substantially improved model fit.

Examination of the posterior distributions revealed differences only in drift rate ( $\nu$ ). First, there was strong evidence that decisional evidence was accumulated more rapidly from self-associated compared to friend-associated characters ( $M_s$ : 1.63 vs. 1.53,  $p_{\text{Bayes}}[\text{self} > \text{friend}] = 0.031$ ). Second, there was extremely strong evidence that, compared to 60 % reward probability condition, the drift rate ( $\nu$ ) was larger for both 100 % ( $M_s$ : 1.64 vs. 1.50,  $p_{\text{Bayes}}[100\% > 60\%] = 0.007$ ) and 80 % ( $M_s$ : 1.61 vs. 1.50,  $p_{\text{Bayes}}[80\% > 60\%] = 0.004$ ) reward probability conditions. No evidence was observed for a difference between the 100 % and 80 % conditions ( $M_s$ : 1.64 vs. 1.61,  $p_{\text{Bayes}}[100\% > 80\%] = 0.234$ ). Third, there was extremely strong evidence that information uptake was faster for self-associated (vs. friend-associated) stimuli in a 100 % reward probability condition ( $M_s$ : 1.76 vs. 1.52,  $p_{\text{Bayes}}[\text{self} > \text{friend}] = 0.001$ ). No evidence for such a difference was observed in the 80 % ( $M_s$ : 1.60 vs. 1.62,  $p_{\text{Bayes}}[\text{self} > \text{friend}] = 0.587$ ) or 60 % ( $M_s$ : 1.54 vs. 1.46,  $p_{\text{Bayes}}[\text{self} > \text{friend}] = 0.121$ ) reward probability conditions (see Fig. 5).

#### 4. Discussion

While previous research has revealed differences in self-related (vs. other-related) learning in deterministic and probabilistic task contexts (Golubickis & Macrae, 2022; Lockwood et al., 2018), quite how the knowledge (i.e., target-stimulus associations) acquired in these settings influences subsequent behavior remains unknown. Accordingly, to address this matter, here we used an associative-learning paradigm (i.e., PST) in combination with a stimulus-classification task to explore the effects of learning under conditions of certainty and uncertainty on self-prioritization (Golubickis et al., 2018; Sui et al., 2012). Despite the information (i.e., Hiragana characters) pertaining to self and friend being learned equally well, self-prioritization nevertheless emerged (i.e., responses were faster to self-associated compared to friend-associated stimuli). Crucially, however, this effect was only observed when target-stimulus associations had previously been learned under conditions of certainty. That is, only deterministic (vs. probabilistic) target-stimulus relations triggered self-bias. A further computational (i.e., DDM) analysis traced the origin of this effect to differences in the efficiency of stimulus processing (i.e., rate of information uptake) during decision-making (Falbén et al., 2020a; Golubickis et al., 2017; Hu et al., 2020; Sui et al., 2023). Notably, evidence was accumulated more rapidly from self-related compared to friend-related characters.

##### 4.1. Searching for self-relevance

So why was self-bias only observed when target-stimulus associations were acquired under conditions of certainty? Following others, our assumption is that self-prioritization is sensitive to the strength of the memorial representations that drive performance in stimulus-classification tasks (Caughey et al., 2021; Golubickis & Macrae, 2023; Reuther & Chakravarthi (2017). Reporting to whom a Hiragana character refers (i.e., self or friend) relies upon representations in working memory (i.e., stimulus-target associations) that serve as search templates during decision-making. Operationally, these search templates direct attention to matching information, thereby facilitating task performance when internal representations and external stimuli correspond (Oberauer, 2019; Olivers et al., 2011). Of course, to guide attentional processing successfully, target-stimulus associations must remain available and active in working memory, with stronger representations increasing the effectiveness of template-stimulus matching. In this respect, here we showed that variability in the strength of target-stimulus associations (i.e., self vs. friend) elicits self-prioritization only when material is learned under conditions of certainty (i.e., 100 % reward probability). This finding chimes with the observation that people have extensive experience forging deterministic (vs. probabilistic) self-stimulus linkages outside the laboratory, thus only these relations have the necessary associative strength to trigger self-bias (Lockwood et al., 2018).

Predating the current inquiry, Reuther and Chakravarthi (2017) also identified the strength of target-stimulus relations as a critical determinant of self-bias. In an interesting experiment, these researchers attempted to eliminate self-prioritization by equating memory performance (i.e., target-stimulus associations) for self-related and other-related material (cf. Sui et al., 2012). Specifically, they introduced a training phase in which error-free learning was established for all the shape-label stimulus pairs (i.e., non-words that represented self and others paired with geometric shapes) prior to completing a shape-label matching task. Importantly, self-prioritization still emerged despite this extensive pre-task preparation and indistinguishable levels of self/other learning. As in the current investigation, Reuther and Chakravarthi (2017) attributed this effect to the potency of self-shape (vs. other-shape) relations in working memory against which stimuli were compared during the shape-label matching task (Constable et al., 2019; Svensson et al., 2022; Wade & Vickery, 2017). Of theoretical significance, this work yielded initial evidence that self-prioritization is not the product of specialized perceptual processes (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017), but rather ordinary memorial and attentional operations (Caughey et al., 2021; Golubickis & Macrae, 2023; Reuther & Chakravarthi, 2017; Woźniak & Knoblich, 2022).

The results of the current computational modeling analysis provided additional confirmation for the role of memorial and attentional processes in the generation of self-bias. Underpinning the observed self-prioritization effect (i.e., 100 % reward probability condition) were differences in the drift rate parameter of the DDM. Drift rate captures the speed at which information is gathered during decision-making and is determined by the quality of evidence provided by a stimulus (Ratcliff et al., 2016). When the quality of evidence is high, so too is the drift rate, resulting in rapid and accurate responses. When, in contrast, the quality of evidence is low, the drift rate is reduced, and responses are slower and less accurate. Across a range of task contexts, the quality of decisional evidence is

determined by the strength of memorial representations. For example, in the case of item recognition, the match between a target stimulus and corresponding representation in memory governs the rate of information uptake (Ratcliff, 1978). In the current stimulus-classification task, drift rate was similarly regulated by the strength of memorial representations — specifically, the potency of target-stimulus associations (i.e., search templates) in working memory (Golubickis & Macrae, 2023; Oberauer, 2019; Olivers et al., 2011; Reuther & Chakravarthi, 2017). Given the acknowledged benefits of self-relevance in forging target-stimulus relations (Sui & Rotshtein, 2019; Symons & Johnson, 1997), evidence was correspondingly accumulated more rapidly from self-associated compared to friend-associated Hiragana characters during decision-making.

Although the standard formulation of the DDM has provided valuable insights into the nature of self-referential cognition, research to date is limited as it has relied only on a single model specification, thereby overlooking other sequential sampling approaches (Forstmann et al., 2016; Krajbich, 2019; Ratcliff & Smith, 2004). Accordingly, here we computed several alternative formulations of the DDM, with the Weibull model yielding the best fit. This model assumes that, during the process of evidence sampling, decisional thresholds collapse in a gradual and non-linear manner over time. From a psychological standpoint, the model's superior fit implies the operation of sophisticated cognitive strategies that extend beyond differences in response caution. For example, the time-dependent, non-linear collapse of decisional thresholds potentially indicates periodic shifts in the allocation of attention or fluctuating levels of commitment to responses during decision-making (Fengler et al., 2021). In other words, the model provides a nuanced account of the temporal sensitivity of decisional processing (Hawkins et al., 2015; Malhotra et al., 2018; Palestro et al., 2018).

#### 4.2. Eliciting self-bias

In revealing that only target-stimulus associations acquired under conditions of certainty (vs. uncertainty) triggered self-prioritization, the current findings are consistent with extant research on self-bias (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017). Whether probed using object ownership or shape-label matching tasks, self-prioritization has been observed following the creation of deterministic target-stimulus associations (e.g., Golubickis et al., 2017, 2018, 2021; Macrae et al., 2018; Sui et al., 2012, 2013, 2015, 2023; Svensson et al., 2022). This then raises an interesting question. In task settings in which self owns the same object (e.g., self owns pens) or is denoted by the same shape (e.g., self is a triangle), does self-prioritization inevitably ensue? That is, do deterministic target-stimulus associations always trigger self-bias? We suspect not (see also Caughey et al., 2021; Desebrock et al., 2022; Falbén et al., 2019; Siebold et al., 2015; Stein et al., 2016; Svensson et al., 2022; Woźniak & Knoblich, 2022). Instead, self-prioritization is likely sensitive both to the properties of objects that have been linked with the self and the task context in which these connections have been established (Golubickis & Macrae, 2023).

Initial evidence indicating that self-prioritization is moderated by the characteristics of objects comes from work exploring the effects of valence on self/other decision-making (Golubickis et al., 2021; Hu et al., 2020; Vicovaro et al., 2022; Ye & Gawronski, 2016). While the association of desirable objects with the self clearly provides a pathway through which a favorable self-image can be maintained (Baumeister, 1998; Beggan, 1992), whether undesirable items serve a similar psychological function is questionable. As it turns out, this is seemingly the case. When self and friend own both an attractive and an unattractive poster (i.e., positive and negative self-object associations are represented in memory), self-prioritization is only triggered by the positive item (i.e., object valence moderates self-bias; Golubickis et al., 2021). Similarly, in a shape-label matching task in which stimuli are paired with components of the self — good-me and bad-me — benefits of self-relevance are most pronounced for the good-self (Hu et al., 2020). Finally, in a recent investigation, Vicovaro et al. (2022) required participants to associate self and stranger with either symmetrical (i.e., positive stimulus) or asymmetrical (i.e., negative stimulus) shapes, associations which were then probed in a classification task. Importantly, self-prioritization only emerged in the self-symmetrical/stranger-asymmetrical condition (i.e., when self was linked with a positive stimulus). Collectively, these findings underscore the sensitivity of self-bias to the valence of target-stimulus associations (Ma & Han, 2010; Macrae et al., 2018; Sui et al., 2016). It is probable that other object-related properties, such as value and popularity, exert a similar influence on self-prioritization, a possibility that future research should explore (for related work exploring the self-prioritization of abstract numeric symbols, see Keil et al., *in press*).

Aside from the properties of objects, the conditions under which items are linked with the self may also be a crucial determinant of stimulus appraisal (Gray, 2012; Waytz et al., 2010). That is, degrees of ownership (i.e., mine-ness) may moderate the magnitude of self-prioritization. Outside the laboratory, self-object associations are formed in variety of ways. For example, a purple sweater can be selected and purchased directly by self, or alternatively received as a gift from either a treasured or reviled relative. Similarly, a range of objects — including rental cars, power tools, and wine glasses — are commonly associated with self, but only temporarily. It is probable that stimulus prioritization is impacted by the circumstances under which objects are linked with the self, as multiple factors influence the weighting of self-object associations in memory (Oberauer, 2019). For example, target-stimulus relations should be stronger when items are acquired intentionally (vs. unintentionally), from a friend (vs. a foe), and owned permanently (vs. temporarily), with resultant implications for the emergence (and magnitude) of self-prioritization (Cloutier & Macrae, 2008). Given these observations, future research should consider a hitherto unexplored, but crucial, aspect of self-function, how the conditions under which target-stimulus relations are established (i.e., degrees of ownership) influence the emergence, magnitude, and persistence of self-prioritization. Work of this kind is essential as it will develop understanding of the everyday social contexts in which self-bias does (and does not) arise (Golubickis & Macrae, 2023).

Consideration should also be given both to the characteristics of instrumental learning tasks and how self-prioritization is assessed. A feature of the current PST was the interleaving of deterministic and probabilistic feedback. As such, the presence of pairs with a 100% reward probability (i.e., deterministic condition) may have led participants to attend disproportionately to these stimuli, thereby impacting the target-character associations formed from the probabilistic pairings. It remains possible that in a PST employing only

probabilistic feedback (Golubickis & Macrae, 2022), pairs with an 80 % reward probability (i.e., the most rewarding stimuli) would generate self-prioritization. A useful task for future research will be to establish how the structure of the learning environment influences the emergence of self-prioritization. Additionally, to determine the generality of the current effects, following learning, self-prioritization should be probed using a range of measures. In particular, tasks that assess stimulus detection would be informative (Constable et al., 2019; Macrae et al., 2017). Work of this kind is needed to verify whether stimulus prioritization emerges when self-relevance is a non-salient aspect of the immediate task context (Golubickis & Macrae, 2023).

Finally, attention should also be directed to the neuroanatomical structures that support self-referential processing and associated decisional biases (Heatherston et al., 2004; Northoff et al., 2006). An influential theoretical account of self-function has suggested that stimulus prioritization is supported by activity in a dedicated neural network. Specifically, through reciprocal connections between regions of the prefrontal (i.e., ventromedial prefrontal cortex [vmPFC]) and temporal (i.e., posterior superior temporal sulcus [pSTS]) cortices, a Self-Attention Network (SAN) enhances the salience of self-relevant material, thereby generating self-bias (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017). As it turns out, however, evidence indicating the operation of a specialized neural network remains limited and inconclusive (Mainz et al., 2020; Schäfer & Frings, 2019; Sui et al., 2013, 2015; Martínez-Pérez et al., 2020; Yin et al., 2019, 2021). Although Yin et al. (2021) have demonstrated that activity in vmPFC drives self-prioritization in working memory, a useful task for future research will be to corroborate the extent to which activity in frontoparietal (i.e., executive) areas — specifically regions implicated in the temporary storage of material and goal-based processing (Braunlich et al., 2015; Dixon et al., 2018; Menon, 2011; Miller & Cohen, 2001; Myers et al., 2017; Seeley et al., 2007; Uddin et al., 2019) — underpin self-prioritization.

## 5. Conclusion

Using a PST to establish target-stimulus associations in memory, here we considered the extent to which different learning experiences (i.e., deterministic vs. probabilistic) influence self-bias (Golubickis & Macrae, 2022; Lockwood et al., 2018). The results revealed that self-prioritization was only observed when target-stimulus relations were acquired under conditions of certainty (vs. uncertainty). A further computational (i.e., DDM) analysis indicated that differences in the efficiency of stimulus processing (i.e., rate of information uptake) underpinned this self-prioritization effect. Specifically, evidence was extracted more rapidly from self-associated compared to friend-associated stimuli (Falbén et al., 2020a; Golubickis et al., 2017; Sui et al., 2023). Collectively, these findings advance understanding of when and how self-relevance facilitates decisional processing.

## 6. Data avail ability

Available at <https://osf.io/dzub9/>.

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## CRedit authorship contribution statement

**Parnian Jalalian:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Marius Golubickis:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Yadvi Sharma:** Conceptualization, Methodology, Writing – original draft. **C. Neil Macrae:** Supervision, Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data is posted on OSF.

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