Value-based attentional capture influences context-dependent decision-making

Sirawaj Itthipuripat, Kexin Cha, Napat Rangsipat and John T. Serences

Neurosciences Graduate Program, University of California, San Diego, La Jolla, California; and Department of Psychology, University of California, San Diego, La Jolla, California

Submitted 6 April 2015; accepted in final form 19 May 2015

I

MATERIALS AND METHODS

Subjects. Twenty-eight (15 women, 13 men; 3 left-handed; age 18–32 yr) and twenty-seven (16 women, 11 men; 2 left-handed; age 18–45 yr) human subjects were recruited to participate in a behavioral study (Exp1) and an EEG study (Exp2), respectively. All participants were neurologically intact and had normal or corrected-to-normal color vision, and all signed an informed consent form for the study, which was approved by the Institutional Review Board at the University of California, San Diego. Subjects were compensated $10 and $15 per hour and received up to $10 and $20 of additional compensation contingent on behavioral performance during Exp1 and Exp2, respectively. In Exp2, 1 subject did not complete the experiment, leaving 26 subjects in the final analysis. Exp1 lasted ~1.5 h. Exp2 lasted ~3 h, including EEG preparation and recording.

Stimuli and tasks. We presented stimuli on a PC running Windows XP using MATLAB (MathWorks, Natick, MA) and the Psychophysics Toolbox (version 3.0.8; Brainard 1997; Pelli 1985). Participants were instructed to make a choice response in response to each stimulus presented. Each trial consisted of four phases: stimulus presentation; response period; feedback period; and intertrial interval. Stimuli were rendered either in a color that was previously associated with a high or a low reward value (Fig. 1). The experimental objective was to maximize the obtained reward across the course of the experiment.

This work is licensed under a Creative Commons Attribution-NonCommercial-No Derivatives 4.0 International License. The images or other third party material in this article are included in the article’s Creative Commons license, unless indicated otherwise in the credit line; if the material is not included under the Creative Commons license, users will need to obtain permission from the license holder to reproduce the material. To view a copy of this license, visit http://creativecommons.org/licenses/by-nc-nd/4.0/
Fig. 1. Behavioral binary-choice task. On each trial, subjects selected 1 of 2 choice stimuli that were on either side of fixation. A task-irrelevant distractor simultaneously appeared below the fixation point. Different reward values (1, 5, or 9) were assigned to different stimulus colors (red, green, and blue) every 36 trials. On each trial, one of the choice stimuli yielded a reward if it was selected (termed a baited stimulus) and the other did not (termed a decoy). If subjects selected the baited target, they received 1, 5, or 9 points(s). If they selected the decoy, they received 0 points. The left stimulus was baited on 50% of the trials, and on the other 50% of trials the right stimulus was baited. The distractor could never be selected and thus could never yield a reward (termed the response-irrelevant distractor). The colors assigned to the left and right choice stimuli and to the distractor were pseudorandomized across trials so that the color of either of the 2 choice stimuli in the current trial could become the color of the distractor in the following trials (red and blue arrows).
index of attentional gain in early visual cortex (e.g., Busse et al. 2005; Hillyard et al. 1998; Hillyard and Anllo-Vento 1998; Itthipuripat et al. 2014a; Johannes et al. 1995; Luck et al. 1990; Luck and Hillyard 1994; Mangun and Buck 1998; Mangun and Hillyard 1987, 1988, 1990, 1991; Noesselt et al. 2002; Störmer et al. 2009; Van Voorhis and Hillyard 1977; Woldorff et al. 1997; Zimmer et al. 2010). Recent studies have further linked these components to the value-based modulation of sensory and perceptual processing (Baines et al. 2011; Hickey et al. 2010; MacLean and Giesbrecht 2015b). The N2pc component has been used to index the focus of visuospatial attention as determined by explicit attention cues, stimulus salience, or learned stimulus value (Hickey et al. 2006, 2008, 2009, 2010; Kiss et al. 2008; Luck et al. 1997; Qi et al. 2013; San Martín et al. 2014; Woodman et al. 2009; Woodman and Luck 1999). If the efficiency of choice behavior is impaired via value-based attentional capture, then we should observe a reduction in the differential amplitude of these lateralized ERP components as a function of distractor value.


Fig. 2. Distractor value increases decision uncertainty and decision time. A: probability of right choices as a function of left and right choice values for when distractor value is low, medium, and high (top, middle, and bottom). B: same data as A plotted as a function of differential choice value (right minus left choice values) and distractor value (low, medium, and high). Overall, higher distractor value reduces the tendency of subjects to choose higher-valued over lower-valued choices. C: reaction times (RTs), collapsed across left/right choices and across differential choice value bins, plotted as a function of distractor value. Overall, RTs increase as distractor value increases. Error bars for choice probability and RT data represent within-subject SE. ** Significant main effect of distractor value (P < 0.001). ††† Significant main effect of differential choice value (P < 0.001). xx,xxx Significant interaction between distractor value and differential choice value (P < 0.01 and P < 0.001, respectively).

EEG data were recorded with a 64+8 channel BioSemi ActiveTwo system (Amsterdam, The Netherlands) at a sampling rate of 512 Hz. Two reference electrodes were placed at the mastoids. We monitored vertical eye movements and blinks via four extra electrodes placed below and above the eyes. Horizontal eye movements were assessed via another pair of electrodes placed near the outer canthi of the eyes. The EEG data were referenced online to the BioSemi CMS-DRL reference, and all offsets from the reference were maintained below 20 μV. The data were preprocessed with a combination of EEGLab11.0.3.1b (Delorme and Makeig 2004) and custom MATLAB scripts.

After data collection, we referenced the continuous EEG data to the mean of the two mastoid electrodes and applied 0.25-Hz high-pass and 55-Hz low-pass Butterworth filters (3rd order). An additional 22-Hz low-pass filter was applied to plot the data, but all reported statistics were performed on the 55-Hz low-pass filtered data (Luck 2005; also see similar methods in Hickey et al. 2010). The data were then segmented into epochs extending from 500 ms before to 2,000 ms after the trial onset and baseline-corrected based on the mean response from 0–200 ms before stimulus onset. Prominent eyeblink artifacts were first rejected by independent component analysis (Makeig et al. 1995). We then discarded epochs contaminated by residual eyeblinks and vertical eye movements (more than ±80–150 μV deviation from zero, with thresholds chosen for each individual subject), horizontal eye movements (more than ±75–100 μV deviation from zero), excessive muscle activity, or drifts, using threshold rejection and visual inspection (10.21% of trials ± 1.29% SE). The artifact-corrected epochs were then sorted on the basis of the hemifield of the selected choice (left or right), the absolute differential value of the selected and unselected choices (low, medium, or high), and then on the value of the response-irrelevant distractor (low, medium, or high). ERPs were then calculated in each of the resulting 18 condition bins with standard signal averaging procedures. Note that in Exp2 we collapsed across positive and negative differential choice values because we obtained an EEG measurement related to both stimuli on every trial. Thus there were only three levels of differential choice value in Exp2 as opposed to five levels in Exp1 (i.e., in Exp1 we had levels of 8, 4, 0, 4, and 8 points).

We then examined the impact of distractor value on the lateralized ERPs recorded from posterior-occipital sites (PO3, P3, and P5, for the left hemisphere and PO4, P4, and P6 for the right hemisphere), where the distractor value effects were maximal. We compared the mean differential amplitude between ERPs contralateral and ipsilateral to the selected choice stimulus as a function of the differential value between the two choice stimuli and the value of the distractor. This comparison was carried out across three temporal windows: from 100 to 750 ms (P1), from 160 to 185 ms (N1), and from 215 to 300 ms (N2pc). For each of these ERP components, we used a two-way repeated-measures ANOVA with factors for the differential value between the two choice stimuli (3 levels: low, medium, and high) and...
distractor value (3 levels: low, medium, and high) to evaluate the influence of these two factors on the amplitude of the lateralized difference components. In addition, we defined the amplitude of the LPD component as the average response from 300 to 500 ms after stimulus in centroparietal electrodes (Cp1, CpZ, Cp2). A two-way repeated-measures ANOVA with factors for differential choice value and distractor value was used to evaluate modulations of LPD amplitude.

RESULTS

The value of a task-irrelevant distractor interferes with choice behavior and increases reaction times. In both experiments, subjects exhibit a significant bias to select higher-valued choices over lower-valued choices (Fig. 2, A and B). This bias gives rise to a significant main effect of differential choice value (right minus left choice values) on the probability of choosing the right choice (% right choices) in both Exp1 \( F(4,108) = 27.99, P < 0.0001 \) and Exp2 \( F(4,100) = 68.31, P < 0.0001 \). Importantly, this bias toward the higher-valued choice decreases as the value associated with the response-irrelevant distractor increases, leading to a significant interaction between differential choice value and distractor value in both Exp1 \( F(8,216) = 3.14, P = 0.0022 \) and Exp2 \( F(8,200) = 3.47, P = 0.00091 \). We then fit a cumulative Gaussian function to the behavioral data for each distractor value condition to

![Fig. 3. Choice behavior and RT data across trials. A: probability of right choices as a function of differential choice value (right minus left choice values) and distractor value (low, medium, and high) computed across the first 6–36 cumulative trials within each miniblock of 36 trials. Data from Exp1 and Exp2 are combined to improve analysis power. Overall, subjects exhibit a bias toward higher-valued choices within the first 6 trials, and the modulation of this bias by distractor value emerges within the first 12 trials. Error bars represent within-subject SE. B: corresponding \( \sigma \) parameters from fitting the choice probability data with a cumulative Gaussian function. Error bars indicate within-subject 95% confidence intervals. C: RTs plotted as a function of distractor value across the first 6–36 cumulative trials. Similar to choice behavior, the modulation of RTs by distractor value emerges within the first 12 trials. Error bars represent within-subject SE. ** Significant main effect of distractor value \( P < 0.01 \) and \( P < 0.001 \) with false discovery rate (FDR) correction for multiple comparisons]. \( \dagger \dagger \) Significant main effect of differential choice value \( P < 0.001 \) (FDR-corrected). *, **, *** Significant interactions between differential choice value and distractor value \( P \leq 0.012, P < 0.01, \text{ and } P < 0.001 \), FDR-corrected).](http://jn.physiology.org/)

Table 1. Parameters from fitting choice probability data from Fig. 2B with a cumulative Gaussian function

<table>
<thead>
<tr>
<th>Exp</th>
<th>Low distractor value</th>
<th>Med distractor value</th>
<th>High distractor value</th>
<th>Low distractor value</th>
<th>Med distractor value</th>
<th>High distractor value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>27.5</td>
<td>37.2</td>
<td>45.9</td>
<td>−0.04</td>
<td>0.3</td>
<td>−0.6</td>
</tr>
<tr>
<td></td>
<td>[18.5 32.3]</td>
<td>[32.9 45.4]</td>
<td>[40.5 54.3]</td>
<td>[−1.0 1.2]</td>
<td>[−0.4 1.0]</td>
<td>[−2.1 0.6]</td>
</tr>
<tr>
<td>2</td>
<td>25.6</td>
<td>30.6</td>
<td>40.8</td>
<td>1.6</td>
<td>2.4</td>
<td>3.3</td>
</tr>
<tr>
<td></td>
<td>[19.8 29.9]</td>
<td>[26.6 34.3]</td>
<td>[35.9 48.2]</td>
<td>[1.0 2.2]</td>
<td>[1.9 2.9]</td>
<td>[2.6 4.3]</td>
</tr>
</tbody>
</table>

All confidence intervals (CIs) are based on the bootstrapping procedure described in MATERIALS AND METHODS. \( \sigma \), Standard deviation; \( \mu \), mean.
estimate the standard deviation (σ) and the mean (μ) of the underlying function (where the σ parameter determines the slope of the function and the μ parameter determines horizontal position; see Table 1 for statistics and CIs). Across the two experiments, σ increases as a function of increasing distractor value (i.e., the slope of the best-fitting cumulative Gaussian decreases). In Exp1, μ does not differ across distractor value conditions, indicating that there is no overall preference for the left or right stimulus. However, in Exp2 there is a slight bias to respond to the left choice. Similar response biases have been observed in a previous study (Louie et al. 2013); however, as in the present study, these biases seem to vary idiosyncratically across subjects/groups.

In addition, RTs significantly increase as a function of distractor value in both Exp1 [F(2,54) = 9.57, P = 0.00028] and Exp2 [F(2,50) = 12.44, P < 0.001; see Fig. 2C]. Auxiliary analyses also demonstrate that subjects gradually learned the values associated with each color within the first six trials of a minisession, and the magnitude of these decision biases increases over the course of each miniblock (see Fig. 3 and Table 2 for results and statistics). The influence of distractor value on decision biases (i.e., the interaction between distractor value and differential choice value) and RTs emerges later (within the first 12 trials). Overall, the behavioral data from Exp1 and Exp2 suggest that even though the distractor is neither relevant nor available for selection, the learned value associated with the distractor color systematically captures attention and leads to less optimal and slower decisions.

Distractor value reduces the amplitude of lateralized ERP differences evoked by choice stimuli. Figure 4A illustrates averaged stimulus-locked ERPs measured from electrodes that are contralateral and ipsilateral to the selected stimulus (red and black traces, respectively) in the posterior-occipital electrodes. For illustrative purposes, data are from trials with a high differential choice value and a low distractor value, as this condition yields the largest difference between the lateralized ERPs. Overall, the magnitude of the lateralized N1 difference (contralateral minus ipsilateral) decreases as distractor value increases [Fig. 4, B and D; F(2,50) = 4.83, P = 0.012]. There is a similar modulation for the lateralized N2pc difference [Fig. 4, C and E; F(2,50) = 8.16, P = 0.00086]. There is no main effect of distractor value across the P1 window [F(2,50) = 1.97, P = 0.15]. Together, significant modulations of the lateralized N1 and N2pc components suggest that distractor value interferes with the early processing of choice stimuli (indexed by the modulation of the N1) and draws spatial attention away from the relevant choices (indexed by the modulation of the N2pc).

Distractor value modulates the amplitude of the late positive-going deflection. LPD amplitude decreases significantly with increasing distractor value [Fig. 5; F(2,50) = 10.25, P = 0.00018]. This modulation suggests slower postsensory processing (O’Connell et al. 2012) and is consistent with the observed increase in RTs as a function of distractor value (Fig. 2C). In addition, LPD amplitude decreases as differential choice value decreases [F(2,50) = 7.77, P = 0.0012], potentially reflecting increased decision uncertainty or decision conflict when the value of each choice is more similar (cf. Cavanagh et al. 2011; Hillyard et al. 1971; Itthipuripat et al. 2014a; O’Connell et al. 2012; Shenhav et al. 2014; Wiener and Thompson 2015).

**DISCUSSION**

Attentional capture induced by the learned value of an irrelevant visual stimulus has been shown to impair perfor-

---

**Table 2. Statistical results for cumulative trials analyses on choice behavior and RTs in Fig. 3**

<table>
<thead>
<tr>
<th>No. of Cumulative Trials</th>
<th>Main effect of differential choice value F(4,212) [P value]</th>
<th>Main effect of distractor value F(2,106) [P value]</th>
<th>Interaction F(8,424) [P value]</th>
<th>RTs (Fig. 3C) Main Effect of Distractor Value F(2,106) [P value]</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>8.77 [0.0001+++                           0.41 [0.066]                           1.76 [0.083]                           0.95 [0.39]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>21.52 [0.0001+++                         1.02 [0.37]                           3.16 [0.052]                           6.64 [0.084]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>37.35 [0.0001+++                         1.15 [0.32]                           3.16 [0.052]                           6.64 [0.084]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>47.12 [0.0001+++                         0.48 [0.62]                           2.48 [0.012]                           9.28 [0.0002***]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>54.95 [0.0001+++                         0.22 [0.81]                           3.25 [0.001**]                          11.68 [0.0001**]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>65.00 [0.0001+++                         0.13 [0.87]                           3.01 [0.0027**]                          [&lt;0.0001***]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>75.89 [0.0001+++                         0.34 [0.71]                           3.06 [0.0023**]                          [&lt;0.0001***]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>81.69 [0.0001+++                         0.00 [1.00]                           4.41 [&lt;0.0001***]                         [&lt;0.0001***]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>82.52 [0.0001+++                         0.22 [0.80]                           4.47 [&lt;0.0001***]                         [&lt;0.0001***]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>33</td>
<td>84.06 [0.0001+++                         0.30 [0.74]                           5.41 [&lt;0.0001***]                         [&lt;0.0001***]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>36</td>
<td>80.05 [0.0001+++                         0.48 [0.62]                           6.50 [&lt;0.0001***]                         [&lt;0.0001***]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

RT, reaction time. **,***Significant main effects of distractor value [P < 0.01 and P < 0.001, false discovery rate (FDR)-corrected]. +++Significant main effect of differential choice value (P < 0.001, FDR-corrected). **,**,***Significant interactions between distractor value and differential choice value (P ≤ 0.012, P < 0.01, and P < 0.001, FDR-corrected).
mance during visual search (Anderson et al. 2011a, 2011b; Anderson and Yantis 2012, 2013; Hickey et al. 2010; MacLean and Giesbrecht 2015a; Qi et al. 2013). Here we tested the hypothesis that this value-driven attention capture contributes to context-dependent modulations during value-based decision-making (e.g., Hunt et al. 2014; Louie et al. 2013). Across two experiments, human subjects respond more slowly and are less likely to choose the higher-value choice as distractor value increases. Simultaneously recorded EEG data show that the amplitudes of the lateralized N1 and N2pc difference waves, as well as the amplitude of decision-related LPD, all decrease as distractor value increases. These results suggest that distractor value interferes with early sensory and attention-related processing of relevant choices, and we speculate that these early modulations then propagate to influence the speed and the outcome of decision-making. Taken together, our data strongly speak against normative theories of decision-making (Luce 1959; Samuelson 1947; Stephens and Krebs 1986) that posit context independence during decision-making. Moreover, our data suggest that value-based attentional capture by a response-irrelevant stimulus is one important factor that contributes to this context dependence.

Fig. 4. Distractor value reduces the amplitudes of lateral-ized event-related potentials (ERPs). A: averaged stimulus-locked posterior-occipital ERPs contralateral to selected (red) and unselected (black) choice stimuli in the condition with high differential choice value but low distractor value. B and C: zoomed-in view of lateralized N1 and N2pc components plotted as a function of differential choice value and distractor value. D and E: mean amplitude difference of the lateralized ERPs across the N1 and N2pc windows, plotted as a function of differential choice value and distractor value. Overall, the amplitude difference of the early N1 and attention-shift-related N2pc components decreases (became less negative) as distractor value increases. F and G: topographical maps of the lateralized N1 contralateral-minus-ipsilateral difference and the N2pc contralateral-minus-ipsilateral difference between the high and low distractor value conditions (shown in the right hemisphere of the head model; the left hemisphere is the mirror image of the right hemisphere with the opposite sign). The effect of distractor value on these 2 components is maximal at the lateral posterior-occipital and posterior electrodes (red circles). Error bars represent within-subject SE. *, ** Significant main effects of distractor value ($P < 0.05$ and $P < 0.001$, respectively).
Recent studies using ternary-choice tasks have shown that preference for the highest-value option over the second-highest-value option can be impacted by the value of a third low-value option (Hunt et al. 2014; Louie et al. 2013). These observations can be explained by divisive normalization (Carandini and Heeger 2012), a computational principle that has been used to account for gain control in sensory systems (Heeger 1992; Rabinowitz et al. 2011; Reynaud et al. 2012; Tsai et al. 2012; Zoccolan 2005) and attentional modulation of sensory signals (Herrmann et al. 2010; Iththuripat et al. 2014b; Reynolds et al. 1999; Reynolds and Heeger 2009). Specifically, value-based normalization models postulate that the neural representation of each option is divided by the summed activity that represents the value of all available options (Louie et al. 2011, 2013; Rangel and Clithero 2012). Thus an increase in the value of the third stimulus will normalize the differential value of the other two stimuli and decision-making will be less consistent.

The present observation that increased distractor value leads to less efficient decision-making and attenuated ERP responses is consistent with divisive normalization. However, there are several differences between the present task and tasks used in past studies that support value-based normalization models (e.g., Hunt et al. 2014; Louie et al. 2011, 2013). First, we used a binary-choice task instead of a ternary-choice task in which all three stimuli could be selected by the observer. This design change allowed us to selectively examine the impact of attentional capture by a response-irrelevant distractor. Second, the present task had a shorter response window and less predictable reward rates (i.e., a 50% probability of reward combined with a change in the association between reward and color every 36 trials). This speed pressure and increase in uncertainty may have led subjects to adopt a fundamentally different strategy than in previous experiments (e.g., Hunt et al. 2014; Louie et al. 2011, 2013). We view this as unlikely, however, as subjects learned the value that was associated with each color within the first six trials following a change (Fig. 3). Thus, even though our experimental design differed somewhat compared with previous studies, our behavioral data suggest that distractor value has an impact on decision-making in a manner that is consistent with value-based normalization (Louie et al. 2011, 2013; Rangel and Clithero 2012). In addition, across all trial types and value manipulations, the probability that a left or right choice stimulus would be rewarded was equated. Therefore, the effect of distractor value on behavioral choice cannot be attributed to a difference in reward uncertainty across conditions. Finally, the dynamic modulation of EEG markers is consistent with previous observations that cortical areas along the dorsal visual pathway encode value in a relative manner (Anderson et al. 2014; Buschschulte et al. 2014; Hickey and Peelen 2015; Louie et al. 2011; Persichetti et al. 2015; Schiffer et al. 2014; Serences 2008; Serences and Sapiro 2010; Stänisör et al. 2013) and that divisive normalization operates to regulate responses in these regions (Carandini and Heeger 2012; Louie et al. 2011, 2013; Reynolds et al. 2010; Stänisör et al. 2009). Taken together, the data suggest that value-driven attentional capture interacts with divisive normalization to mediate context effects during decision-making.

Reward learning in this task may bias decision-making by modulating attentional priority via interactions between reward-related mesolimbic, attentional control, and sensory systems. Previous work suggests that attentional selection depends on a neuronal network centered on the basal ganglia that receives converging inputs from substantia nigra, ventral tegmental area, thalamus, amygdala, and cerebral cortex (Anderson et al. 2014; Bromberg-Martin et al. 2010; Gottlieb et al. 2014; Hickey and Peelen 2015; Hikosaka et al. 2013; Krauzlis et al. 2014; Nakano et al. 1990; Peck et al. 2013; Seo and

Fig. 5. Distractor value reduces the amplitude of the late positive-going deflection (LPD or P300). A: stimulus-locked centroparietal ERPs across differential choice values (low to high from left to right) and distractor values (low, medium, and high). B: mean amplitude of the LPD component, plotted as a function of differential choice value and distractor value. LPD amplitude decreases as distractor value increases (see topography in C). In contrast, LPD amplitude increases as differential choice value increases (see topography in D). Error bars represent within-subject SE. ††,***Significant main effect of differential choice value (P < 0.01) and distractor value (P < 0.001), respectively.
Goldman-Rakic 1985; Zorrilla and Koob 2013). Consistent with this idea, past studies have demonstrated that reward-based learning can enhance the saliency of a stimulus and can flexibly and selectively alter attentional priority maps (Anderson et al. 2011a, 2011b; Anderson and Yantis; 2012, 2013; Awh et al. 2012; Chelazzi et al. 2014; Hickey et al. 2010; Krebs et al. 2011; Lee and Shomstein 2014; Schiffer et al. 2014) thought to be encoded by population-level activity throughout occipital and parietal cortex (Itti and Koch 2001; Serences and Yantis 2007; Sprague and Serences 2013). Moreover, patients with dysfunctions in the mesolimbic dopaminergic pathway, such as drug addicts and patients with Parkinson’s disease, exhibit deficits in visual attention (Botha and Carr 2012; Fénelon 2008; Field et al. 2004a, 2004b; Field and Cox 2008; Hepp et al. 2013; Horowitz et al. 2006; Lubman et al. 2000; Maddox et al. 1996; Stormark et al. 1997). Thus the interplay between the reward-related mesolimbic pathway and attentional priority maps may allow the brain to control the balance between bottom-up and top-down inputs that are necessary for representing the value of individual alternatives during decision-making. Future research could extend these results by using different measurement techniques combined with modeling methods (Hunt et al. 2014; Louie et al. 2013; Sprague and Serences 2013) to examine how interactions between reward-related and attentional systems jointly influence value-based decision-making.

ACKNOWLEDGMENTS

We thank Siyi Chen for help with data collection and Thomas Sprague, Vy Vo, Edward Ester, Stephanie Nelli, Scott Freeman, and Evan Carr for useful discussions.

GRANTS

This work was supported by a Howard Hughes Medical Institute international student fellowship to S. Ithipuripat and by National Institute of Mental Health Grant R01-MH-092345 and a James S. McDonnell Foundation grant to J. T. Serences.

DISCLOSURES

No conflicts of financial or otherwise, are declared by the author(s).

AUTHOR CONTRIBUTIONS

Author contributions: S.I. and J.T.S. conception and design of research; S.I., K.C., and N.R. performed experiments; S.I., K.C., and N.R. analyzed data; S.I. prepared figures; S.I. drafted manuscript; S.I. and J.T.S. edited and revised manuscript; S.I., K.C., N.R., and J.T.S. interpreted results of experiments; S.I. prepared figures; S.I. drafted manuscript; S.I. and J.T.S. approved final version of manuscript.

REFERENCES

Anderson BA, Laurent PA, Yantis S. Learned value magnifies salience-based attentional capture. PLOS One 6: e27926, 2011a.


