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Self-Relevance Enhances Evidence Gathering During Decision-Making

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Abstract

Despite repeated demonstrations that self-relevant material is prioritized during stimulus appraisal, a number of unresolved issues remain. In particular, it is unclear if self-relevance facilitates task performance when stimuli are encountered under challenging processing conditions. To explore this issue, using a backward masking procedure, here participants were required to report if briefly presented objects (pencils and pens) had previously been assigned to the self or a best friend (i.e., object-ownership task). The results yielded a standard self-ownership effect, such that responses were faster and more accurate to self-owned (vs. friend-owned) objects. In addition, a drift diffusion model analysis indicated that this effect was underpinned by a stimulus bias. Specifically, evidence was accumulated more rapidly from self-owned compared to friend-owned stimuli. These findings further elucidate the extent and origin of self-prioritization during decisional processing.

Keywords: self-prioritization, ownership, self-relevance, evidence accumulation, drift diffusion model.

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1. Introduction

Self-relevant stimuli occupy a position of prominence during social-cognitive functioning. Compared to material associated with other people, items coupled with the self are easier to detect, classify, and recall (e.g., Alexopoulos et al., 2012; Bargh & Pratto, 1986; Keyes & Brady, 2010; Kuiper & Rogers, 1979; Shapiro et al., 1997; Symons & Johnson, 1997). These effects, moreover, extend beyond traditional stimulus materials (e.g., faces, names), emerging also for geometric shapes, abstract symbols, and colors/sounds that have been linked with the self (e.g., Schäfer et al., 2015, 2016; Sui et al., 2012; Wang et al., 2016; Yin et al., 2019; Woźniak & Knoblich, 2019). Underpinning self-prioritization, it has been argued, is a mind that is preferentially tuned to personally meaningful information, such that self-relevance triggers the enhanced processing of sensory inputs (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017; Sui & Rotshtein, 2019). But is this actually the case? Using an object-ownership task, we explored this issue in the current investigation.

Despite repeated assertions that self-relevant items are privileged during stimulus processing, evidence supporting this viewpoint is scant and garnered primarily (and indirectly) from shape-label matching tasks (e.g., Macrae et al., 2018; Sui et al., 2012, 2015). Indeed, across other paradigms, the beneficial effects of self-relevance have been noticeably absent. For example, in a rapid oculomotor search task, Siebold et al. (2015) reported no facilitation in eye movements to lines previously associated with the self (see also Wade & Vickery, 2018). Similarly, using breaking continuous flash suppression (b-CFS) to investigate the ease with which items (i.e., Gabors) access visual awareness during a stimulus-localization task, Stein et al. (2016) observed no effect of self-relevance on the time taken for Gabors to overcome interocular suppression (cf. Macrae et al., 2017). Together with related research, these findings contest the perceptual basis of self-prioritization, suggesting instead that task performance is underpinned by a response bias

(Constable, Welsh et al., 2019). Specifically, rather than enhancing the efficiency of stimulus processing, self-relevance triggers a preference for self-relevant (vs. other-relevant) responses.

A similar response-based account of self-prioritization has emerged from closely related research exploring the effects of ownership on object processing. As psychological extensions of the self — even when acquired unintentionally and without value — people's possessions loom large during stimulus appraisal (Pierce et al., 2003). Accordingly, it has been suggested that ownership (vs. perceptual-matching tasks) comprises an ecologically appropriate task context for investigating the effects of self-relevance on thinking and doing (e.g., Constable et al., 2011, 2014; Cunningham et al., 2008; Falbén et al., 2019; Golubickis et al., 2018; Truong et al., 2017; Turk et al., 2011). In perceptual-matching tasks, abstract stimuli serve as proxies for various individuals (e.g., self is a triangle, friend is a square), a methodologically expedient although somewhat artificial strategy for forming target-stimulus mappings (Sui et al., 2012). In object-ownership tasks, in contrast, associations are forged between persons and their possessions, an entirely naturalistic and commonplace aspect of daily life (Constable, Welsh et al., 2019; Cunningham et al., 2008). As such, ownership has served as a valuable vehicle for exploring the dynamics of self-referential processing. Crucially however, whether items serve as self-proxies or self-associates, prioritization effects (i.e., self-prioritization effect, self-ownership effect) can be interpreted within Humphreys and Sui's (2016) Self-Attention Network (SAN) model, whereby self-relevance facilitates the processing of personally meaningful inputs through the interplay of top-down (i.e., self activation) and bottom-up (i.e., attentional orienting) processes.

In work investigating the effects of ownership on stimulus processing, a consistent pattern of effects has emerged. Compared to other people's belongings, personal possession confers significant advantages during object detection and classification (i.e., self-ownership effect). Constable, Welsh et al. (2019), for example, demonstrated that when judging which of two objects initially appeared on the computer screen (i.e., temporal-order-judgment task) — a mug owned-by-self or a mug owned-by-the-experimenter — participants were biased toward reporting that self-owned items appeared first (i.e., prior-entry effect). This effect was eliminated, however, when the requested judgment probed a stimulus-related dimension unrelated to ownership (e.g., did the mug appear to the left or right of fixation?), thereby implying that a criterion shift during response preparation (and not stimulus enhancement) underpinned self-prioritization (i.e., participants were biased toward reporting that self-owned objects appeared first; for a competing viewpoint, see Truong et al., 2017).

Related research by Golubickis et al. (2018, 2019) has also furnished a response-based account of the self-ownership effect. In a series of experiments, participants were presented with objects (i.e., pencils & pens) that ostensibly belonged either to the self or a best friend (or mother) and their task was simply to classify the items (i.e., owned-by-self vs. owned-by-friend) as quickly and accurately as possible. The results yielded a self-ownership effect, indicating response facilitation for self-owned (vs. friend-owned) objects. Furthermore, using a drift diffusion model analysis to interrogate the processes underpinning task performance (i.e., stimulus and/or response biases; Ratcliff et al., 2016; Voss et al., 2013; White & Poldrack, 2014), this effect was traced to the operation of a response bias (i.e., variability in the evidential requirements of response generation). Specifically, less information was needed to generate owned-by-self compared to owned-by-friend responses. Crucially, no difference in the efficiency of stimulus processing (i.e., rate of information uptake - stimulus bias) was observed as a function of ownership,[1] thereby demonstrating that self-relevance expedites performance through its influence on response-related operations (Constable, Welsh et al., 2019; Miyakoshi et al., 2007; Siebold et al., 2015; Stein et al., 2016; Wade & Vickery, 2018).

[1] In the drift diffusion model stimulus bias is indexed by the drift rate, a parameter that captures the process of understanding/interpreting/integrating visual information. It is a post-encoding component of perception indicative of the mean amount of information accumulated per unit of time (Ratcliff et al., 2016).

Again using drift diffusion modeling, several recent studies have confirmed that the self-ownership effect resides in the operation of a response bias (e.g., Falbén et al., in press; Golubickis et al., 2019, in press). For example, Golubickis et al. (2019) showed that both European and Asian participants were biased to expect items (i.e., pencils & pens) that were owned-by-self compared to owned-by-mother during an object-classification task. Similarly, using an identical task, Falbén et al. (in press) manipulated the likelihood with which to-be-judged self-owned and friend-owned items were presented. The results revealed that, regardless of ownership, responses were facilitated toward the most frequent items, an effect that was underpinned by differences in the evidential requirements of response generation (i.e., response bias). Interestingly, although stimulus biases have also emerged in these studies (e.g., Golubickis et al., 2019, Expt. 2), these effects are occasional and can go in the wrong direction (e.g., friend > self, Falbén et al., in press, Expt. 1). Thus, in object-ownership tasks, stimulus prioritization is characteristically driven by a response bias.[2]

Based on the existing literature, both the extent of self-ownership effects and whether they originate exclusively in differences in the evidential requirements of response generation are issues that merit additional scrutiny. In the task adopted by Golubickis et al. (2018, 2019) — consistent with prior work on self-prioritization (Sui et al., 2012) — to-be-judged items were presented under non-challenging processing conditions (e.g., 100 ms stimulus duration). It remains to be seen, therefore, whether a comparable self-ownership effect would emerge when stimuli are encountered under more taxing circumstances. For example, can the self-relevance (or otherwise) of items be established from stimuli that are presented very briefly? Given the contention that self-prioritization is a pivotal component of social cognition, one would expect this to be the case (Humphreys & Sui,

[2] The cognitive processes underlying self-prioritization in perceptual-matching tasks have also been explored using drift diffusion modeling (Golubickis et al., 2020; Hu et al., 2020; Macrae et al., 2017). Contrasting ownership effects, response facilitation in these tasks has been shown to originate in a stimulus bias, specifically the efficient extraction of decisional evidence from self-relevant (vs. other-relevant) material during matching trials. Between task differences in stimulus-response mappings (i.e., self-owned or friend-owned vs. matching or nonmatching) likely account for these divergent effects when probing the origins of self-prioritization using ownership and shape-label matching tasks.

2016; Sui & Humphreys, 2015, 2017; Sui & Rotshtein, 2019). That is, information-processing benefits would be most pronounced if self-relevance were extracted successfully from even fleetingly encountered stimuli.

In addition, under conditions of rapid stimulus presentation, it is possible that prioritization may originate in the operation of a stimulus bias. In object-ownership tasks, much like any other decisional context, performance is driven by a combination of stimulus and response-related processes, with each influenced by particular aspects of the experimental paradigm under consideration (White & Poldrack, 2014). Whereas response biases are modulated by factors such as item probability and reward, stimulus biases are sensitive to variation in the quality of sensory inputs (De Loof et al., 2016; Leite & Ratcliff, 2011; Mulder et al., 2012; Ratcliff, 2014; Voss et al., 2004). This suggests that, in a challenging task context, ownership may facilitate object classification via a stimulus bias — specifically, differences in the rate at which decisional evidence is accumulated from self-relevant (vs. friend-relevant) objects. Through the rapid presentation and backward masking of self-owned and friend-owned objects, we examined this hypothesis in the current experiment. To explore the processes underpinning task performance, data were submitted to a drift diffusion model analysis.

2. Method

2.1 Participants and Design

Thirty-six undergraduates (14 male, M_{age} = 19.54, *SD* = 2.22) took part in the research.[3] One male participant failed to follow the instructions by responding with invalid key presses, thus was excluded from the analyses. All participants had normal or corrected-to-normal visual acuity.

[3] Based on Golubickis et al. (2018), G*Power revealed a requirement of 36 participants (d = 0.5, α =.05, power = 80%).

Informed consent was obtained 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, Scotland. The experiment had 2 (Owner: self vs. friend) X 6 (Presentation Time: 10 ms vs. 20 ms vs. 30 ms vs. 40 ms vs. 50 ms vs. 60 ms) repeated-measures design.

2.2 Stimulus Materials and Procedure

Participants arrived at the laboratory individually, were greeted by the experimenter, seated in front of a desktop computer, and informed the experiment comprised a classification task featuring two categories of objects: pencils and pens (Falbén et al., in press; Golubickis et al., 2018, 2019). Next participants were told that, prior to the start of the task, the computer would randomly assign one category of objects to be owned by them and the other category of objects to be owned by their best friend. That is, participants would own all the items (i.e., pencils or pens) from one of the categories, and their friend would own all the items from the other category. They then pressed the spacebar on the keyboard and text appeared revealing who had been assigned the pencils and pens, respectively (e.g., you = pen, friend = pencil). Assignment of the objects to self and friend was counterbalanced across the sample. The experimenter then explained that, on the computer screen, participants would be presented with a series of pictures of individual pencils and pens and their task was simply to report (via a button press), as quickly and accurately as possible, whether the item belonged to them or their friend. Responses were given using two buttons on the keyboard (i.e., N & M). Key-response mappings were counterbalanced across participants and the labels ‘mine’ and ‘friend’ were located above the relevant response buttons.

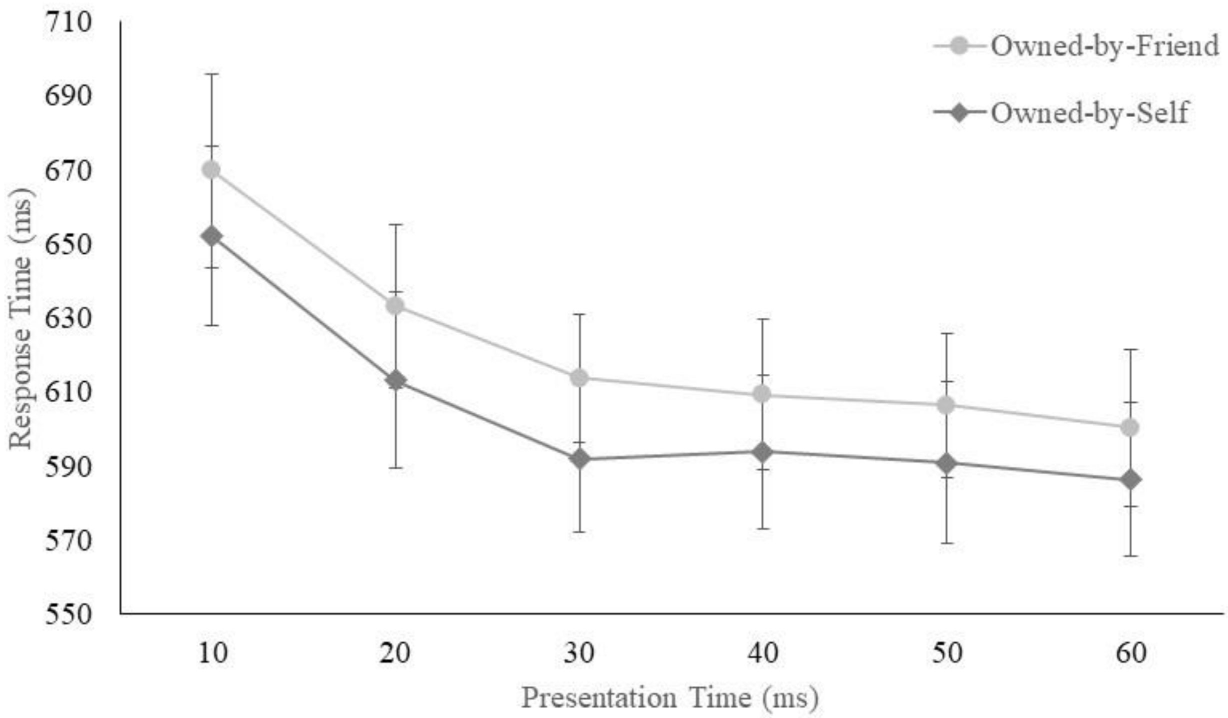
Each trial began with the presentation of a central fixation cross for 500 ms, followed by a picture of a pencil or a pen for 10, 20, 30, 40, 50 or 60 ms, which was then replaced by a mask for 300 ms. After the mask, the screen turned blank until participants reported the owner (i.e., self or friend) of the item (see Supplementary Material). Following Golubickis et al. (2018), the two categories of stimuli comprised photographs of 28 unique objects (14 pencils & 14 pens). Images were 140 x 140 pixels in size, greyscale, matched for luminance, and oriented obliquely from the left-bottom to right-top corner. The mask comprised 9 images of merged pencils and pens combined with Gaussian noise, with the items presented in the same orientation as the target stimuli. The mask was 500 x 500 pixels in size and greyscale. Participants initially performed 12 practice trials, followed by eight blocks of 60 trials in which all stimuli occurred equally often in a random order. In total, there were 480 trials, with 240 trials in each condition (i.e., self-owned trials vs. friend-owned trials). On completion of the task, participants were debriefed, thanked, and dismissed.

2.3 Results

2.3.1 Response Time and Accuracy

Responses faster than 200 ms were excluded from the analysis (Golubickis et al., 2018), eliminating approximately 2% of the overall number of trials. A multilevel model analysis was used to examine the response time (RT) and accuracy data (see Figure 1). Analyses were conducted with the R package ‘lmer4’ (Pinheiro et al., 2015), with Owner and Presentation Time as fixed effects and participants as a crossed random effect (Judd et al., 2012). Analysis of the RTs yielded a main effect of Owner (b = -.008, SE = .002, t = -4.89, p < .001), such that responses were faster to owned-by-self (M = 605 ms, SD = 129 ms) compared to owned-by-friend (M = 622 ms, SD = 125 ms) objects. In addition, a main effect of Presentation Time (b = -.023, SE = .002, t = -13.05, p < .001) revealed that, the longer the items remained on the screen, the faster the RTs (M_{10ms} = 661 ms, SD_{10ms} = 148 ms, M_{20ms} = 623 ms, SD_{20ms} = 135 ms, M_{30ms} = 603 ms, SD_{30ms} = 110 ms, M_{40ms}= 602 ms, SD_{40ms} = 122 ms, M_{50ms} = 599 ms, SD_{50ms} = 122 ms, M_{60ms} = 593 ms, SD_{60ms} = 124 ms).

A multilevel logistic regression analysis on the accuracy of responses yielded a significant main effect of Owner (b = .067, SE = .020, z = 3.33, p = < .001), indicating that responses were more accurate to self-owned (*M* = 78%, *SD* = 13%) compared to friend-owned (*M* = 76%, *SD* = 16%) objects. In addition, a significant main effect of Presentation Time (b = .415, SE = .020, z = 20.649, p < .001) revealed that, the longer the items remained on the screen, the more accurate the responses (M_{10ms} = 62%, SD_{10ms} = 20%, M_{20ms} = 72%, SD_{20ms} = 14%, M_{30ms} = 79%, SD_{30ms} = 14%, M_{40ms} = 82%, SD_{40ms} = 13%, M_{50ms} = 82%, SD_{50ms} = 13%, M_{60ms} = 83%, SD_{60ms} = 12%).



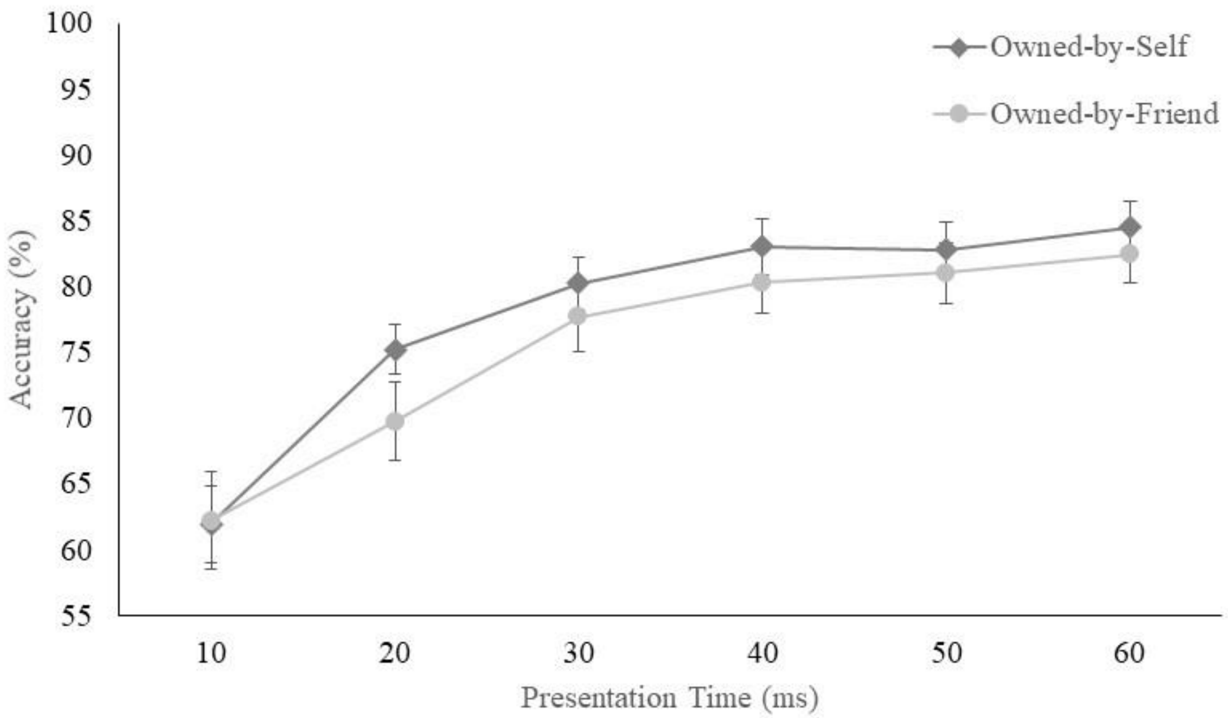


Figure 1. Task Performance (upper panel = RT, lower panel = accuracy) as a function of Owner and Presentation Time. Error bars represent ±1 standard error of the mean (SEM).

2.3.2 Drift Diffusion Modeling

The drift diffusion model (DDM) uses both accuracy and response latency to represent the decision-making process as it unfolds over time, thereby enabling the latent cognitive operations associated with task performance to be estimated (Ratcliff et al., 2016). During binary decision-making (e.g., is an object owned-by-self or owned-by-friend?), information is continuously gathered from a stimulus until sufficient evidence is acquired to make a response. The advantage of this analytic approach resides in the ability of the DDM to distinguish between biases in stimulus and response-related processes. In the drift diffusion framework these biases are conceptually distinct, with different underlying origins and theoretical interpretations (Ratcliff et al., 2016; Voss et al., 2013; White & Poldrack, 2014).

The drift rate (*v*) estimates the speed and quality of information acquisition (i.e., larger drift rate = faster information uptake), thus is interpreted as a measure of the efficiency of visual processing during decision-making. For example, during stimulus appraisal, self-relevance may facilitate information uptake for self-owned compared to friend-owned objects, thus demonstrating that self-prioritization is underpinned by a stimulus bias. Boundary separation (*a*) estimates the distance between the two response thresholds (i.e., how much information is required before a decision is made) and the starting point (*z*) specifies the position between the response thresholds at which evidence accumulation begins. If *z* is not centered between the thresholds, this indicates a bias in favor of the response that is closer to the starting point (i.e., less evidence is required to reach the preferred threshold). For example, self-relevance may modulate information-sampling requirements, such that less evidence is needed to generate owned-by-self than owned-by-friend responses, indicating that self-prioritization is underpinned by a response bias. Finally, the duration of all non-decisional processes (e.g., stimulus encoding, response execution) is given by the parameter t_0.

To identify the operations underpinning task performance, data were submitted to a hierarchical drift diffusion model (HDDM) analysis (Vandekerckhove et al., 2011). HDDM is an open-source software package written in Python for the hierarchical Bayesian estimation of drift diffusion model parameters (Wiecki et al., 2013). This approach assumes that the model parameters for individual participants are random samples drawn from group-level distributions and uses Bayesian statistical methods to estimate all parameters at both the group and individual-participant level (Vandekerckhove et al., 2011). Models were response coded, such that the upper threshold corresponded to an owned-by-self response and the lower threshold to an owned-by-friend response (Golubickis et al., 2018, 2019). Seven models were estimated for comparison (see Table 1). First, to investigate whether task performance was underpinned by differences in the rate of information uptake (i.e., stimulus bias), a model that allowed the drift rate (*v*) to vary as a function of Owner (i.e., self vs. friend) and Presentation time (i.e., 10 ms vs. 20 ms vs. 30 ms vs. 40 ms vs. 50 ms vs. 60 ms) was estimated. In the second model, starting point (*z*) was allowed to vary as a function of Owner to establish if task performance was underpinned by a response bias (i.e., less decisional evidence needed). In the third model, the drift rate (*v*) and the non-decision time (t_0) were allowed to vary. The final two models (i.e., model 4 and 5), examined whether task performance was underpinned by stimulus and response biases, allowing both drift rate (*v*) and starting point (*z*) to vary across Owner and drift rate (*v*) to vary across Presentation Time. In model 5, non-decision time (t_0) also varied across Presentation Time. In all of the models, inter-trial variability was estimated for drift rate (*sv*), non-decision time (*st*) and, when available (i.e., models 2, 4 & 5), starting point (*sz*).

Table 1. Deviance information criterion (DIC) for each model.

Model	Owner	Presentation Time	Fixed	DIC
1.	*v*	*v*	z, t_0	7655
2.	*z*	-	v, t_0	3518
3.	*v*,	v, t_0	*z*	2184
4.	*v*, *z*	*v*	t_0	2242
5.	*v*, *z*	v, t_0	-	2216

Note. *v* = drift rate, *z* = starting point, t_0 = non-decision time.

Bayesian posterior distributions were modeled using a Markov Chain Monte Carlo (MCMC) with 10,000 samples (with 1,000 burn in). As can be seen in Table 1, model 3 yielded the best fit (i.e., lowest Deviance Information Criterion value, DIC). The DIC was adopted as it is routinely used for hierarchical Bayesian model comparison (Spiegelhalter et al., 1998). As diffusion models were fit hierarchically rather than individually for each participant, a single value was calculated for each model that reflected the overall fit to the data at the participant- and group-level. Lower DIC values favor models with the highest likelihood and least number of parameters. To provide a graphical assessment of model fit, a standard model comparison procedure used in Bayesian parameter estimation — Posterior Predictive Check (PPC) — was performed (Wiecki et al., 2013). For the best fitting model, the posterior distributions of the estimated parameters were used to simulate data sets. We then assessed the quality of model fit by plotting the observed data against the simulated data for the .1, .3, .5, .7, and .9 response-time quantiles for each experimental condition (Krypotos et al., 2015). This revealed good model fit (see Supplementary Material for associated plots).

It should be noted that model 3 parameterization resulted in a relatively low number of trials for each drift rate estimate (i.e., 40 trials). A key benefit of HDDM is that, compared to other modeling approaches, parameters can be estimated reliably with fewer experimental trials (Lerche et al., 2017; Ratcliff & Childers, 2015; Wiecki et al., 2013). In addition, as models are fitted at the group-level rather than individually (Wiecki et al., 2013), larger participant numbers (i.e., > 30) also improve parameter estimation. These observations aside, however, it is important to highlight that parameter estimation would have been improved with additional experimental trials, thus the current results should be interpreted with a degree of caution.

Inspection of the posterior distributions for the best fitting model indicated that task performance was underpinned by a stimulus (drift rate, *v*) bias (see Table 2). Specifically, an effect of Owner indicated that decisional evidence was accumulated more rapidly for owned-by-self compared to owned-by-friend (p_{Bayes}(owned-by-self > owned-by-friend) = .007) objects.[4] In addition, information uptake increased as a function of Presentation Time, but only up to 40 ms

[4] Bayesian *p* values quantify the degree to which the difference in the posterior distribution is consistent with the hypothesis. For example, a Bayesian *p* of .05 indicates that 95% of the posterior distribution supports the hypothesis.

(p_{Bayes}(10ms < 20 ms) < .001; p_{Bayes}(20ms < 30 ms) = .005; p_{Bayes}(30ms < 40 ms) = .061; p_{Bayes}(40ms < 50 ms) = .527; p_{Bayes}(50ms < 60 ms) = .268). No difference in non-decision times (t_0) was observed.

Table 2. Parameter means and the upper (97.5q) and lower (2.5q) quantiles of the best fitting model.

Diffusion Model Parameter	Mean	Quantile 2.5q	Quantile 97.5q
a	1.088	1.011	1.182
$v_{owned\text{-}by\text{-}self/10ms}$	0.521	0.170	0.882
$v_{owned\text{-}by\text{-}friend/10ms}$	-0.611	-0.930	-0.282
$v_{owned\text{-}by\text{-}self/20ms}$	1.329	0.982	1.672
$v_{owned\text{-}by\text{-}friend/20ms}$	-1.014	-1.352	-0.683
$v_{owned\text{-}by\text{-}self/30ms}$	1.780	1.452	2.135
$v_{owned\text{-}by\text{-}friend/30ms}$	-1.483	-1.825	-1.153
$v_{owned\text{-}by\text{-}self/40ms}$	2.037	1.687	2.396
$v_{owned\text{-}by\text{-}friend/40ms}$	-1.749	-2.081	-1.414
$v_{owned\text{-}by\text{-}self/50ms}$	2.004	1.660	2.357
$v_{owned\text{-}by\text{-}friend/50ms}$	-1.775	-2.122	-1.424
$v_{owned\text{-}by\text{-}self/60ms}$	2.132	1.787	2.494
$v_{owned\text{-}by\text{-}friend/60ms}$	-1.855	-2.213	-1.500
$t_{0/10ms}$	0.378	0.348	0.406
$t_{0/20ms}$	0.368	0.339	0.394
$t_{0/30ms}$	0.365	0.337	0.393
$t_{0/40ms}$	0.375	0.347	0.403
$t_{0/50ms}$	0.370	0.342	0.398
$t_{0/60ms}$	0.361	0.332	0.372
sv	0.679	0.540	0.810
st	0.249	0.240	0.257

Note. v = drift rate, t_0 = non-decision time, sv = inter-trial variability in drift rate, st = inter-trial variability in non-decision time.

3. Discussion

The benefits of self-relevance on information processing have been observed across a range of stimuli, tasks, and sensory modalities (Humphreys & Sui, 2016; Sui & Humphreys, 2015; Schäfer et al., 2016; Sui & Rotshtein, 2019). Notwithstanding multiple demonstrations of self-prioritization, however, the scope and origin of this effect remains a matter of debate. Whilst early work asserted that self-relevance facilitates performance via enhanced stimulus processing (Sui et al., 2012, 2015), recent studies have challenged this viewpoint, maintaining instead that self-prioritization is underpinned by a response bias (e.g., Constable, Welsh et al., 2019; Falbén et al., in press; Golubickis et al., 2018, 2019; Siebold et al., 2015). Notably, in object-ownership tasks, responses to self-owned (vs. friend-owned) items are speeded because of a reduction in the evidential requirements of response generation and not the enhanced processing of self-relevant inputs (Golubickis et al., 2018, 2019). It is noteworthy therefore that, during judgments of ownership, just such a stimulus-based effect was observed in the current investigation. That is, evidence was extracted more efficiently from self-owned compared to friend-owned objects when stimuli were presented rapidly (i.e., 10-60 ms) and masked.

The demonstration that self-ownership effects can originate in different underlying mechanisms is to be expected. In the context of binary decision-making — the task routinely used to explore self-prioritization (Constable, Welsh et al., 2019; Golubickis et al., 2018; Sui et al., 2012) — decisional bias (i.e., faster and more accurate responses to self-relevant vs. other-relevant stimuli) will be determined by crucial aspects of the task instructions and experimental methodology (Ratcliff et al., 2016). For example, given that response biases signal a preference for a particular response even before a stimulus has been presented (i.e., expectancy or reward bias, Dunovan et al., 2014; Leite & Ratcliff, 2011; White & Poldrack, 2014), Falbén et al. (in press) demonstrated self-ownership effects — underpinned by changes in the starting point of evidence accumulation (*z*) — for both self-owned and friend-owned items when these stimuli predominated in an object-classification task. In contrast, given that differences in the efficiency of stimulus processing reflect changes in the quality of sensory inputs (White et al., 2012), here we showed an increased rate of information uptake (i.e., drift rate, *v*) for self-owned compared to friend-owned objects (cf. Golubickis et al., 2018). This suggests that self-prioritization arises via task-dependent stimulus and response-related pathways.

In the current experiment, differences in the efficiency of stimulus processing (i.e., drift rates) likely reflected changes in task difficulty as a function of the experimental manipulations (i.e., presentation time, self-relevance; see Ratcliff et al., 2016; Voss et al., 2004; White & Poldrack, 2014). As drift rates are sensitive the quality of stimulus inputs, information uptake naturally increased the longer the to-be-judged items remained on the screen (i.e., the task got easier). Of course, this does not explain why evidence was accumulated more rapidly for self-owned compared to friend-owned objects. Underpinning this effect, we suspect, are differences in the strength of target-object associations in working memory (e.g., self-owns-pen, friend-owns-pencil), associations against which sensory inputs must be compared to perform the object-classification task (Caughey et al., in press; Falbén et al., 2019; Hommel, 2004, 2018; Reuther & Chakravarthi, 2017). It is widely acknowledged that, through enhanced connectivity, self-referential encoding facilitates memory (Conway & Pleydell-Pearce, 2000; Heatherton et al., 2004; Symons & Johnson, 1997). As Sui and Humphreys (2015) have observed, “self-reference acts as a form of integrative glue.” (p. 719). Accordingly, serving as criterion against which judgments are made (i.e., owned-by-self vs. owned-by-friend), these potent self-object (vs. friend-object) associations facilitated task performance via the enhanced processing of self-relevant (vs. friend-relevant) stimuli (see also Constable, Rajsic et al., 2019).[5]

It could be useful to consider the current results in terms of optimal strategies for decisional processing (Bogacz et al., 2006). Assuming that, as a function of task context, optimal performance

[5] Differences in the strength of target-object associations are less likely to impact the efficiency of information uptake when stimuli are presented for an extended duration (e.g., 100 ms, see Falbén et al., in press; Golubickis et al., 2018, 2019).

reflects relative shifts in the priority given to stimulus- and response-related processes (Leite & Ratcliff, 2011; White & Poldrack, 2014), it may simply be the case that the current object-classification task placed greater emphasis on drift rate over starting point. In the DDM framework, the drift rate reflects the sampling and integration of noisy sensory information towards binary response options (i.e., thresholds). It is possible, therefore, that the long stimulus presentation times (i.e., 100 ms) and non-masked stimuli used in previous ownership tasks (e.g., Falbén et al., in press; Golubickis et al., 2018, 2019) resulted in large signal-to-noise ratios (i.e., high quality of stimulus representation), prompting decisions to rely on a priori evidential requirements rather than the speed of evidence accumulation. In other words, when information sampling speeds are slow (i.e., small drift rates), as was the case in the current investigation, then the use of a response-related strategy (i.e., lower evidence requirements) becomes suboptimal as the acquisition of evidence becomes harder to achieve. In contrast, when information sampling is fast (i.e., large signal-to-noise ratios), response-related strategies (i.e., asymmetrical evidential requirements) become easier to implement (Bogacz et al., 2006; Leite & Ratcliff, 2011). In this way, given the prevailing task context, self-relevance is capable of optimizing decision-making via either stimulus or response biases. By manipulating the relative ease/difficulty of stimulus processing in a single task, future research should explore this issue.

Of course, a limitation of the current investigation was that to-be-judged stimuli were only presented under challenging processing conditions. As such, the suggestion that differences in task difficulty trigger a switch from a stimulus to a response bias during decision-making rests on comparison with prior work exploring the effects of self-relevance (vs. other-relevance) on object classification (Falbén et al., in press; Golubickis et al., 2018, 2019). A useful task for future research will therefore be for participants to report the ownership of objects presented for both brief (e.g., 10-30 ms) and extended (e.g., 90-110 ms) durations in a single experiment. If the argument advanced here is correct, then self-prioritization should be underpinned by a stimulus bias (i.e., rate of evidence gathering) under difficult processing conditions, but a response bias (i.e., evidential requirements of response generation) when additional time is available to encode the items. In other words, the pathway to prioritization is a function of the relative difficulty of the task at hand (White & Poldrack, 2014).

Given the potentially varied origins of self-prioritization, of general theoretical interest is task settings in which self-relevance impacts decisional processing through its effects on both stimulus and response biases (White & Poldrack, 2014). Noting the widespread preference for meaningless or inconsequential stimuli (e.g., geometric shapes, Gabors, pens, mugs) in existing work on this topic, Golubickis et al. (in press) considered how the desirability of objects influences self-prioritization. In particular, capturing an important facet of self-object interactions outside the laboratory, do people continue to prioritize self-owned (vs. friend-owned) stimuli when the items in question are undesirable (e.g., appealing vs. unappealing posters)? Two aspects of the resultant findings were noteworthy. First, self-prioritization only emerged when desirable (vs. undesirable) posters were owned-by-self (Ye & Gawronski, 2016). Second, this effect was underpinned by a combination of response and stimulus biases. Specifically, less evidence was required when making owned-by-self compared to owned-by-friend responses and evidence was extracted more efficiently from self-owned posters when they were appealing than unappealing. This demonstration that self-relevance triggers a positivity bias at the early stages of decisional processing is consistent with decades of social-psychological research and theorizing and affirms the use of drift diffusion modeling to identity to cognitive processes underpinning self-prioritization (Baumeister, 1998; Sedikides & Gregg, 2008; Voss et al., 2013).

What has yet to be established, of course, is the extent to which the current effects extend to other tasks and measures. A common assertion in the literature is that self-prioritization is an obligatory facet of social-cognitive functioning (Janczyk et al., 2019; Sui et al., 2012; Sui et al., 2014). As it turns out, however, this conclusion rests on the adoption of tasks in which the self-relevance (or otherwise) of stimuli is an essential component of the experimental instructions (e.g., perceptual-matching tasks, ownership tasks; Golubickis et al., 2018; Sui et al., 2012). Indeed, when this is no longer the case, self-prioritization is eliminated (Caughey et al., in press; Constable, Welsh et al., 2019; Dalmaso et al., in press; Falbén et al., 2019; Siebold et al., 2015; Stein et al., 2016; Wade & Vickery, 2018). For example, Constable, Welsh et al.'s (2019) prior-entry effect (i.e., self-owned vs. other-owned objects appear to be presented first during temporal judgments) was abolished when participants were asked to report if a mug appeared to the left or right of fixation (for related research, see Caughey et al., in press; Falbén et al., 2019; Siebold et al., 2015; Stein et al., 2016). It therefore remains an open question whether the stimulus bias observed here would emerge if self-relevance were not an explicit component of the task set and self-object associations were created and probed in different ways.

Extending previous research, the current findings provided evidence that the self-ownership effect can be underpinned by a stimulus bias (cf. Falbén et al., in press; Golubickis et al., 2018, 2019). When presented briefly and masked, compared to items owned by a friend, self-relevant stimuli were classified more quickly and accurately, an effect that was underpinned by differences in the rate of information uptake during decisional processing. Specifically, evidence was accumulated more rapidly from self-owned compared to friend-owned objects. These findings further understanding of the extent and basis of self-prioritization.

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