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Classic EEG motor potentials track the emergence of value-based decisions

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ABSTRACT

Making a value-based decision is a cognitively complex phenomenon and divisible into several sub-processes, such as the perception, evaluation, and final selection of choice options. Although previous research has attempted to dissociate these processes in the brain, there is emerging evidence that late action selection mechanisms are influenced continuously throughout the entire decision act. We used electroencephalography (EEG) and an established sequential decision making paradigm to investigate the extent to which the readiness potential (RP) and the lateralized readiness potential (LRP), two classic preparatory EEG motor components, reflect the ongoing evaluation process in value-based choices. During the task, human participants sequentially sampled probabilistic information to buy or reject offers of unknown value (using both hands) and were allowed to respond at any time. The pressure to respond was manipulated by charging low or high costs for collecting information. We modeled how and when decisions were made and found that participants adaptively lowered their threshold for required evidence with information costs and elapsed time. These shifts were accompanied by an increased RP-like signal during the decision process. The RP was further influenced by the amount of accumulated evidence. In addition, an LRP could be measured from the start of the decision process, well in advance and independent of the final decision. Our results are consistent with a continuous involvement of the brain's motor system in emerging value-based decisions and advocate using classic EEG motor potentials for studying neurocognitive theories of decision making.

Introduction

Decisions are not made instantaneously but they require time for intermediate processing steps, like searching and accumulating evidence, that lead to the final motor response (Gold and Shadlen, 2007; Heekeren et al., 2008). Recently, the focus of research on value-based decisions has shifted from merely predicting the output of the decision process to understanding how it develops over time by testing behavioral and neuronal predictions from computational models that make inferences on the time course of decisions (Basten et al., 2010; Gluth et al., 2012; Hare et al., 2011; Krajbich et al., 2010; Tsetsos et al., 2012). These *sequential sampling models* (SSM) assume the decision maker to sample evidence for choice options over time until an internal decision criterion is met and a response is given (Otter et al., 2008; Ratcliff and Smith, 2004; Summerfield and Tsetsos, 2012; Townsend and Ashby, 1983).

In a previous study (Gluth et al., 2012), we investigated the neuronal mechanisms underlying the emergence of value-based decisions using functional Magnetic Resonance Imaging (fMRI) in combination with a sequential decision making paradigm. In this paradigm, participants decide to either buy or reject stock offers based on sequentially delivered ratings that provide probabilistic information about the stocks' value. In contrast to many other sequential decision tasks (De Lange et al., 2010; Gould et al., 2012; Stern et al., 2010; Yang and Shadlen, 2007), participants are free to respond at any time. Using this paradigm, we were able to link cognitive sub-processes to fMRI signals in separate brain structures (e.g., the updating of expected value to striatum and ventromedial prefrontal cortex), but we also observed a tight coupling between emerging decision variables and preparatory activation in cortical motor areas: Activity in the pre-supplementary motor area (pre-SMA) was correlated with the amount of accumulated evidence and also increased over time. Furthermore, lateralized activation of the primary motor cortices was found right from the beginning of the accumulation process well before responses were made. These results are inconsistent with strictly serial theories of decision making (Padoa-Schioppa, 2011; Posner, 1986; Sternberg, 1969), which assume response selection mechanisms to start only after decision processes are completed. They also bear an intriguing prospect for further research: If preparatory motor signals track the development of value-based choices, the high temporal precision with which they can be recorded (with EEG) could be exploited to test neurocognitive theories of decision making.

In the present study, we therefore investigated the interplay of evidence accumulation and preparatory motor signals using EEG and an adapted version of our sequential decision making task (Fig. 1A). We focused on two classic EEG motor potentials, the readiness potential (RP, Kornhuber and Deecke, 1965) and the lateralized readiness

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potential (LRP, Coles, 1989). The RP measured at the central electrode Cz is closely linked to activation of the pre-SMA (Shibasaki and Hallett, 2006) and based on our fMRI study it can be predicted that the RP is modulated by factors that influence the "tendency to respond" (i.e., accumulated evidence and elapsed time). We further introduced a novel manipulation of response pressure to test for a modulation of the RP amplitude. In addition, we hypothesized that the LRP tracks the evidence for different choice options (here: buying vs. rejecting an offer) if these options are assigned to different response hands. As in our previous work, we modeled participants' behavior by means of the SSM approach to gain a deeper understanding of the cognitive mechanisms underlying the decision process.

Methods

Participants

Participants were 30 right-handed healthy persons with normal or corrected-to-normal vision. Data of two participants could not be analyzed due to severe EEG artifacts. Therefore, the final sample included 28 participants (mean age = 26.3 years, ±4.2 SD, 20–40 years; 14 females). The study was approved by the local ethics committee and all participants gave written informed consent. Participants were reimbursed for participation and could earn additional money by winning points in the task (every collected point was rewarded with 0.01 Euro).

Experimental design

The sequential decision problem was adapted from our previous study (Gluth et al., 2012). Participants had to decide whether to buy or reject stock offers based on ratings (of fictitious stock rating companies) that provided probabilistic information about the stock's value (Fig. 1A). Each trial started with the *cost phase* (2000 ms), in which the participant was informed about the costs for observing one rating (rating costs) in that particular trial. Rating costs could be either *low* (–2 points) or *high* (–5 points) according to a randomized order. Rating costs were presented in red, in the middle of the black display screen. The *cost phase* was followed by a *break* (2000 ms), in which a white "x" was shown. Afterwards, the *decision phase* commenced with presentation of the first rating (1500 ms for each rating). Enclosed by a gray frame, the rating appeared (in white) in the middle of the screen and the cumulative costs for observed ratings were presented (in red) above it together with the number of observed ratings (in white). Note that Fig. 1A exaggerates the size of the gray frame and the cues for illustration purposes; all information was presented in a narrow range in the middle of the screen to prevent excessive eye movements (screen size: 19 in.; distance to screen: ~95 cm; horizontal visual angle: ~1.6°; vertical visual angle: ~2.4°). After the participant's response or the presentation of the last (i.e., sixth) rating, the next trial started with a variable delay of 2 to 6 s. Stimulus presentation was realized using the Presentation Software package (Neurobehavioral Systems).

Participants were told that stocks were either *good* (value: +80 points) or *bad* (value: −80 points) and buying a stock would lead to the payment of its value. Participants were instructed to respond whenever they wanted during the *decision phase* but that a response had to be given after disclosure of the sixth rating at the latest (otherwise they would receive the negative value of a bad stock while paying the costs for all six ratings). They were further informed about the possible rating values (i.e., "− −", "–", "+", or "+ +"), the two rating cost conditions, the independence of subsequent ratings from each other, that all ratings were equally important, that the prior probability of good

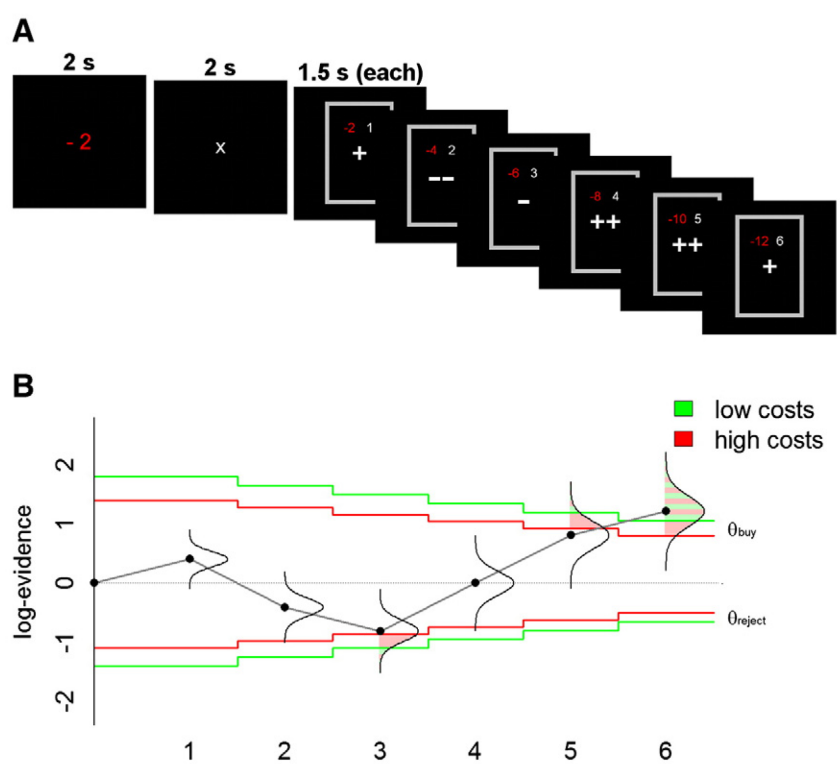

Fig. 1. Experimental design and sequential sampling model. *A*, Example trial of the sequential decision making problem. Participants decided to either buy or reject a stock of unknown value based on up to six sequentially presented ratings determining the probability of a good stock. Participants were free to respond at any time (during rating presentation) and had to invest points for each rating (rating costs). Preceding the *decision phase*, the amount of rating costs (high or low) was indicated during the *cost phase*. *B*, Illustration of the best performing cognitive model (the *time-variant SSM*) for the trial shown in *A*. The log-evidence is updated after each rating and its distance to the decision thresholds determines the probability of buying and rejecting the stock at each time point. The decision thresholds for trials with high costs are closer to each other, implying less evidence accumulation and faster responses. Thresholds also decrease linearly with time points.