Electroencephalographic topography measures of experienced utility

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Abstract: Economic theory distinguishes two concepts of utility: decision utility, objectively quantifiable by choices, and experienced utility, referring to the satisfaction by an obtainment. To date, experienced utility is typically measured with subjective ratings. This study intended to quantify experienced utility by global levels of neuronal activity. Neuronal activity was measured by means of electroencephalographic (EEG) responses to gain and omission of graded monetary rewards at the level of the EEG topography in human subjects. A novel analysis approach allowed approximating psychophysiological value functions for the experienced utility of monetary rewards. In addition, we identified the time windows of the event-related potentials (ERP) and the respective intracortical sources, in which variations in neuronal activity were significantly related to the value or valence of outcomes. Results indicate that value functions of experienced utility and regret disproportionally increase with monetary value, and thus contradict the compressing value functions of decision utility. The temporal pattern of outcome evaluation suggests an initial (250 ms) coarse evaluation regarding the valence, concurrent with a finer-grained evaluation of the value of gained rewards, whereas the evaluation of the value of omitted rewards emerges later. We hypothesize that this temporal double dissociation is explained by reward prediction errors. Finally, a late, yet unreported, reward-sensitive ERP topography (500 ms) was identified. The sources of these topographical covariations are estimated in the ventromedial prefrontal cortex, the medial frontal gyrus, the anterior and posterior cingulate cortex and the hippocampus/amygdala. The results provide important new evidence regarding "how," "when," and "where" the brain evaluates outcomes with different hedonic impact.

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Electroencephalographic Topography Measures of Experienced Utility

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Economic theory distinguishes two concepts of utility: decision utility, objectively quantifiable by choices, and experienced utility, referring to the satisfaction by an obtainment. To date, experienced utility is typically measured with subjective ratings. This study intended to quantify experienced utility by global levels of neuronal activity. Neuronal activity was measured by means of electroencephalographic (EEG) responses to gain and omission of graded monetary rewards at the level of the EEG topography in human subjects. A novel analysis approach allowed approximating psychophysiological value functions for the experienced utility of monetary rewards. In addition, we identified the time windows of the event-related potentials (ERP) and the respective intracortical sources, in which variations in neuronal activity were significantly related to the value or valence of outcomes. Results indicate that value functions of experienced utility and regret disproportionally increase with monetary value, and thus contradict the compressing value functions of decision utility. The temporal pattern of outcome evaluation suggests an initial (~250 ms) coarse evaluation regarding the valence, concurrent with a finer-grained evaluation of the value of gained rewards, whereas the evaluation of the value of omitted rewards emerges later. We hypothesize that this temporal double dissociation is explained by reward prediction errors. Finally, a late, yet unreported, reward-sensitive ERP topography (~500 ms) was identified. The sources of these topographical covariations are estimated in the ventromedial prefrontal cortex, the medial frontal gyrus, the anterior and posterior cingulate cortex and the hippocampus/amygdala. The results provide important new evidence regarding "how," "when," and "where" the brain evaluates outcomes with different hedonic impact.

Introduction

To optimize behavior, an organism needs to assess the experienced utility of actions or objects compared with its expected utility. The expected utility of a prospect is behaviorally inferred from revealed choices (Becker et al., 1964). Conversely, the experienced utility, referring to the hedonic impact of an obtainment (Bentham, 1798), is more difficult to objectively quantify because it represents a transient subjective state of emotion.

Recent research using functional magnetic resonance imaging has identified neuronal structures that are involved in the evaluation of rewarding and punishing outcomes and therefore implicitly provide physiologically based correlates of experienced utility and experienced regret (Knutson et al., 2003; O’Doherty et al., 2003; Coricelli et al., 2007; D’Ardenne et al., 2008). Electroencephalographic (EEG) studies revealed insights to the temporal course of outcome evaluation. Besides others, most prominently two event-related potentials (ERP) have been identified: the feedback error-related negativity (fERN) (Holroyd et al., 2003; Hajcak et al., 2005) and its pendant, the feedback correct-related positivity (fCRP) (Holroyd et al., 2008). The fERN amplitude increases when outcomes are worse than expected, whereas the fCRP is more pronounced, when outcomes are better than expected. Consequently, the difference between the expectation and outcome is thought to define the experienced utility of the outcome (Yeung et al., 2005; Potts et al., 2006).

Until this present study, it has not been investigated how different magnitudes of outcomes are related to the magnitude of global brain activity. From a logical point of view, neuronal activity elicited by stimuli solely differing in reward magnitude must reflect their hedonic impacts. Consequently, the quantification of the magnitude of brain responses of a reasonable sample of different rewards would enable to construct value functions for experienced utility in the case of gain and experienced regret in the case of omission. Value functions for experienced utility and regret may be of profound interest because they could help clarify why people sometimes fail to choose what maximizes their happiness (Hsee and Hastie, 2006).

To derive such value functions, high-density EEG was recorded while subjects played a wheel-of-fortune game, during which they could win graded monetary rewards. In addition, we aimed to extend knowledge on electrophysiological responses to rewards by circumventing common methodological issues: a majority of previous studies investigated only difference waveforms.

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Subjects. Sixteen healthy subjects (10 female, 6 male; mean latency and localization of brain activity covarying (and not only sources of EEG activity. Using this information, we delineated is available and thus can be used to estimate the intracerebral EEG measures, the full spatial and temporal information of EEG topography using the whole set of electrodes. With topographic approach, we investigated outcome-related responses at the ERP previously selected electrodes. These electrodes are not represented in the outermost circumferences (chin and neck) were omitted, because the head model implemented in standardized low-resolution electromagnetic tomography (sLORETA) (Pascual-Marqui, 2002), which was used to localize intracerebral sources, does not cover these electrodes. The remaining 109 electrodes were submitted to additional analysis. The EEG was filtered offline from 1.5 to 30 Hz. Eye movement artifacts were removed from the data using independent component analysis. Trials containing additional artifacts after visual inspection were excluded from the ERP analysis. EEG data was recomputed against the average reference. Artifact-free EEG epochs of 1200 ms were extracted with onsets 200 ms before the presentation of the outcome stimuli (Fig. 1D). The average ± SD number of artifact-free data epochs from each subject was as follows: 134.4 ± 15.2 (of 150) for the rewarded outcomes and 132.0 ± 16.2 (of 150) for the omitted outcomes. ERP maps of each reward condition were averaged for each subject. Grand-average ERPs across subjects were computed for each reward condition and across reward conditions.

Definition of the time window of analysis: Consistent ERP topography across subjects. To restrain the temporal window of analysis, we followed a recently suggested approach (Koenig and Melie-Garcia, 2009, 2010) that detects the time periods in the ERP in which similar intracortical generators are active across subjects. Because similar generators imply similar topographies, topographies across subjects are tested for consistency. For this test, the global field power (GFP) of the grand mean ERPs is taken as the measure of effect size. The null hypothesis states that for each time point, the GFP of the grand mean ERP (i.e., the mean ERP across subjects of the mean ERPs within subjects) may be observed by chance. To test this hypothesis, the GFP of the grand mean ERP was compared with 5000 GFPs of the grand mean ERPs that were constructed by randomly shuffling the measurements across electrodes of the grand mean ERP within each subject. To obtain the probability of the null hypothesis, the percentage of cases was computed in which the GFP obtained after randomization was larger than the GFP obtained in the observed data. This procedure was applied for grand means of won outcomes, lost outcomes, and all outcomes.

Topographic analysis of covariance (TANCOVA) was used to identify the time points in which the global scalp field potentials significantly covaried with the external variables.
This method of analysis introduced by Koenig et al. (2008) relies on the fact that ERP fields are additive. Therefore, the existence of a source that is active proportionally to an external variable results in a single topography that is added to the ERP proportionally to the external variable. To retrieve the topography that is proportional to the external variable at a given point in time, the covariance of the external variable with the potentials at each electrode at that point in time is computed. The obtained covariance map $\beta$ represents the map corresponding to the generators that activate proportionally to the external variable at the given point in time. Using the GFP of this covariance map as an effect size allows testing time frame for time frame for significant covariation by applying randomization statistics as described by Koenig et al. (2008).

For the time windows indicating significant ($p < 0.01$) consistent scalp topographies across subjects, TANCOVs were computed for the variables: reward value of gains (levels: 10), reward value of omitted outcomes (levels: 10), and valence (gains vs omitted rewards) (levels: 2). Because it was not known whether reward value contributes linearly to the scalp field map, we tested different, monotonic functions to relate reward with the electrophysiological data with the goal of maximizing the correspondence of the actual reward value and the electrophysiological index of reward representation. Reward values $x_i$ were therefore transformed using a power function with parameter $\alpha$ ($\alpha < 1$, concave function; $\alpha = 1$, linear function; $\alpha > 1$, convex function):

$$x_i^\alpha = x_i'^\alpha,$$

where $i$ is the reward level, $x$ is the reward (ranging from 0 to 1), and $x_i$ is the covariate used for the computation of the covariance maps. $\alpha$ was varied in the range of 0.01 to 10 with increments of 0.1. For each subject and value of $\alpha$, covariance maps $\beta$ between the transformed reward values and the potentials at each electrode and each included point in time were computed as follows:

$$\beta_{ic} = \sum_{i=1}^{10} v_{ic}x_i,$$

where $v$ is the scalp potential at electrode $e$, time point $t$, and reward level $i$. These covariance maps were then used to compute, for each reward level, an electrophysiological index $\xi_i$ of reward using the following equation (Koenig et al. 2008):

$$s_{ic} = \sum_{e=1}^{m} v_{ic}x_i \beta_{ic},$$

and where $\xi$ is the mean of $s_{ic}$ across time.

The correspondence between $\xi$ and $x_i$ was defined by the squared Pearson’s correlation coefficient $r^2$ between the two vectors, which is equivalent to the percentage of common variance. The individual optimal $\alpha$ was defined at which this correspondence was maximal. In a next step, we assessed whether the $r^2$ and $\alpha$ values of best-fitting functions significantly differ from the corresponding $r^2$ values and a linear function ($\alpha = 1$), using Wilcoxon’s signed-rank tests and paired $t$-tests, when appropriate. The median of the $\alpha$ values of the best-fitting functions entered the randomization test, described in the following section. To visually confirm the goodness of fit of the value functions, the values of $s_{ic}$ were plotted.

According to Koenig et al. (2008), a randomization procedure (5000 iterations) was used to identify at which time points of the ERP the global scalp field potentials significantly covaried with the previously determined best-fitting value function. Because this test calculates whether the ERP topography covaries above chance level for each time frame independently, the problem of multiple testing needs to be addressed. Following the same rationale of randomization statistics as for determining significance levels for each time frame, we calculated whether the duration of a time window of continuous significant covariation might be observed by chance. Thus, the probability of falsely detecting certain duration of a significant effect was computed. Details on this particular test are explicated by Koenig and Melie-Garcia (2009, 2010). Results are reported with a threshold for significance of $p < 0.01$. For significant time windows, the false-positive probability of the duration (FPP-D) is indicated. The whole analytical procedure was conducted for the won outcome conditions and the reward omission outcome conditions separately. Because the variable reward valence has only two levels and can be considered as a special case of a covariational analysis (with parameters of 1 for won and $-1$ for omission) (Koenig et al., 2008), the analysis steps of fitting the best function were unnecessary.

Source localization. Because the generated TANCOVA maps represent a linear transformation of the topographical data, they can directly be submitted to source localization procedures (Koenig et al., 2008). The inverse solution of the ERP data was calculated using sLORETA (http://www.uzh.ch/keyinst/loreta.htm) (Pascual-Marqui, 2002). This method computes the current density magnitude (amperes per square millimeter) of each voxel, localizing the neural generators of the electrical activity by assuming similar activation among neighboring neuronal clusters. The solution space was computed on a spherical head model with anatomical constraints (Spinelli et al., 2000) and comprised 3005 solution points equidistantly distributed within the gray matter of the cerebral cortex and limbic structures of the Montreal Neurological Institute (MNI) 152 average brain. Anatomical labels are reported using an appropriate correction from Talairach–Tournoux to MNI space (Brett et al., 2002). The obtained tomography represents the intracerebral generators of the scalp field data accounting for the effects observed in the external variable with the full spatial resolution of the measured data. The graphical rendering of intracerebral sources and the ERP topographies was performed using the Cartool software (brainmapping.unicg.ch/cartool) (Brunet et al., 2011).

Results

Behavioral results

The behavioral task consisted of pseudorandomly assigned gained and omitted rewards, and the subjects were informed that the chance to win was 50% throughout the experiment. Nevertheless, we were interested how frequently subjects changed their choice of color to bet on, depending on the outcome and type of the previous trial. Results indicated no significant difference in the frequency of changing the choice for a color, depending on neither the value at stake ($F_{(9,135)} = 0.942; p < 0.491$), nor the outcomes (gain/loss) ($F_{(1,15)} = 0.262; p < 0.616$), nor on the interaction of both ($F_{(9,135)} = 0.492; p < 0.878$).

Consistent topography across subjects

The test for consistent ERP topographies of the grand means across subjects revealed significant ($p < 0.01$) consistency for a time window from $-100$ to 564 ms (with the outcome as temporal reference), with an inconsistent time window at 132–140 ms. It is noteworthy that such a short period of inconsistency within a larger time window of consistent ERP topography typically occurs when ERP topographies change polarity, indicating that ERP sources are in transition to new stable states. The topography of the grand mean of gain trials was consistent across subjects from $-72$ to 544 ms. Similarly, the grand mean ERP topography of all omission trials was consistent from $-112$ to 568 ms, with inconsistent time frames at 132–140, 396–408, and 464–24 ms. The information of the obtained consistent time frames was submitted to the proceeding analysis steps of reward value function estimation and the TANCOVA (see Fig. 3A).

Estimation of value functions

The value functions for gains and omissions were estimated subject-wise according to the criterion of the maximal sum of explained variance in the ERP data during the time of consistent topography. For both gains and omissions, convex functions fitted the ERP data best [$\alpha_{\text{gains}}$; median (Mdn), 2.41; median abso-
The TANCOVA on the variable valence revealed significantly (268–304 ms (FPP-D  \( \leq 0.038 \)) after outcome onset. For reward values of omitted outcomes, ERP topographies indicated a trend (\( p < 0.05 \)) for significant covariations with reward value during a time window of 360–380 ms after outcome onset (Fig. 3B). Plots of the electrophysiological index of reward \( s_{ij} \), as function of time and reward level (Fig. 3C) should provide an insight on how the different reward levels contribute to the overall representation of reward across time.

**Source localization**

sLORETA was used to localize the intracranial generators of the ERP covariance maps for each time point in the ERPs. The reported intracranial generators represent the averaged time windows of significant covariance derived in the TANCOVA. Therefore, this approach revealed the relative contribution of intracranial sources covarying with the external variables. Overall, source localization revealed a neuronal network that sensitively responds to information about rewarding (or disappointing in the case of omissions) outcomes that includes the ventromedial prefrontal cortex (VMPFC), anterior and posterior cingulate cortex (ACC/PCC), the hippocampus and amygdala (Hipp/Amy), and the medial frontal gyrus (MFG).

The point of maximal current source density (CSD) for value during the time window of 248–312 ms was found in VMPFC (MNI: \( x = -9, y = 42, z = -16 \)). The time window from 456 to 520 ms indicated maximal CSD in the right Hipp/Amy (MNI: \( x = 29, y = -12, z = -26 \)). The covariance maps of value coding after gains at the time window of 268–304 ms revealed maximal CSD at the left MFG (MNI: \( x = -32, y = 8, z = 60 \)). For the time window of 480–512 ms highest CSD was found at the VMPFC (MNI: \( x = -3, y = 35, z = -21 \)). The covariance maps of value coding after omitted rewards at the time window of 360–380 ms revealed maximal CSD at the right Hipp/Amy (MNI: \( x = 29, y = -12, z = -26 \)) (Fig. 3E).

**Discussion**

This study aimed to extend knowledge on reward processing by investigating ERP responses at the level of the EEG topography. This approach offers several attractions: it combines the full spatial representation of EEG data with a high time resolution and direct access to neuronal signaling. In addition, it is possible to collect a large number of trials within a short time. These factors made it possible to provide novel contributions to the understanding of “how,” “where,” and “when” reward is processed.

**“How” is monetary reward translated into brain activity?**

We determined the form of relation between ERP topographies and associated monetary reward values. This functional form describes how the global response of brain activity is related to stimuli indicating gain and omission of different monetary rewards. Because we ensured that these stimuli solely differed with respect to the magnitude of the outcome, it is conceivable that the response of brain activity (measured at the ERP topography) corresponds to the experienced utility or regret of a more or less favorable outcome. Contrary to our expectations, the results revealed convex value functions for gains and omissions. Therefore, the sensitivity of the electrophysiological response nonlinearly increased for larger values. This finding is in contrast to concave utility functions derived from revealed choices (decision utility) and stimulus–intensity coding functions, following the psychophysics of diminishing sensitivity (Kahneman and Tversky, 1979). It is possible that the discrepancy between the value functions is attributable to the low monetary values at stake in our experiment. However, as reported for value func-
tions of decision utility, it is assumable that value functions for experienced utility might not change with rising stakes (Fehr-Duda et al., 2010). In addition, it has been shown that reward value is neuronally coded in relation to possible outcomes and not at an absolute scale (Nieuwenhuis et al., 2005; Tobler et al., 2005; Elliott et al., 2008; De Martino et al., 2009; Fujiwara et al., 2009). New experiments are called for to examine the robustness of this unforeseen result, thus allowing to propose conscientious psychological interpretations of value functions for experienced utility and experienced regret.

“Where” is value and valence processed?

Source solutions revealed a network of brain areas, which sensitively responded to information about rewarding (or disappointing) outcomes that includes the VMPFC, ACC/PCC, hippocampus/amygdala, and MFG. Interestingly, the characteristic topographies of covariance of the specific time windows and conditions seems not to result from structurally dissociable neuronal processes as suggested previously (Yeung and Sanfey, 2004; Yacubian et al., 2006). Instead, it seems that a common network is involved in the processing of distinct aspects of reward information; the components are differentially engaged depending on the specific step in processing.

For example, the VMPFC responds sensitively to the valence of the outcome and the value of gains but to a lesser extent to the value of omissions. This is in line with previous studies showing that activity in the VMPFC increases after rewarding outcomes compared with omissions (Knutson et al., 2003) and is correlated with experienced value (Smith et al., 2010) and pleasantness ratings (Lebreton et al., 2009). In addition, the MFG predominantly responded to information about value but scarcely to valence. This conforms to linear increasing activity with the reward value of gains (Elliott et al., 2003). The source solution indicated most prominent (but not exclusive) omission-sensitive activity in the hippocampus in vicinity to the amygdala. The potential involvement of the amygdala replicates previous results showing that the amygdala encodes negative prediction errors (e.g., worse than expected outcomes) (Yacubian et al., 2006) but also responds to rewards (Breiter et al., 2001) and is generally believed to encode the emotional significance of stimuli, be it appetitive or aversive (Shabel and Janak, 2009). Similarly, besides the processing of mnemonic functions, the observation of reward-dependent variation of activity in the hippocampus is compatible with the key
role played by this structure in reward and emotion (Blood and Zatorre, 2001).

We are aware that the precision of the EEG source localization is limited, and it likely cannot distinguish activity, for example, in the amygdala from hippocampal activity. Nevertheless, at a more general level, it has been shown that mediotemporal activity or activity in the VMPFC (or orbitofrontal cortex) can be reliably retrieved from scalp EEG using similar source reconstruction techniques as in our study (Lantz et al., 1997, 2001; Pizzagalli et al., 2003; Zumsteg et al., 2005).

“When” is reward information processed?
The results indicate that, at a first stage (~250–300 ms after outcome), two factors of outcomes are processed: a coarse evaluation along a good–bad dimension (valence) and a concurrent, finer-grained evaluation of positive outcomes (value). The value of omitted rewards covaried with the ERP topography at a greater latency (~360 ms after outcome). Importantly, during this time window, ERP topographies did not differ with respect to the valence of outcomes. The results therefore revealed a concurrent processing of valence and value of gained rewards and a later processing of omitted reward values.

We conjecture that this scheme of brain responses may be driven through cortical input of midbrain reward prediction error (RPE) signals. Seminal experiments of Schultz et al. (1997) have shown that, for rewards at chance, a positive RPE is generated, which is represented by a phasic increase in spiking activity. This increase is scaled to the value of gained rewards (Fiorillo et al., 2003; Bayer and Glimcher, 2005). It was suggested that these phasic fluctuations of dopaminergic midbrain activity modulate activity in the ACC (Holroyd and Coles, 2002; Holroyd et al., 2003). Furthermore, in line with our results, several studies revealed that the dopaminergic midbrain is effectively connected (besides others) with the VMPFC, MFG, and hippocampus/amygdala (for review, see Camara et al., 2009). In the case of the omission of a reward, a depression in spiking activity typically follows (Schultz et al., 1997). Therefore, the difference between the depression and any scaled increase of spikes makes it possible that valence and value of gains are concurrently encoded.

For scaled negative RPEs (e.g., modulated through omitted rewards of different magnitude), the quantification of omitted depression appears to be limited (Fiorillo et al., 2003) because the range of the spiking rate of dopaminergic midbrain neurons from the baseline rate (3–8 spikes/s) (Niv and Schoenbaum, 2008) to zero spiking is marginal. This might explain why the value of omitted rewards is not processed at the same time as value of gains in the present study.

However, it has been suggested that scaled negative RPEs are coded by means of the duration of the pauses in spiking (Bayer et al., 2007). Consequently, it only makes sense to pass the information about the value of negative RPEs from midbrain structures to higher cognitive processing after the full expiration of the pause. In line with this, omitted reward values in this study significantly covaried with the ERP topography ~110 ms after the first significant effect of valence coding.

Although we were exploring measures at the level of the ERP topography, by and large our results are supported through findings of research focusing on ERP responses of individual electrodes (Hajcak et al., 2005; Potts et al., 2006; Hewig et al., 2008; Holroyd et al., 2008; San Martin et al., 2010). For example, underpinning the hypothesis of dopaminergically driven ERP topographies, Cohen et al. (2007) showed that, during a time window in the range of the first processing of valence and value of gains, power and phase coherence values of ERPs after wins but not losses were modulated by reward probability, which, like reward value, modulates the magnitude of RPEs. Regarding the omission-sensitive ERP topography, previous studies reported that the amplitude of the (highly similar in terms of topography and latency) P300 reflects a pure coding of value regardless of valence in the P300 component (Yeung and Sanfey, 2004; Sato et al., 2005), whereas others indicated that the P300 is sensitive to valence and value (Hajcak et al., 2005; Holroyd and Krigolson, 2007; Wu and Zhou, 2009).

Besides the above-discussed results, which are within the temporal range of previously reported feedback-related ERPs, the ERP topography in a later time window (~470 ms after feedback) significantly varied as a result of valence and value differences of the gains. Again, the ERP topography did not reflect an influence of the value of omitted rewards. The processing of valence and value of gains similarly involved the VMPFC and hippocampus/amygdala. Activity in the VMPFC more strongly covaried with the value of gains, whereas activity in the Hipp/Amy exhibited the strongest source of valence-dependent variation. The finding of a later, yet not reported, reward-sensitive ERP topography demonstrates one of the key advantages of our analysis approach, namely the a priori unrestricted analysis of all electrodes and time points of the post-outcome epoch.

To conclude, the present results demonstrate a measure of experienced utility by means of brain activity. In addition, ERP responses to different aspects of reward information recruit similar but differently weighted neuronal structures in a specific temporal sequence. The time course of processing argues in favor of dopaminergically driven activity.

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