

# Effects of value on early sensory activity and motor preparation during rapid sensorimotor decisions

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## Abstract

Various computational accounts have been proposed to explain how sensorimotor decisions are biased by value. Although the longstanding dominant account has been the Starting Point Bias model, where the starting point of an evidence-accumulating decision variable is shifted towards the higher value bound, our group recently showed that fast biased decisions are best explained by a Drift Rate Bias model, where the mean tendency of the decision variable is itself biased by value (Afacan-Seref et al., 2018). This account is consistent with an enhancement of representations of higher value alternatives at the sensory level, but there has yet been no empirical neural evidence for such enhancement. Our study examined this by recording EEG data during a value-biased orientation discrimination task under a strict deadline, where each target orientation has a different value.

Our neurophysiological analyses revealed that there was no value modulation of the early sensory activity and behavioural data was best fitted by a model in which Drift Rate biases are implemented through a Biased Urgency signal. These findings further demonstrate the inadequacy of standard models in explaining highly time-constrained, value-biased decisions, and highlight novel computational architectures that may explain the more complex decision formation dynamics unfolding in such scenarios, which are prevalent in real life.

**Keywords:** Decision-making; Value; V1 region; EEG

## Introduction

Researchers of perceptual decision making have long focused on two possible mechanisms by which value can bias the decision process. The most prominent of these accounts suggests a shift in the starting point of the evidence accumulation process towards the higher-value bound. Such Starting Point Bias accounts have been found to provide an excellent quantitative fit to behavioural data across a large number of psychophysical tasks (e.g. Ratcliff & McKoon, 2008; Summerfield & Tsetsos, 2012), far better than the main rival account the Drift Rate Bias model. This approach considers that value biases affect the mean tendency of the decision variable, or drift rate, which is consistent with an enhancement of the representation of the higher value alternative at the sensory level,

because stronger sensory evidence would lead to a steeper build-up of its integral. However, recent evidence shows that fast biased decisions about color are best explained by a Drift Rate Bias model when one allows for temporally increasing drift rate (Afacan-Seref et al., 2018). However, this study was not able to provide a direct evidence of sensory modulation, leaving unclear what were the exact neural mechanisms underlying this drift rate bias.

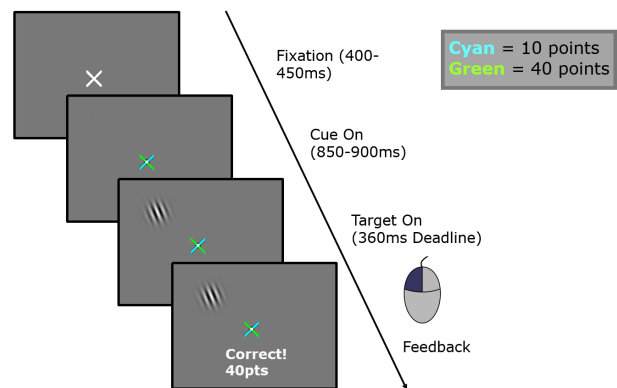


Figure 1: Orientation discrimination task

Visual information is first encoded by primary visual cortex (V1), which a long line of human electroencephalography (EEG) studies have shown is reflected in the earliest component of the visual evoked potential C1 (Clark et al., 1994; Di Russo et al., 2002; Gonzalez et al., 1994). It has been suggested that this initial V1 activity is impenetrable to cognitive influences, and that the earliest top-down modulations occur in extrastriate cortex (e.g. Martinez et al., 1999). However, neurophysiology, neuroimaging and microstimulation studies have suggested that these sensory cortical representations could be biased by their association with value (Cicmil, Cumming, Parker, & Krug, 2015; Rorie, Gao, McClelland, & Newsome, 2010; Serences & Saproo, 2010; Stanisor, van der Togt, Pennartz, & Roelfsema, 2013) (Cicmil, Cumming, Parker, Krug, 2015; Rorie, Gao, McClelland, Newsome, 2010; Serences Saproo, 2010; Stanisor, van der Togt, Pennartz, Roelfsema, 2013), suggesting that the V1 might not be impenetrable to reward-related factors.

In the present study we examined whether drift rate biasing mechanisms under conditions of intense speed pressure extend to decisions about the feature of orientation, and whether early visual cortical representations of orientation are themselves biased by value. To do this we recorded EEG (Biosemi), eye-position (Eyelink) and electromyography (EMG) of the flexor pollicis brevis muscle during a value-biased orientation discrimination task under a strict deadline, where a correct response to one orientation was worth more (40 points) than the other (10).

Twenty-three individuals participated in this study. During the task, participants had to discriminate between left and right oriented gratings. The relative value of these changed across trials and was indicated with the presentation of a cue preceding the target stimulus (Figure 1).

Because V1 architecture is extremely variable across individuals, our group has developed a novel procedure that is able to map the individual retinotopic organization of the V1 region by manipulating flicker-phase offsets among angular segments of a large annular stimulus (Vanegas, Blangero, & Kelly, 2013). We then averaged these results across participants and selected the two locations that produced the most reliable C1 component. The targets in our task were placed on those locations, lying on the right and left side of the vertical meridian and far from the Centro Parietal Positivity.

## Results

As expected, errors were more frequent ( $p < .001$ ) and were committed with greater haste ( $p < .01$ ) on low value trials such that the fastest responses were purely value driven and the slowest entirely sensory-driven (hence correct).

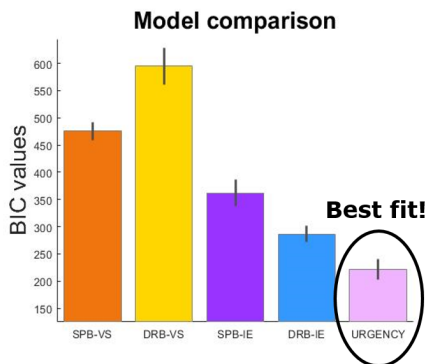


Figure 2: BIC values

The same Starting Point Bias and Drift Rate Bias models from Afacan-Seref et al. (2018) were fitted to the data and Bayesian Information Criterion (BIC) scores were calculated for each of these 4 models (Figure 2). As in Afacan-Seref et al. (2018), a Drift Rate Bias model (DRB-IE, Figure 2) explained behaviour best out of these 4 models.

Despite this, neurophysiological analyses revealed that the initial C1 component of the visual evoked potential (VEP),

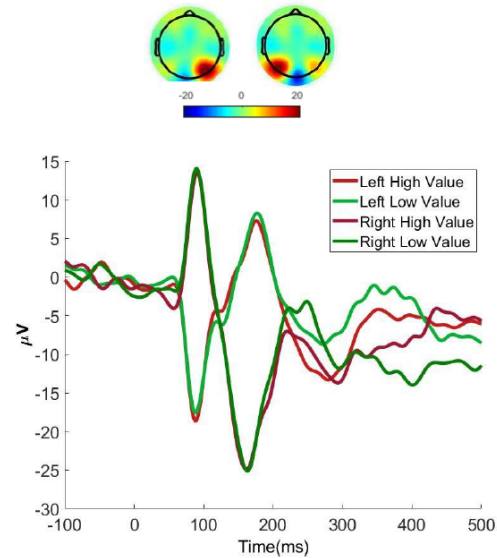


Figure 3: Early sensory activity

thought to reflect primary visual cortical activation, showed no signs of significant value modulation ( $p > .1$ ) for either correct responses or for errors (Figure 3).

A Starting Point Bias mechanism around target onset was observed in the Lateralized Readiness Potential (LRP), across the different value conditions. Interestingly, this starting point bias seemed to increase with time (Figure 4).

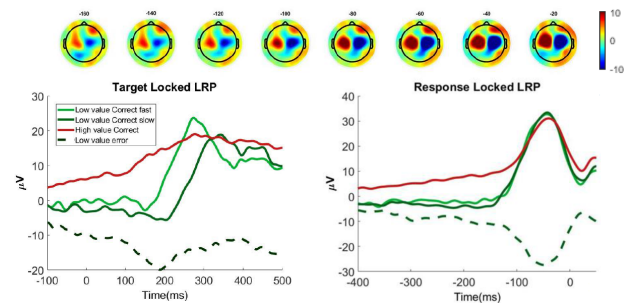


Figure 4: Motor preparation signal (LRP)

Because the models fitted to the data cannot account for such an effect in the LRP signal and their drift rate bias couldn't be explained by a modulation of the C1 activity, a new neurally-informed model was designed (see supplementary information for a better description of the model), following the work of Hanks et al. (2011), where a biased urgency signal was introduced for prior probability effects, that could account for such LRP deflections and provided a mechanism for the implementation of Drift Rate Bias (Figure 5).

When fitted to the behavioural data, the new model fitted better than any of the other models (Figure 2, 5th model labelled Urgency). In order to test the ability of this model to

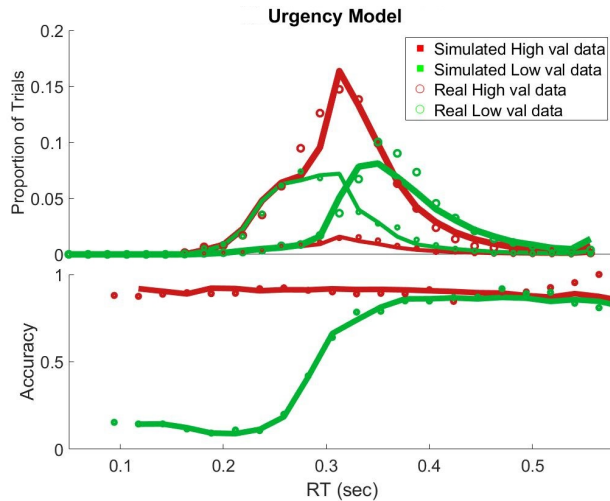


Figure 5: Urgency model

quantitatively reproduce both the neural dynamics and behaviour, we constrained a parameter marking the time of onset of the growing urgency signal so that it matched that of the real LRP - a value of -0.4 sec. Qualitatively, this did not compromise the behavioural fit of the model and when used for simulating LRP data, it was able to mimic the real signals behaviour (Figure 6).

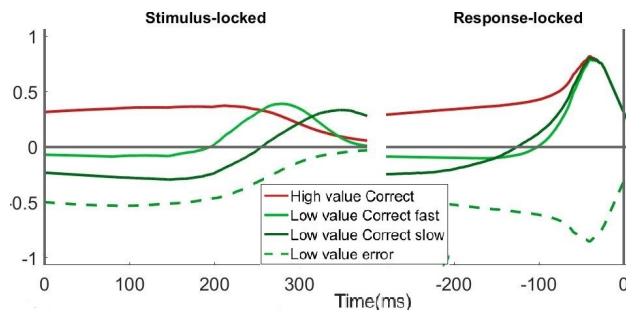


Figure 6: LRP Simulation

## Conclusion

We have replicated Afacan-Seref et al. (2018) results in an orientation discrimination paradigm, where a model that includes Drift Rate Biases fits better than a Starting Point Bias one. However, no value modulation of the sensory information was found. There is another possibility in which drift rate biases could be implemented, other than at the sensory level, they could be implemented at a later processing stage such as the motor level. We have presented a neurally informed model, which implements drift rate biases in the form of urgency signals and is able to account for behavioural and neural data, better than any of the other models fitted so far.

This study then, provides evidence against value modulations of the sensory information during rapid value-biased decisions and suggests a novel neurally informed computational account that can explain behavioural data, evidence accumulation and motor preparation dynamics. These results are important because the brain processes that underlie value-guided sensorimotor decisions are fundamental to natural behaviour and are dysfunctional in a wide range of disorders including depression, addiction and obsessive-compulsive disorder. This study could shed light on the mechanisms underlying these dysfunctions.

## Supplementary material

The dynamics of the one-dimensional decision variable (DV),  $x$ , described by the discrete difference equation.

$$x(t) = x(t-1) + urate * dt + [d * dt + N(0, s)]e(t)$$

$$urate = N(\pm ub, su)$$

$$e(t) = \begin{cases} 0 & \text{when } t < evonT \\ 1 & \text{when } t \geq evonT \end{cases}$$

Where  $dt$  is the discrete time increment,  $urate$  is the rate of increase of the urgency signal,  $N(0, s)$  refers to Gaussian noise with zero mean and variance  $s$ ,  $e(t)$  represents the appearance of the evidence and so, the start of the evidence accumulation process.  $Ub$  is the mean of the urgency signal which has a positive sign for High Value conditions and a negative one for Low Value ones. Whereas  $su$  is the standard deviation for the urgency rate and  $d$  is the mean of the noisy evidence that onsets at time  $evonT$ .

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