**To cite this Article**: Suomala, J. ; Hlushchuk, Y. ; Kauttonen, J. ; Heinonen, J. ; Palokangas, L. ; Numminen, J. (2017) Distributed brain networks reflect salary offer in accord ance with the prospect theory's value function. Journal of neuroscience, psychology, and economics 10:4, 167-180.

doi: 10.1037/npe0000083

URL: http://dx.doi.org/10.1037/npe0000083

Distributed Brain Networks Reflect Salary Offer in Accordance with Prospect Theory Value Function

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**Running head**: Salary Choice and Prospect Theory

**Keywords:** fMRI, Prospect Theory, Salary expectation, Maximization scale, Choice

## Abstract

Previous studies have found an association between the Prospect Theory's (PT) value function and the networks in the prefrontal cortex and the striatum during routine choice, but little is known about the brain activity and the role of the PT during choices regarding a salary expectation. We constructed an experiment in which the subjects' wage expectations were used as a Reference Point (RP) and representatives of two distinct psychological profiles in decision-making served as subjects. Sixteen university students – 8 maximizers and 8 satisficers - were recruited to participate in the fMRI study.

Maximizers normally put more effort and time to optimize their choices. Our design featured a constraint on time and maximal number of offers. Behavioral data showed that maximizers, unlike satisficers, tried to optimize the outcome even under such constraints.

FMRI responses in the areas of the prefrontal cortex (pMFC; right rPFC), occipital cortex (left LinG; occipital visual areas), inferior parietal lobule (IPL) on the right and the angular gyrus (AngG) correlated positively with increased wage offers weighted accordingly to PT-value function. Furthermore, maximizers and satisficers differed markedly in how brain activation were engaged in the medial prefrontal cortex (MPFC).

Previous neuroimaging studies on PT-value function have employed status quo as a RP, whereas our results demonstrated activity in distributed brain networks when salary expectation

served as RP. Furthermore, the PT-value function effect of frontal cortex according to the psychological profile, being stronger among maximizers than satisficers.

## Introduction

Humans are unique in their capacity to form expectations of future situations (Geary, 2005; Heath, Larrick, & Wu, 1999; Szpunar, Watson, & McDermott, 2007). For example, when students pursue the goal of graduating from university, they form subjective expectations of their future earnings and this expectation has a significant impact on the related choices (Brunello, Lucifora, & Winter-Ebmer, 2004).

For example, consider an employer who offers 2500 euros per month to two graduated job seekers; the first accepts the offer, whereas the other rejects it. Albeit both job seekers face the same offer, their choices differ. There is growing evidence that people value the outcomes in light of the expectations act as RP (Abeler, Falk, Goette, & Huffman, 2011; Camerer, Babcock, Loewenstein, & Thaler, 1997; Heath et al., 1999; Koszegi & Rabin, 2006). Neuroscientific research has demonstrated that the decisions vary between subjects, because their brains give different subjective value to the offers (Levy & Glimcher, 2012; Rangel, Camerer, & Montague, 2008). In contrast, behavioral research has explained individual differences based on psychological profiles of individuals. For example, maximizers have greater reliance on external sources of information than satisficers and they invest more heavily in gathering information from external source and invest more search cost than satisficers (Iyengar, Wells, & Schwartz, 2006). Even though individual differences between maximizers and satisficers have been shown in the field studies (Iyengar et al., 2006; Schwartz et al., 2002), it is unclear up to now whether and how this psychological tendency relate to individual differences in behavioral and neural processing, when salary expectation is RP.

The Prospect Theory (PT) value function explains how a chooser transforms objective values of offers to subjective values at the present of RP according to s-shaped value function (Kahneman, 2003; Kahneman & Tversky, 1979; Thaler, 2015; Tversky & Kahneman, 1981). Here we concentrate on the PT value function $v(x)$ defined as $x^{\alpha}$ for $x \geq 0$ and $-\lambda(-x)^{\alpha}$ for $x<0$ where $0<\alpha<1$ creates the s-shape and $\lambda>0$ adjusts the symmetry between gain and loss. The PT has successfully described human choice in situations, where a chooser's status quo at the time of each choice dictates the subjective RP (Kahneman, 2003). In these situations a chooser perceives any negative departure from her status quo as a loss, while perceiving any positive departure from the same status quo as a gain (Louie & De Martino, 2014; Tversky & Kahneman, 1981). While the status quo as RP is widely used, it fails to explain aforementioned salary choices, where both offers present increase will result in a positive deviation from the status quo of graduated students' current salary.

The few behavioral studies (Abeler et al., 2011; Camerer et al., 1997; Heath et al., 1999) have shown that one's goal as RP can affect people's choice, similarly to the status quo as RP. However, these studies have employed designs in which goals have been determined exogenously (Abeler et al., 2011; Heath et al., 1999) and thus could not have subjective expectations in contrast to the example situation described at the beginning of this chapter.

Previous studies have found neural correlates between the PT-value function and brain activity in the frontal cortex (the ventromedial prefrontal cortex (VMPFC)), in the orbitofrontal cortex (OFC), in the anterior cingulate cortex (ACC) and in the subcortical brain areas (Bechara &

Damasio, 2005; De Martino, 2006; Hsu, Krajbich, Zhao, & Camerer, 2009; Tom, Fox, Trepel, & Poldrack, 2007; Venkatraman, Clithero, Fitzsimons, & Huettel, 2012).

There are three essential features of previous PT-based fMRI-studies. Firstly, valuation in a monetary gamble requires determining the probability of the occurrence of a monetary payoff. Secondly, most of the previous choice studies have focused on the routine and prosaic choice and RP that was decided exogenously (Louie & De Martino, 2014; Odean, 1998). Thirdly, RP in those studies has been determined by people's current status quo rather than their expectations.

The object of the study was to investigate networks of the brain that are related to wage offers, and especially whether there are differences between maximizers and satisficers. We hypothesized that salary expectations serve as RP and alter the values of outcomes as described in the principles of the PT-value function (Heath et al., 1999; Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). The study investigates whether the previously indicated frontal and subcortical areas in value-based choice (Bechara & Damasio, 2005; De Martino, 2006; Hare, Camerer, & Rangel, 2009; Hsu et al., 2009; Levy & Glimcher, 2012; Plassmann, O'Doherty, & Rangel, 2007) also encode for the value of salary offers according to PT-value function.

This study uniquely included a salary expectation that acted as a subjective RP for the fMRI scan. In this way, the study sought to reveal new brain correlations between a subjective expectations and the PT-value function. Testing salary expectation as potential candidate for RP extends previous research which has restricted attention mainly to the status quo as RP.

## Materials and Methods

### Participants

Eighteen healthy, right-handed students from Laurea University of Applied Sciences participated in the study. At the preprocessing stage of data analysis, we had to discard the data for two subjects due to artifacts; as such, the results presented are based upon data of only 16 subjects (6 males, mean age: 29.6 years; range: 21.4 – 48.0). The ethics committee of the Hospital District of Helsinki and Uusimaa approved the study. The subjects gave their written informed consent before participating.

Two types of subjects were recruited, maximizers (n=8) and satisficers (n=8), who were classified using a specific maximization scale (Schwartz et al., 2002). The subsets were chosen from an earlier study that was based on web-based maximization questionnaires (Casagrande, 2007). The subjects from this earlier study gave personal permission for the follow-up study and formed the subject pool for this fMRI study (n=923). Following Schwartz et al.'s (2002) criteria, subjects who scored at least 65 points were classified as maximizers, whereas satisficers scored below 41 out of a maximum of 91 points. The subject pool thus comprised of 91 maximizers and 170 satisficers, with eight subjects from each group were scanned in this fMRI study. The mean maximization score was 67.6 (SD = 2.6) in the maximizer group and 32.0 (SD = 6.1) in the satisficers group.

### Tasks and Procedure

Subjects were scanned at the Advanced Magnetic Imaging (AMI) Centre, Aalto University, Finland. Imaging was performed using a General Electric Signa™ EXCITE™ 3 T MR scanner (GE Medical Systems).

Before entering the scanner, the subjects were asked about their personal wage expectation after graduation. The answer was used as a subjective RP in the fMRI experiment. The wage offers were then scaled according to this subjective RP. Thus the goals and stimuli-sets vary between participants and no absolute level of the offers have been used. However, we used conventional parametrization for PT of $\alpha$=0.85 and $\lambda$=2 for PT as a yardstick in order to compare participants' responses. The offers were based upon two different uniform probability distributions in order to minimize the possibility of learning during the experiment (Braunstein & Schotter, 1982). The range of the first uniform distribution was -30 % of the subjective RP (30 % less than RP) to +60 % of the subjective RP (60 % more than RP). The distance between offers was 5 %. The probability that an offer came from this distribution was 0.3. The range of the second uniform distribution was -30 % to +30 % of the subjective RP, and the distance between offers was 10 %. The probability that the offer came from this second distribution was 0.7. For simplicity in the data-analysis, only seven offer types were used. This included three offers below RP (-30 %, -20 %, -10 %), one offer at RP, and three offers above RP (+10 %, +20 %, +30 %).

Before the fMRI-experiment, the following instruction was given in Finnish:

*Imagine that you are searching for a job after graduation. You receive a set of job offers. You are offered one offer at a time, and your task is to accept or reject the offer. If you reject, you will move to the following offer in the series. If you accept, you will move to the next series. The maximum number of the offers in the series is five. Your experiment payment varies from €20 to €80, depending upon your choice. Inside the series, each additional offer cost you €1. However, you will not know whether the next offer is better or worse than the offer presented right now.*

The trials were first practiced outside of the scanner. To signal the rejection or acceptance of an offer in the scanner, the subjects pressed one of two buttons using the right index (rejection) or middle finger (acceptance), respectively.

The experiment consisted of several series that included one to five trials (offers) each. The trials were identical in their temporal structure (Fig. 1A). Within a trial, the subject observed a wage offer (on-screen time: 3.6 s), which could either be rejected or accepted (3.6 s), followed by fixation on a crosshair (1.8 s to 5.4 s; jitter) prior to the onset of the next trial or series. Each trial lasted from 9 s to 12.6 s, depending upon the jitter. If the subject rejected the offer, the next offer in the series followed; however, if the subject accepted the offer or rejected the last (fifth) offer of the series, the next series began. Within the sessions, the order of stimuli was randomized.

Insert Figure 1 here

The wage offer experiment was divided into two sessions, each lasting 18 min and 36 sec. The total amount of offers varied from 174 to 191 (M = 182.9; SD = 4.6) and the number of series in the experiments varied from 57 to 125 (M = 91; SD = 21.52), depending upon the subject's decisions.

After the experiment, the subjects' participation fee was constructed according to the following formula: one randomly selected accepted wage offer divided by the amount of offers + 20€ (basic fee), minus the cost of possible additional offers in the selected trial.

## Imaging

Visual stimuli were projected onto a screen behind the head coil that participants could observe via a mirror system attached to the head coil frame. Whole-brain echo planar images (EPI) were acquired with the following parameters: 27 contiguous oblique axial slices, 64 x 64 matrix, FOV 22 cm, slice thickness 5 mm, TR 1800 ms, TE 32 ms. Both experimental runs comprised 620 volumes. In addition, FLAIR images (33 slices, 256 x 1192 matrix, FOV 24 cm, TR 10 000 ms, TE 1200 ms) and high-resolution (1.02 mm x 1.35 mm x 1.0 mm) T1-weighted anatomical images were acquired. The stimuli were presented using Presentation® software (Neurobehavioral Systems Inc., Albany, CA).

**Behavioral Data Analysis**

The behavioral valuation function for seven wage offer levels was calculated in the following way: –1 was given for every rejected offer and +1 for every accepted offer. Thus, 0 corresponds to a 50 % acceptance rate (number of accepted offers = number of rejected offers). Then, the mean for every offer level was calculated separately. The average values for the maximizer and satisficers subsets were then determined. In addition, the differences between the maximizers and satisficers were compared by a two-tailed independent group t-test of the reference salary, the reaction times of rejection/acceptances, and the depth of the search. The depth of the search variable was calculated as the average number of rejected offers in a series.

The effect of the offer number (1-5) on the responses was studied by fitting response data with linear function with sigmoid decision boundary. We assumed that the probability of accepting an offer $i=1,\ldots,5$ was given by $p(i)=1/(1+\exp(-m(A+B\times i))$ where $A$ and $B$ set the decision boundary (via intersect point and slope) and $m>0$ adjusts subject's robustness in his/her answers and effectively sets the steepness of the decision boundary. We used Matlab (function *fmincon*) to find those $A$, $B$ and $m$ that maximized the likelihood for the observed responses (i.e., accept/reject) independently for each subject. While the optimal selection thresholds for the 5-offer task does not strictly follow a linear function, it was deemed as a valid approximation of the underlying nonlinear function.

## fMRI Data Analysis

An image analysis was performed using SPM8 (http://www.fil.ion.ucl.ac.uk/spm/; Wellcome Trust Centre for Neuroimaging, UCL). All preprocessing was done using functional Data Processing Assistant (fDPA) toolbox (Chao-Gan & Yu-Feng, 2010) developed by Yevhen Hlushchuk and Eerik Puuska based on DPARSF toolbox (Chao-Gan & Yu-Feng, 2010). The first three volumes/timepoints of each functional data set were discarded prior to further analysis. The remaining fMRI data were then corrected for head motion, co-registered to the subject's T1-weighted anatomical image, and then normalized to MNI space (Evans et al., 1993) through the unified segmentation of anatomical images. FDPA preprocessing incorporated artifact removal with the in-built ArtRepair toolbox (Mazaika, Hoeft, Glover, & Reiss, 2009). Artifact correction included deviation of signal of 1.5 % or 3 standard deviations or rapid (within-volume) movement of 0.5 mm/TR qualified volumes. Prior to artifact removal, the fMRI data were detrended to remove scanner-related drift (linear drifts might lead to erroneous artifact removal in ArtRepair toolbox). The normalized data were smoothed with 8 mm full-width-at-half-maximum Gaussian kernel (voxel acquisition size = 3 x 3 x 3 $mm^3$, normalized voxel size = 2 x 2 x 2 $mm^3$).

Pre-processed images were analyzed using a general linear model (GLM) with an event-related design. A high-pass filter with a default cutoff period of 128 s was applied in order to remove low-frequency drifts from the time series. The BOLD responses were modeled by the canonical hemodynamic response function.

**First-level analysis.** The analysis was conducted in terms of % deviations from the expected wage (RP) and each wage offer level (-30RP to +30RP in 10 % steps) was modeled as a combination of two predictors. The first predictor encoded a "wage offer event" (irrespective of the offer size, the same for all wage offers) while the second predictor encoded a "wage offer size" according to the

PT model. A conventional parameterization according to PT was used, in which losses are weighted approximately two times more than equivalent gains (Kahneman & Tversky, 1979). Using parameters $\alpha$=0.85 and $\lambda$=2, the following weights were used for parametric modulation (first-order=linear) of the "wage offer size" predictor:

(1) Wage offer 30 % below reference point; weight -36.

(2) Wage offer 20 % below reference point; weight -26.

(3) Wage offer 10 % below reference point; weight -14.

(4) Wage offer reference point; weight 0.

(5) Wage offer 10 % above reference point; weight 7.

(6) Wage offer 20 % above reference point; weight 13.

(7) Wage offer 30 % above reference point; weight 18.

To account for the effect of the offer number in our behavioral data, we have added "wage offer number" predictor that was modeled as the weights 1, 2, 3, 4 and 5 (first-order parametric modulation = linear) of the "wage offer event" predictor. Altogether, first level model contained thus three linear predictors: "wage offer event", "wage offer size", and "wage offer number".

**Second-level analysis.** First-level contrast images were subjected to a second-level random effects analysis using one and two-sample t-tests. The statistical threshold at the voxel-level was set at $p = 0.001$ (uncorrected) and the cluster-size threshold was set to 200 normalized voxels. Clusters at $p < 0.05$ (FDR-corrected at the cluster-level) were considered significant. Anatomical labeling of the clusters was done with AAL toolbox (Tzourio-Mazoyer et al., 2002).

**Testing loss-aversion parameter.** We analyzed the effect of the loss aversion parameter $\lambda$ in PT model with respect to the fMRI data with fixed $\alpha$=0.85. For this purpose, we used regions of interest (ROI) analysis using Brainnetome Atlas (Fan et al. 2016) containing 246 bilateral regions that cover cortical and subcortical grey-matter. We extracted mean signal from each ROI and fitted them with three models with number of predictors ranging from 1 to 3: Only the PT model with offer size (***model 1***), PT model with offer number (***model 2***) and separated PT model with offer size with unrestricted linear and nonlinear parts (i.e., function $v(x)$-$x$) and offer number (***model 3***). For model 3 large deviations from the PT model are allowed as fit coefficient for linear and nonlinear parts are no longer fixed, while the PT model predictor (as in models 1 and 2) is recovered only with coefficients being equal. Models were fitted independently to all ROI signals after the removal of (unmodulated) wage offer predictor which remained constant for all models and values of $\lambda$. This allowed us to concentrate on non-constant components of ROI signals and enabled easier comparison of models and $\lambda$ parameters. Model predictors were constructed by convolving boxcar signals with hemodynamic response function (SPM's function *spm_hrf*) followed by a high-pass filtering (150s; also applied to ROI signals). After fitting all models for all subjects, we computed the mean variance captured by each model and $\lambda$ parameters. Only those ROIs that surpassed $p<0.01$ (uncorrected Wilcoxon sign-rank test against zero) for PT model or its linear/nonlinear part for any of the three models and lambda parameters were included into the final averaging. Models were fitted for 30 equally separated points for $\lambda$ between 0.95 and 4, where $\lambda=1$ results in symmetric gain-loss valuation.

## Results

### Behavioral Results

There were no significant differences between the groups in the reaction time (M = 953 ms, SD = 188 ms), reference salary (M = 2434 €/ month, SD = 488 €) and depth of search (M = 2.13, SD =

0.579) variables. In addition, behavioral valuation profiles in the wage offer task (Fig. 1B) showed no difference between the maximizers and the satisficers.

However, when analyzing responses as a function of the offer number, we found that maximizers had tendency to optimize their responses. At the beginning of each trial (offers 1 and 2) they had higher threshold for accepting the salary offer as compared to the end of the trial (offers 4 and 5): Median fit parameter for the slope was -3.210 with median absolute deviation (MAD) of 2.891 for the maximizers and 0.001 (MAD 0.220) for the satisficers. The difference in the slope was significant between groups ($p$=0.021, 2-tailed Mann-Whitney U-test). Fig. 2 depicts responses and slope fits for two example subjects, a maximizer (Fig. 2A) and a satisficer (Fig. 2B), along with the slope coefficients for all subjects (Fig. 2C).

Insert Figure 2 here

**fMRI Results**

**Brain responses correlate with the PT-value of the wage offer.** The level of wage offers weighted by the PT-value function ("wage offer size" predictor) correlated positively with brain activation in five clusters (Fig. 3, red color): two frontal cortex clusters encompassed the posterior medial frontal cortex (pMFC) (Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004) and the most rostral portion of prefrontal cortex (rPFC) on the right (Koechlin & Hyafil, 2007). Of two visual cortex clusters, one cluster bilaterally encompassed occipital visual areas with parts from calcarine cortex and cuneus, and the other one covered the lingual gyrus (LinG) on the left. The remaining 5$^{th}$ cluster encompassed the angular gyrus (AngG) and inferior parietal lobule (IPL) on the right. This analysis revealed no significant clusters for negative correlations.

**PT-value of the wage offer: maximizers vs satisficers**. Two-sample t-test with the contrast "maximizers > satisficers" revealed only one significant cluster in the whole brain (Fig 3, green color). This cluster in the medial prefrontal cortex (mPFC) covered the gap between the two frontal clusters mentioned above and featured 58% overlap with those (Fig 3, yellow color). The reverse contrast, "satisficers > maximizers", revealed no significant clusters in the brain.

Insert Figure 3 here

**Brain responses to the "wage offer number".** One cluster covering IPL, SupraMarginal Gyrus (SMG) and AngG on the right correlated positively with the offer number (Fig. 4). This cluster was partially overlapping (16%) with the 5th cluster in the whole-group PT analysis. "Satisficers vs maximizers" revealed no significant group differences for this predictor.

Insert Figure 4 here

**ROI analysis for loss aversion parameter.** Total 54 ROIs resulted in statistically significant fit parameters for PT predictor (models 1 and 2) and/or its linear/non-linear parts (model 3). These 54 ROIs were kept the same for all models and subjects to ensure comparability. Figure 5 depicts the mean ROI signal variance explained by each model as a function of loss aversion parameter $\lambda$ computed over all 54 ROIs and subjects. The averaging over ROIs and subjects resulted in smooth curves, whose maxima of explained variances were at 1.27 (model 1), 3.70 (model 2) and 1.37 (model 3) with the arithmetic mean of the three being 2.11. All three models favored non-symmetric gain-loss with loss-aversion parameters $\lambda>1$, while value $\lambda=1$ would reflect symmetric PT-models.

Insert Figure 5 here

## Discussion

This study revealed a distributed brain network in which activity reflects the PT-value function, when subjective salary expectations were RP in the wage offer experiment. Upon incorporating these salary expectations as RP, the behavioral choice profiles were different among maximizers and satisficers (Fig. 2A-2C). We discuss these results more specific below.

### Effect of the wage offer number

Maximizers were more prone to decline first offers unless they were particularly high and only accepted them later (Fig. 2A-2C). This strategy of offer acceptance threshold being non-constant is theoretically better with higher expectation value. For satisficers the offer number did not have this effect and they were more likely to accept offers above some threshold regardless of the offer number. Despite we were unable to find the group difference for fMRI data, we found that activity in IPL, (SMG) and AngG on right was positively modulated by the offer number (Fig. 4). Previously the right IPL with SMG have been associated with sustaining attention, detecting novel events and switching between task-sets (Heinonen et al., 2016; Sing-Curry & Husain, 2009). Furthermore, the activation of AngG has been associated with self-awareness, autobiographical memory, optimal resource allocation and to the ability to mentally project oneself into the future (Geary, 2005; Tulving, 2002). These cognitive and attentional processes helps an individual to behave optimally, when s/he decided to accept the offer or to continue to search to the next offer in the wage offer experiment. These same cognitive and attentional processes may have involved also, when subjects try to keep their reference salary in the memory during the experiment, because the brain activation patterns in the right IPL and right AngG had associations to the wage offer size in the wage offer experiment (Fig.3, red color).

Although previous studies (Iyengar et al., 2006; Schwartz et al., 2002) have shown that maximizers applied for more jobs and received higher salary offers than did satisficers, we found no such behavior difference in our wage offer analysis. Unlike the above mentioned studies, our fMRI protocol design, however, imposed time-constraints that allowed for little if any variation in the number of considered offers between subjects. Thus there were no statistically significant group differences between reaction time, reference salary and depth of search and their behavioral profile approximately corresponds to the PT-value function (Fig. 1B). Along with the reference-dependence of the offers this might have diminished apparent differences in participants' behaviors despite distinct psychological tendency's differences as measured by maximization scale.

**Effect of the wage offer size**

Intriguingly, we found that the value of a salary expectation is computed in the brain by using the PT-value function (Fig. 3, red color). Also the behavioral choice profiles of participants also corresponded to the PT-value function (Fig. 1B). Most of the positive, PT-like activities of participants belong to the distributed brain network, which includes areas from the PFC, occipital and parietal cortices. This network has distinct connections to other parts of the brain and is thought to have an essential role in valuation and choice. In addition, these brain areas have associations to the evaluation of monetary gain, subjective goals and reward encoding process (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005; Hsu et al., 2009).

Both the pMFC and rPFC belong to the large frontal region, which has an essential role both when an individual provides subjective value for different goods (Levy & Glimcher, 2012) and when an individual processes self-referential stimuli (Bechara & Damasio, 2005; Sajonz et al., 2010). These areas also have an important role in flexible monitoring and coordination of choice and decision-making in uncertain and complex environments (Ridderinkhof et al., 2004) and allocate cognitive and emotional resources when people need to choose between immediate and long-term benefits (Koechlin & Hyafil, 2007). Thus, the functions of the pMFC and rPFC might support an individual to maintain goal-directed behavior by monitoring ongoing options and outcomes. One might conceive that our subjects experienced stronger relief with larger offers as they were further away from unsatisfactory offers and our rPFC cluster could reflect that. For example, Fujiwara et al. (2009) showed that a region in the anterior ventrolateral prefrontal cortex encodes the level of relief as quantified by the positive difference between chosen and unchosen outcomes. Visual comparison our rPFC cluster with the ventrolateral prefrontal cortex activation in the relief coding fMRI study, however, fails to support such notion (cf. Figure 3 in Fujiwara et al., 2009).

Intriguingly, we found a positive correlation between the LinG activation on the left and the PT-value function. There could be a number of different explanations for the role of the LinG in this study. First, it is possible that lingual activation may reflect valuation-dependent meaning of the wage offer. Several previous studies have presented evidence of associations with the LinG activation both for a multitude of valuation-dependent decisions (Elliott, Newman, Longe, & Deakin, 2003; Tricomi, Delgado, & Fiez, 2004; Vartanian & Goel, 2004) and memory functions (Burianova, McIntosh, & Grady, 2010; Ghosh, Basu, Kumaran, & Khushu, 2010; Leshikar, Duarte, & Hertzog, 2012). Similar to our study, the right LinG activation and bilateral LinG (Elliott et al., 2003) has been found to be responsive to monetary reward. In addition, the right LinG was related to aesthetic evaluation of paintings (Vartianian & Goel, 2004).

Regarding memory functions, Ghosh et al. (2010) argued that the LinG is part of the temporal semantic store, which process semantic information online. Similarly, Burianova et al. (2010)

foundthat the left LinG belongs to a large-scale network that has a specific role in working memory maintenance and memory retrieval. Thus, the LinG bilaterally, not only the left LinG, has an association with visual processing as well as with language processing and memory in all modalities.

Second, it is also possible that our findings could simply reflect a visual perception phenomenon (i.e., eye-fixation) in that the LinG may be responding to differences between the reject-option (when a participant's gaze direction was on the left) and the accept-option (when a participant's gaze direction was on the right) (Deutchländer et al., 2005). Thus the LinG activation is associated with the different patterns of eye movement.

In addition, Stoppel et al. (2009) found that the LinG was preferentially activated to process novel events without semantic meaning that were outside the focus of spatial attention. This finding supports the role of the LinG as a novelty detector during early perception. Because, we did not use an eye-tracker during experimentation, we cannot exclude the contribution of a visual perception phenomenon.

Thus, in some of the findings, these valuation approaches (Vartanian & Goel, 2004) parallel the ones obtained in this study, which suggests that the left LinG belongs to the common valuation processes at the time of choice. The importance of the role of the LinG in the brain's valuation network deserves more investigation.

Further, the occipital visual cortex (calcarine cortex and cuneus) was bilaterally activated in a manner that corresponds to the PT-value function. The neural mechanisms of visual attention operate at almost all stages of the visual system, as well as in many areas outside of the classically defined visual cortex (Sprague & Serences, 2013). We found that clusters in the occipital visual cortex were activated according to the PT-value function along with other areas in the parietal and frontal cortex. Consistent with this result, past studies have demonstrated that reward-based learning can enhance the conspicuous of a stimulus (Chelazzi et al., 2014; Itthipuripat, Cha, Rangsipat, & Serences, 2015; Lee & Shomstein, 2014; Schiffer, Muller, Yeung, & Waszak, 2014) thought to be encoded by population-level activity throughout the occipital and parietal cortex (Itthipuripat et al., 2015; Itti & Koch, 2001; Sprague & Serences, 2013). Therefore, the interplay between the valuation network and attentional visual areas may allow the brain to control the balance between different options that are necessary for representing the value of individual alternatives during choice.

Consistent with the roles of the PFC, the LinG and the occipal visual areas in the valuation process, we also found the IPL and the AngG activations association with PT-value function. In addition to description of the IPL's functions in the chapter "Effect of the number", it is important to emphasize that the IPL is a heterogeneous region (Uddin et al., 2010) that is engaged in the value of the money (Kahnt et al., 2014).

When using PT value function (wage offer size) the brain activation signals in the MPFC correlated stronger among maximizers than satisficers (Fig 3, green color). It might be that the maximizers were more engaged during the experiment than the satisficers, and this was evident in the brain activity level in the MPFC.

Our findings contribute to the growing body of literature that implies an essential role of the distributed brain network in expectation-directed choice; however, there are also discrepancies with previous studies. We found no significant activation in the amygdala, dorsolateral PFC, or ventral striatum, which have previously been implied in decision-making and choice-related tasks (Hare et al., 2009; Hsu et al., 2005, 2009; Plassmann et al., 2007; Tom et al., 2007).

Salary expectations may have their basis in areas that do not trigger strong emotional areas in the brain as do monetary gambles. Whereas previous studies have described specific dopaminenergic and prefrontal mechanisms in Pavlovian and habit-like decisions (Daw, Niv, & Dayan, 2005; McClure et al., 2004; Seymour & McClure, 2008), the mechanisms in choice relating to salary expectations are unknown. It has been argued that striatum responses to financial outcomes reflect a prediction-error signal rather than a goal value signal (Hare et al., 2009; Nieuwenhuis et al., 2005). This does not mean that a pursuit towards a salary expectation is purely cognitive. Rather, many areas in the PFC, especially the VMPFC and other rostral PFC-areas (Pessoa, 2008), are part of larger networks that integrate emotional and cognitive signals (Pessoa, 2008).

The brain requires mechanisms to maintain salary expectation. However, it is not metabolically efficient to “feel” this expectation strongly all the time when pursuing the goal (Glimcher, 2011). The brain might maintain salary expectation, and when it is time to make a decision based on this goal, the valuation networks activate and guide choice. Thus, we assume that salary expectations belong to the brain’s “dispositional space,” in a manner that is similar to “the town of Brigadoon waiting to come alive for a brief period” (Damasio, 2000, p. 332) and that these dispositions have a neurophysiological basis. In suitable situations, the dispositions will be activated.

We used salary expectations as subjective RP in our experiment task. We assumed that salary expectations is a believable indicator of the subjects’ “real” RP. The aim of this study was to expand on conventional neuroeconomic and behavioral studies, describing the role of the salary expectations – in choice making. While the stimuli typically used in behavioral economic and neuroeconomic studies are neutral, insignificant or ordinary and given exogenously, we constructed an experiment in which the stimulus primarily represents an essential aspect of the participants life.

Herewith the PT-like value signal not only includes risk/ambiguity signals (Hsu et al., 2005, 2009) that are weighted by probabilities of an expected reward, but also has more psychological meaning in human choice and behavior (Heath et al., 1999). Our results indicate that PT-value function has a more general role in human behavior than it has been regarded in previous neuroeconomics studies. Reference-based goal-encoding is metabolically cheaper than objective/linear encoding (Glimcher, 2011) and reference-based value signals permit a human to transform objective values to subjective values at any point. We showed that in this subjectivization process, value signals follow the properties of PT value signals, which are categorized based on RP.

**Limitations of the work**

Two potential caveats of our study deserve more discussion. First, the low sample size (8 individuals per group) in this study could be the reason for the limited statistical power in the tests demonstrating differences between maximizers and satisficers. While we found statistically significant differences for the PT predictor, there were no significant differences for the offer number predictor. Studies with bigger sample might enable pinpointing further differences in the neural processing between maximizers and satisficers. Second, it is also possible that the subjective RP acted as an ”anchor” (Kahneman, 2003) in the experiment; it was the only standard in the uncertain experiment and acted as RP. In every case, we showed that there are brain networks that are sensitive for salary expectations according to the non-symmetric PT-value function (i.e., loss aversion parameter $\lambda>1$). Whether the subjective RP regarding the salary expectation is susceptible to manipulation or behavioral conditions remains an important question for future studies. Despite having shown that the PT-like activity in the distributed brain correlates to increased wage offers among participants, the study has not addressed why these increased PT-like brain activations are elicited.

## Conclusion

Previous neuroimaging studies on PT-value function have employed status quo as RP, whereas our results demonstrated activity in distributed brain networks when salary expectation served as RP. Furthermore, the PT-value function effect of the MPFC varied according to the psychological profile, being stronger among maximizers than satisficers. Further research is needed in order to explain why PT-like value function modulates human decision-making.

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**Figure legends**

**Figure 1.**

Stimulus design and behavioral results for acceptance rate. **A)** Timeline of a single stimulus trial where the fixation cross was first presented for 1-3 TR (1800-5400 ms). This was followed by offers of varying size; 3600 ms later, the subjects were asked to indicate their choice with the corresponding button push (“reject” or “accept”). Group-wise (satisficers in blue, maximizers in red and overall mean in green) behavioral valuation of the offers presented in **B)**. The behavioral valuation effectively corresponds to the acceptance ratio of the offers scaled to (-1; 1) range, with 0 corresponding to a 50 % acceptance rate (number of accepted offers = number of rejected offers)

**Figure 2.**

Behavioral results for offer number. **A)** Example responses of a maximizer with a linear fit for the accept/reject decision boundary. Accepted offers are shown as green squares and rejected offers as red circles. All points include 2% random jitter to allow easier inspection of overlapping dots. **B)** Example responses of a satisficer with a linear fit. **C)** Slope coefficients of linear fits for all 16 subjects. Group difference is statistically significant at $p < 0.05$ (two-tailed Mann-Whitney U-test).

**Figure 3.**

Brain regions correlate with the value of the offer. Clusters that exhibited positive fit coefficient with PT-model predictor (red color) and its group difference contrast “maximizers > satisficers” (green color; overlap in yellow). The threshold at voxel-level is $p < 0.001$ uncorrected with cluster-size threshold set at 200 normalized voxels. All clusters surpassed the cluster-level threshold at $q < 0.05$ (FDR-corrected).

**Figure 4.**

Brain regions correlate with the offer number. Clusters that exhibited positive fit coefficient with offer number (red color). The threshold at voxel-level is $p < 0.001$ uncorrected with cluster-size threshold set at 200 normalized voxels. Cluster surpassed the cluster-level threshold at $q < 0.05$ (FDR-corrected).

**Figure 5.**

Mean regions-of-interest (ROI) signal variance explained by three models (models 1-3; see text) as the function of loss aversion parameter $\lambda$ with 30 evenly distributed points between 0.95 and 4.0. Explained variance was averaged over all 16 subjects and 54 ROIs each surpassing $p<0.01$ (Wilcoxon signed rank test, uncorrected). Maximum points are marked with circles.

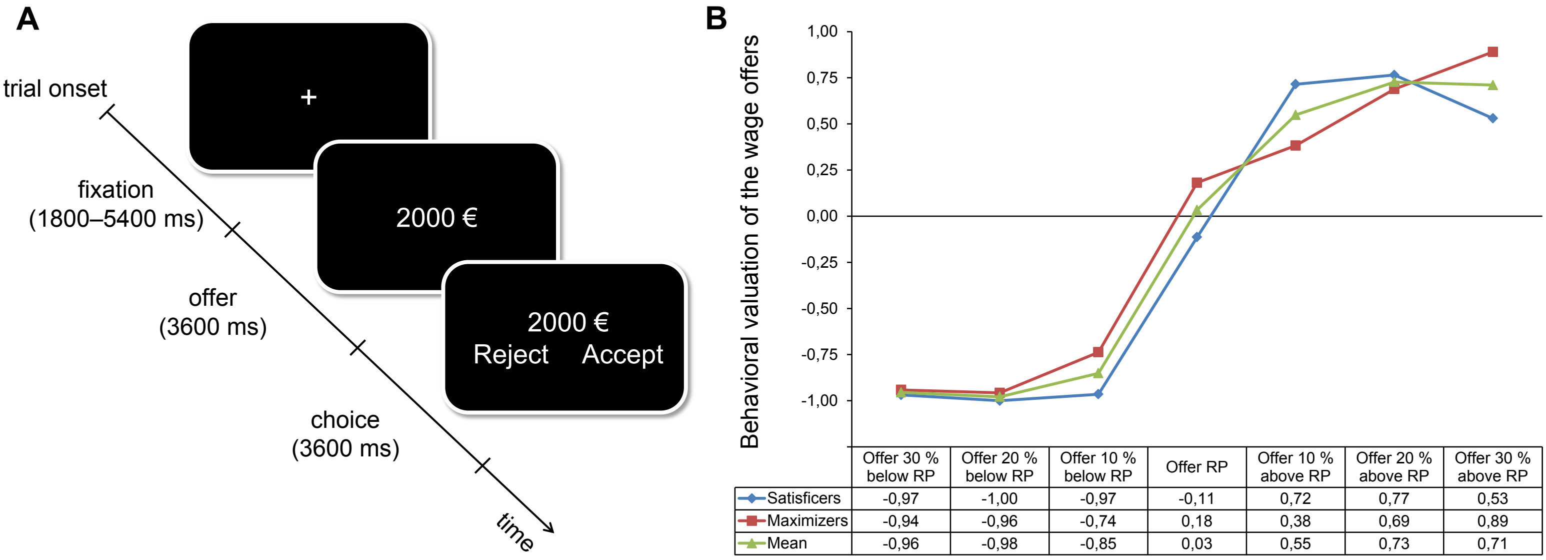
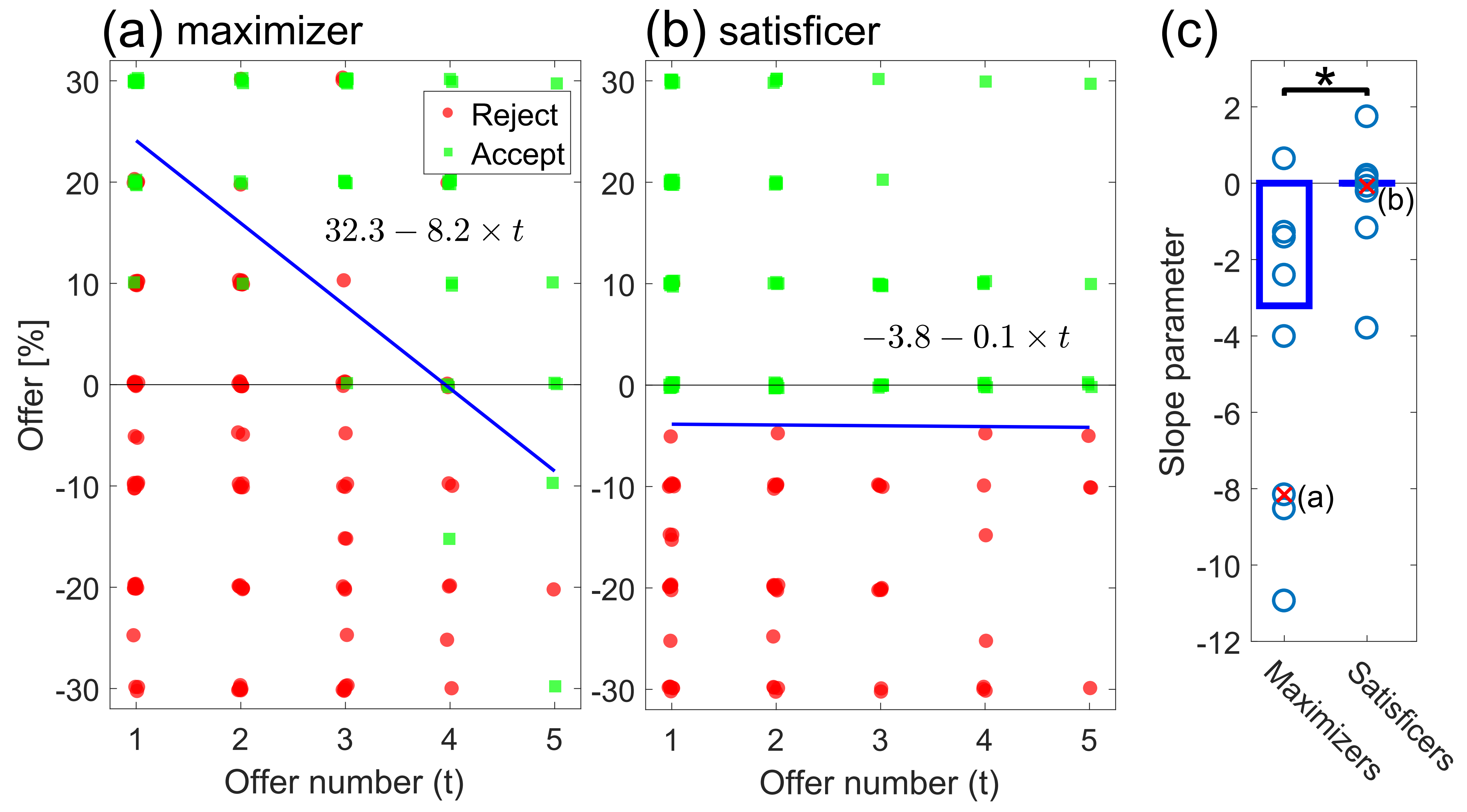



Figure1. SalaryChoiceAndProspectTheory. Suomala et al.


(a) maximizer
(b) satisficer
(c)
Reject
Accept
$32.3 - 8.2 \times t$
$-3.8 - 0.1 \times t$
Offer [%]
Offer number (t)
Offer number (t)
Slope parameter
*
(a)
(b)
Maximizers
Satisficers
30
20
10
0
-10
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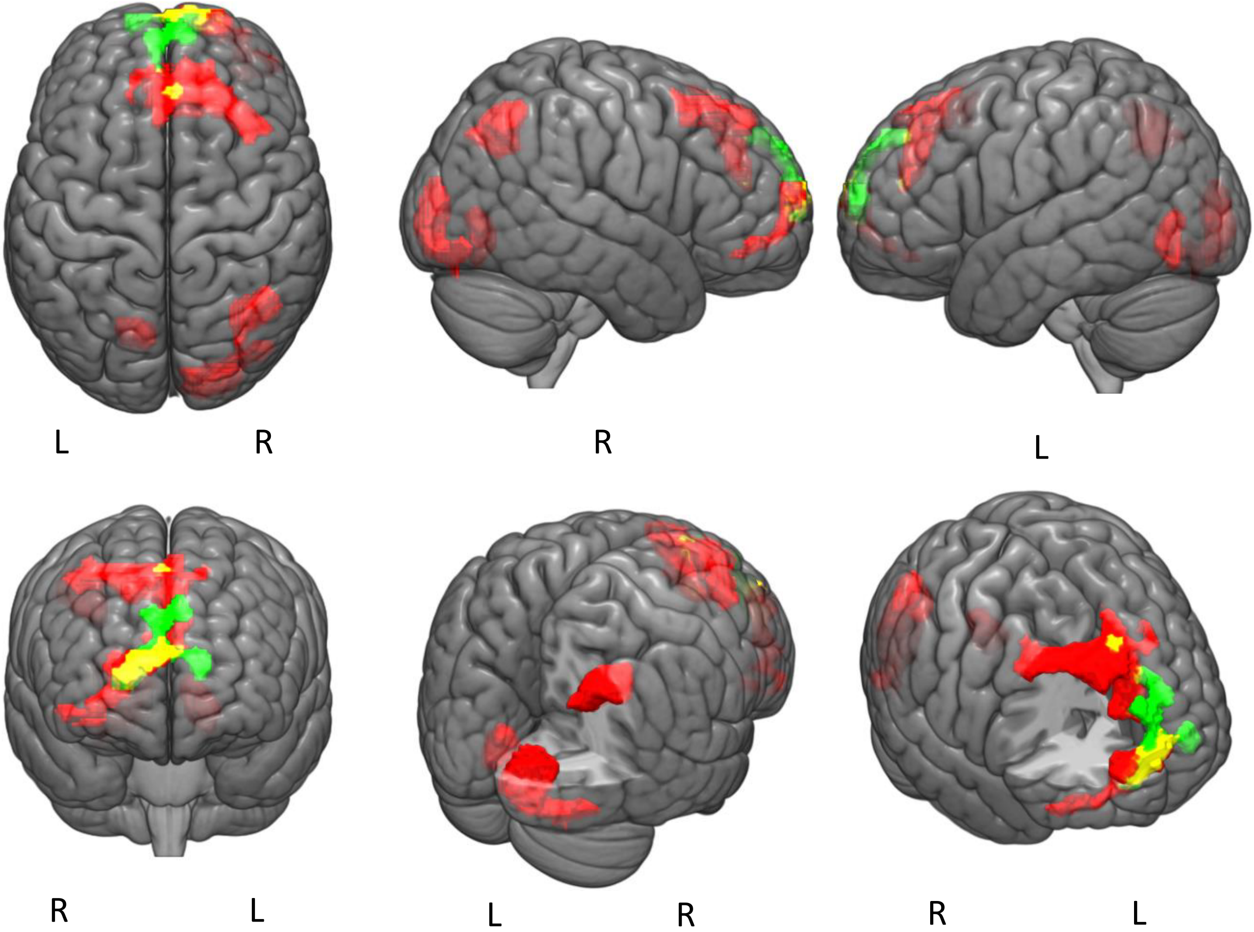
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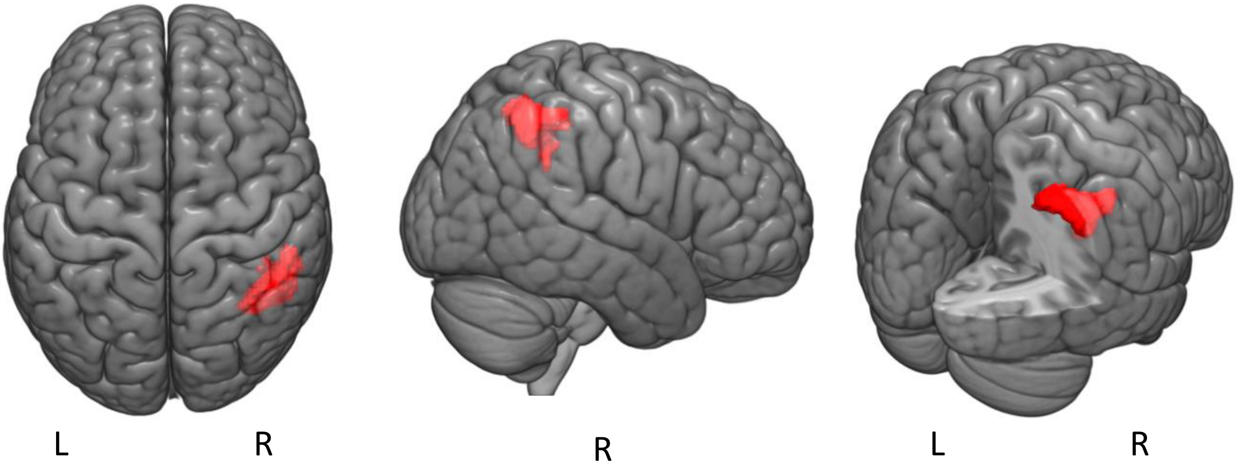
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