

## Why we stay with our social partners: Neural mechanisms of stay/leave decision-making

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### ABSTRACT

How do we decide to keep interacting (e.g., stay) with a social partner or to switch (e.g., leave) to another? This paper investigated the neural mechanisms of stay/leave decision-making. We hypothesized that these decisions fit within a framework of value-based decision-making, and explored four potential mechanisms underlying a hypothesized bias to stay. Twenty-six participants underwent functional Magnetic Resonance Imaging (fMRI) while completing social and nonsocial versions of a stay/leave decision-making task. On each trial, participants chose between four alternative options, after which they received a monetary reward. Crucially, in the social condition, reward magnitude was ostensibly determined by the generosity of social partners, whereas in the nonsocial condition, reward amounts were ostensibly determined in a pre-programmed manner. Results demonstrated that participants were more likely to stay with options of relatively high expected value, with these values updated through Reinforcement Learning mechanisms and represented neurally within ventromedial prefrontal cortex. Moreover, we demonstrated that greater brain activity in ventromedial prefrontal cortex, caudate nucleus, and septo-hypothalamic regions for social versus nonsocial decisions to stay may underlie a bias towards staying with social partners in particular. These findings complement existing social psychological theories by investigating the neural mechanisms of actual stay/leave decisions.

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### Introduction

As a social species, human beings typically engage in direct interactions through which they form social connections with each other. These connections may range from the very brief (i.e., greeting a stranger on the street) to the life-long (i.e., being married). Why does a connection end, or why does a first interaction turn into a life-long relationship? To gain insight into questions like these, this paper investigated the neural mechanisms underlying the decision to keep interacting (e.g., stay) with the same interaction partner or to switch (e.g., leave) to an alternative interaction partner (hereafter termed stay/leave decisions).

Decision Neuroscience has established that various types of choices fit within a neurobiological framework of value-based decision-making (Rangel, Camerer, & Montague, 2008) and engage a neural valuation network that includes ventromedial prefrontal cortex<sup>1</sup> (vmPFC) and striatum (Bartra, McGuire, & Kable, 2013). In a nutshell, the


framework of value-based decision-making states that an agent (1) creates a representation of the decision problem and identifies its options (i.e., stay or leave); (2) assesses the expected value (EV) of each option; (3) selects an option based on the EVs; (4) assesses the outcome value of the selected option; and (5) uses this outcome value to optimize the decision-making process (e.g., to learn).

Importantly, it has been well-established that the neural valuation network is engaged in various types of both social and non-social reward-processing (Fareri & Delgado, 2014; Levy & Glimcher, 2012; Lin, Adolphs, & Rangel, 2012) and decision-making (Rilling & Sanfey, 2011; Ruff & Fehr, 2014). Specifically, vmPFC and striatum do not just represent nonsocial (Anderson et al., 2003; Blood & Zatorre, 2001; Camille, Griffiths, Vo, Fellows, & Kable, 2011; Chib, Rangel, Shimojo, & O'Doherty, 2009; De Araujo, Rolls, Velazco, Margot, & Cayeux, 2005; Knutson, Adams, Fong, & Hommer, 2001; Knutson, Fong, Adams, Varner, & Hommer, 2001; Knutson,

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<sup>1</sup>Following Bartra and colleagues (2013), vmPFC includes regions labelled as mOFC and gyrus rectus as well as anterior cingulum and superior medial frontal cortex.

 The supplemental material for this article can be accessed [here](#).

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Westdorp, Kaiser, & Hommer, 2000; Kringelbach, O'Doherty, Rolls, & Andrews, 2003; McClure et al., 2004; O'Doherty, Dayan, Friston, Critchley, & Dolan, 2003; O'Doherty, Deichmann, Critchley, & Dolan, 2002; O'Doherty et al., 2000; Plassmann, O'Doherty, & Rangel, 2007, 2010; Plassman, O'Doherty, Shiv, & Rangel, 2008; Small, Zattore, Dagher, Evans, & Jones-Gotman, 2001; Small et al., 2003) value. On the contrary, vmPFC and striatum also encode social value (Behrens, Hunt, Woolrich, & Rushworth, 2008; Bhanji & Delgado, 2014; De Quervain et al., 2004; Fareri, Niznikiewicz, Lee, & Delgado, 2012; Hare, Camerer, Knoepfle, O'Doherty, & Rangel, 2010; Jones et al., 2001; Moll et al., 2006; Phan, Sripada, Angstadt, & McCabe, 2010; Rilling & Sanfey, 2011; Zaki & Mitchell, 2011), such as the value of an attractive face (Aharon et al., 2001; Kampe, Frith, Dolan, & Frith, 2001; O'Doherty, Winston, et al., 2003), the value of social approval/acceptance or having a good reputation (Izuma, Saito, & Sadato, 2008; Jones et al., 2011; Lin et al., 2012), the value of cooperation (Krill & Platek, 2012; Rilling et al., 2002; Stallen & Sanfey, 2013; Watanabe et al., 2014), and the value of charitable giving (Hare et al., 2010; Moll et al., 2006). Additionally, for both social and nonsocial contexts also discrepancy between expected and outcome values (e.g., reward prediction errors; Delgado, Nystrom, Fissel, Noll, & Fiez, 2000; Fareri, Chang, & Delgado, 2012; Fouragnan et al., 2013; Harris & Fiske, 2010; Jones et al., 2001; O'Doherty, Dayan, et al., 2003; Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006; Phan et al., 2010; Poore et al., 2012; Schönberg, Daw, Joel, & O'Doherty, 2007; Schülz, Dayan, & Montague, 1997; Schülz & Dickinson, 2000) have reliably been found to correspond to neural activity in the striatum. Together, this suggests that the framework of value-based decision-making – as described above – applies to both nonsocial as well as complex social decisions (see Behrens, Hunt, & Rushworth, 2009; Lee, 2008).

Hence, we propose that social stay/leave decisions also fit within a framework of value-based decision-making, and that they adhere to general principles of value-based learning and choice. That is, we suggest that stay/leave decisions are effectively based upon value-considerations such that people aim to maximize the outcomes they derive from their social interactions. Placing social stay/leave decisions within such a framework of value-based decision-making allows us to formulate testable hypotheses concerning the psychological and neural mechanisms underlying actual decisions to stay with or leave an interaction partner.

Specifically, we first hypothesized that people are more likely to stay with partners from whom they generate a relatively high expected value (EV), with these

values computed via basic reward-learning mechanisms (e.g., *Reinforcement Learning*; Lee, Seo, & Jung, 2012; Sutton & Barto, 1998). Additionally, we predicted the involvement of neural valuation regions such that the EV of staying is represented across a network of vmPFC and/or striatum (Bartra et al., 2013; Haber & Knutson, 2010). Importantly, in these respects we expect no fundamental differences between social and nonsocial stay/leave decision-making processes.

However, though social stay/leave decision-making likely relies upon value-based mechanisms, it seems improbable that this decision is based upon purely economic considerations *alone*. Specifically, based on a theorized *need to belong* (Baumeister & Leary, 1995), which is described as an intrinsic motivation to form and maintain social bonds and a resistance to breaking them (see also Bowlby, 1969), we hypothesized that – in addition to economic considerations – people are biased to stay with their social partners; a bias that should, for obvious reasons, be absent in a nonsocial stay/leave decision-making context.

How could such a bias be implemented on a neural level? Here, we explored four mechanisms that could, in concert, result in a greater likelihood of staying with social partners. Firstly, we proposed that deciding to stay with a social partner carries intrinsic reward value, above and beyond the “objective” EV of staying itself. This could be implemented through relatively more activation in regions associated with positive valuation (e.g., vmPFC and/or striatum) for social versus nonsocial “stay” decisions, controlling for EV. Secondly, we proposed that the involvement of attachment mechanisms could underlie a greater likelihood of staying with social partners. This would be evident from increased neural activity in septo-hypothalamic region (Insel & Young, 2001; Moll et al., 2012) for social versus nonsocial “stay” decisions. Thirdly, we proposed a psychological aversion to breaking social bonds. We expected that this aversion would be visible as increased neural activity in anterior insula (AI) for social versus non-social “leave” decisions as AI is associated with (negative) valuation as well as with the breaking of social bonds – as manipulated experimentally by social exclusion or rejection (Cacioppo et al., 2013; Eisenberger, 2013). Fourthly, we proposed that a greater likelihood of staying with social partners could result from the involvement of socio-cognitive processes. This could be evident from increased neural activity in right temporoparietal junction (TPJ) and/or medial prefrontal cortex (mPFC) which are key regions of a social cognition network.

In sum, this study explored neural mechanisms of stay/leave decision-making between social and non-social contexts. We predicted that both social and non-social decision-making processes fit within a broad framework of value-based decision-making, and also investigated four distinct mechanisms as to how the social context specifically could impact stay/leave decision-making.

## Methods

### Participants

Twenty-six right-handed healthy students of Radboud University in Nijmegen, the Netherlands participated in the experiment (mean age: 23.04, range 19–30; 50% female). Participants were excluded from participation if they took any form of medication that could interfere with the Blood-Oxygenated-Level-Dependent (BOLD) signal; if they ever had head trauma or an operation on their head; if they ever experienced psychological or neurological problems; if they had a history of drug abuse; if they had irremovable metal parts or active implants in their body; if they were epileptic, claustrophobic, pregnant or under eighteen years of age. All participants gave informed consent prior to participation under the ethical approval provided by the local Institutional Review. Due to technical problems during scanning, one participant's dataset was incomplete and hence was excluded from data analysis.

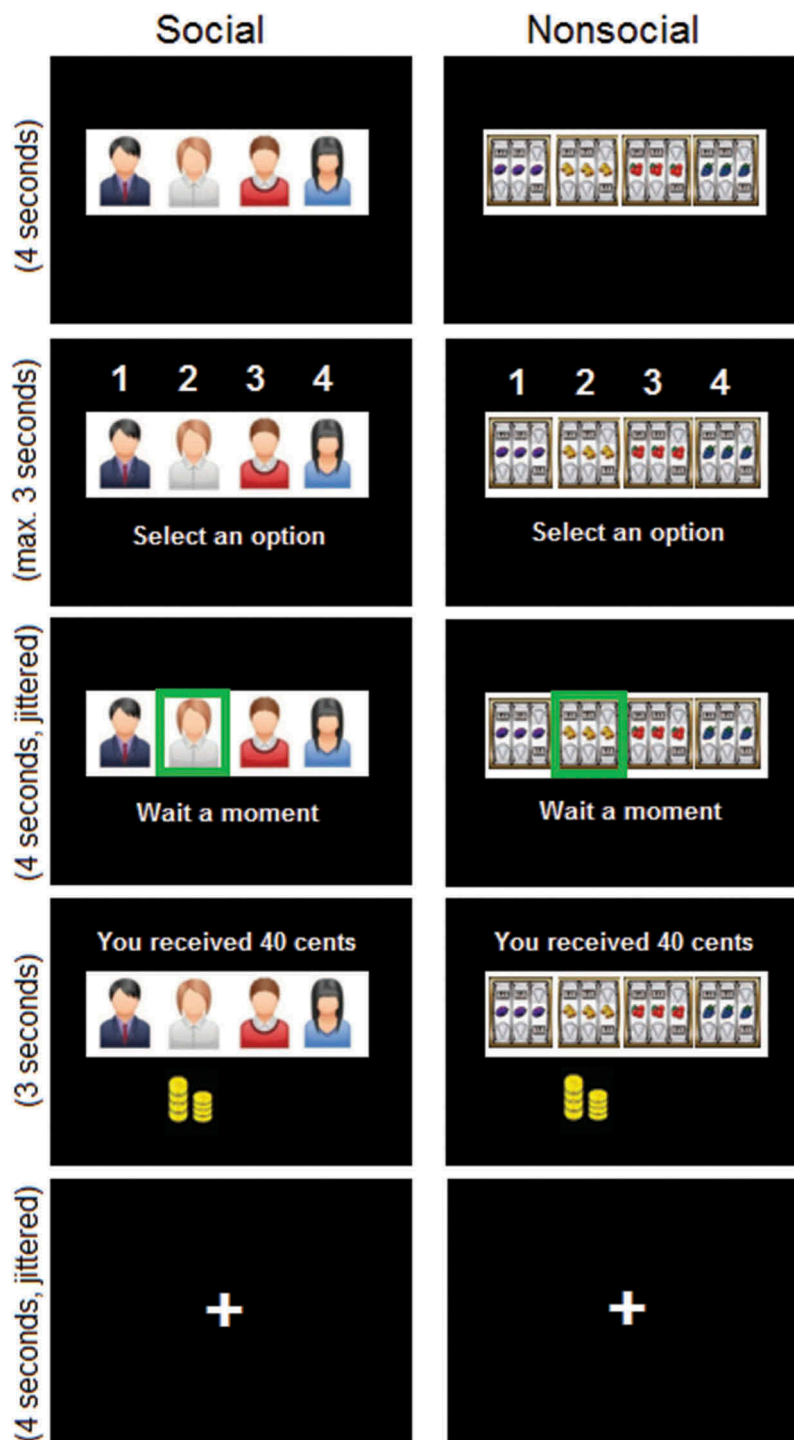
### Task

While undergoing functional Magnetic Resonance Imaging (fMRI), participants played both a social and non-social control version of a structurally identical task. Each version consisted of 100 trials, and was administered in a separate block in counterbalanced order. With a brief scanning break after each 50 trials, the task consisted of four scan runs in total.

On each trial (see [Figure 1](#)) of both social and non-social conditions, participants saw four choice options that were always the same (decision phase; 4 seconds), after which they selected one of the options via button-press (response phase; max 3 seconds). If they failed to respond in time, the trial ended. If they responded within the allotted time, after a brief delay (waiting phase;  $4 \pm 2$  seconds), a new trial automatically began. Each trial except the first, was coded as either a "stay" or "leave" trial depending on whether the participant had selected the same (i.e. stay) or a different (i.e. leave) option on the previous trial.

In the social condition, the four choice options – depicted as four avatars – ostensibly represented four other participants (i.e., hereafter termed "Dictators") with whom participants played a Dictator Game in the role of recipient on each trial. The Dictator Game is a two-player game in which the first player (e.g., the Dictator) decides whether, and how much, of a monetary endowment (i.e., here one Euro) to share with the second player. The second player (i.e., here the participant) simply receives the money that was shared with him or her (between 0 and 1 Euro, increments of 1 cent) and, thus, plays a completely passive role. Importantly, participants were told that the outcome on each trial was the amount of money that the chosen Dictator had decided to share with them. The rationale for using the Dictator Game is that it enables a brief social interaction that lets participants learn about the prosocial preferences of interaction partners; it results in a monetary outcome which allows an objective comparison with the non-social control condition (see below); and that it does not require additional decisions (such as acceptance or rejection of an Ultimatum offer) from the participant that could interfere with their stay/leave decisions. Additionally, to keep stay/leave decisions devoid of strategic attempts to influence the amount of money Dictators would share with them, we told participants that Dictators' decisions had been collected prior to the scanning session. Specifically, participants were told that these Dictators had played a multi-shot Dictator Game in which they decided to share 1 Euro with an anonymous other participant in each game. Additionally, ostensibly due to changes in the Dictator's game environment, their trial-level decisions would fluctuate around a true mean across the 100 trials.

To examine the neural activity associated with stay/leave decision-making in general from that associated with a potential behavioural bias to stay with a human partner, participants also played a non-social control condition that was structurally identical to the social condition. In this condition, the four Dictators were replaced by four one-armed bandits that generated monetary rewards according to an algorithm. Thus, participants were told that the amount of money they received on each trial was determined by a non-intentional algorithmic process rather than by an intentional human action. Additionally, participants were told that the portion of the money retained by the Dictator on each trial (i.e. the amount not sent) would be added to one of that Dictator's bonuses from the social condition.



**Figure 1.** Timeline of each trial. On each trial, participants first saw their four choice options (e.g., the decision phase; 4 seconds); and were then asked to select option 1, 2, 3 or 4 by pressing the corresponding button on the button box (e.g., the response screen; maximally 3 seconds); they next waited for the outcome (e.g., the wait screen; 4 seconds +/- a random jitter of 1 second); and finally saw how much money they received on that trial (e.g., outcome screen; 3 seconds). All trials were separated from each other by a fixation cross (e.g., the inter-trial-interval; 4 seconds +/- a random jitter of 1 second). Choice options could be four different Dictators or four slot machines in social or non-social condition respectively. Monetary outcomes were additionally visually represented during the outcome phase by means of two piles of coins: One representing the participants' reward and the other representing the remainder of the maximum reward of one Euro.

Prior to the experiment, participants were told that some choice options – in both social and nonsocial condition – could provide higher rewards than others.

By selecting the option that provided the highest reward, participants could thus try to maximize their rewards. To incentivize participants to perform well on

the task, we paid a performance-dependent bonus of a maximum of ten Euros in addition to the standard participation fee of twenty Euros. This monetary bonus was computed as 10% of participants' entire earnings across all trials.

Despite different cover stories regarding the source of the amount of the monetary rewards, monetary rewards for both conditions were generated by a reward matrix. In this way, each of the four options provided equal rewards on average. Over time though, the options alternated as to which currently offered the best outcome. To achieve this, we used a Gaussian decay process to generate a reward matrix for each option on each trial. Specifically, the reward of choice option  $i$  is the result of a Gaussian random walk with standard deviation  $\sigma_0 = 4$ ; and the mean defined as  $\mu_{i,t+1} = \lambda * \mu_{i,t} + (1 - \lambda) * \theta + v$ . In the equation,  $\mu_{i,t}$  is the mean reward for option  $i$  at trial  $t$ ;  $\theta$  is the decay, the rate of decay, was set at 0.893; and  $v$ , the diffusion term, was set to  $N(0, 2.8)$ . Specific parameters – except  $\theta$  – for the Gaussian process were set according to Daw, O'Doherty, Dayan, Seymour, and Dolan (2006). We set  $\theta$  to 25, such that rewards would range between 0 and 50 Eurocents. This was done because any rewards outside of this range would be unrealistic as Dictators are typically highly unlikely to share more than half of their endowment (Engel, 2011). We chose this specific strategy because our fMRI analyses require a large number of both stay and leave decisions. If one choice option systematically provided higher rewards than others and participants would, naturally, gravitate towards that option, greatly reducing the number of leave decisions.

At the conclusion of the experiment, participants completed a questionnaire in which they indicated their strategy and motives separately for the social and nonsocial conditions. Answers to this questionnaire indicated that participants believed that they were playing with real participants in the social condition.

### Imaging procedure

High-resolution T1-weighted structural scans were acquired on a Siemens 3.0 Tesla Skyra scanner using an MPRAGE sequence with an acceleration factor of 2 and an 8° flip angle; the FOV was 256 × 256 with 1.0 × 1.0 × 1.0 mm voxels. Four functional runs were then acquired using a 5-shot multi-echo planar GRAPPA sequence with acceleration factor 3 and a flip angle of 90°. The FOV was 224 × 224 mm and contained a 64 × 64 matrix of voxels with dimensions 3.5 × 3.5 × 3.0 mm. Slice thickness was thus 3.0 mm and the gap between slices was 0.51 mm (e.g., 17% of 3mm).

Because we use a 5-shot multi-echo sequence, five echoes are acquired within each volume with varying TE's between the five echoes. The rationale for this is that TE is optimal when it equals T2\*, but that T2\* varies across the brain. When interested in areas across the whole brain, it is therefore difficult to choose one appropriate TE. A multi-echo sequence solves this problem by acquiring multiple echoes at different TE's within one volume. Within the first thirty pulses of the first functional run, the T2\* of each voxel is measured and used to compute the appropriate TE for that voxel. These thirty volumes and the first five volumes (to account for T1 equilibrium effects) of the other three functional runs are discarded from analyses.

### Preprocessing

As multi-echo data collection results in multiple scans per TR, these multiple scans were first combined to one scan per TR. As part of the combination process, scans are already corrected for motion (Buur, Norris, & Hesse, 2008; Buur, Poser, & Norris, 2009). The rest of the data preprocessing was performed using SPM8 (<http://www.fil.ion.ucl.ac.uk/spm/software/spm8>). Images were corrected for slice time acquisition, and each participant's average high resolution structural scan was overlaid to their functional images. These co-registered images were then segmented in grey and white matter and cerebro-spinal fluid; and spatially normalized to the MNI template by applying a 12-parameter affine transformation and 4th Degree B-Spline interpolation. Finally, the images were smoothed using a 7 mm full width at half maximum Gaussian kernel and high-pass filtered in the temporal domain with a filter width of 800s given the blocked design of the study.

### Analyses

#### Behavioral analyses

We first investigated whether stay/leave decisions in general are affected by value-considerations. If so, the EV of staying should impact participants' stay/leave decisions in both conditions. Additionally, assuming a need to belong, we predicted that participants would be more likely to stay, when controlling for EV, in the social rather than the nonsocial condition. Using the statistical software package R (R Development Core Team, 2008), we built a mixed model (Jaeger, 2008) with the main effects and interaction term of (z-scored) EV of chosen options (see trial-by-trial analyses below)

and condition (social, nonsocial) to predict participants' decisions to stay or leave. To account for the repeated measures design of the study, we included a fixed intercept and a random participant-specific adjustment to that intercept.

### **Trial-by-trial analyses**

We predicted that the EV to stay would be computed and updated via Reinforcement Learning mechanisms. To test this, we modeled participants' choices (Daw, 2011) as a function of their previous choices and acquired rewards using a temporal-difference learning algorithm (Rescorla & Wagner, 1972; Sutton & Barto, 1998) with separate learning rates for positive and negative prediction errors (Bayer & Glimcher, 2005; Cazé & van der Meer, 2013; Seymour, Daw, Dayan, Singer, & Dolan, 2007; Yacubian et al., 2006). Specifically, each time an option  $i$  was selected, the EV ( $Q_{i,t+1}$ ) of that option on trial  $t$  was updated with the prediction error ( $\delta_t$ ), which is the difference between EV ( $Q_{i,t}$ ) and obtained reward ( $r_{i,t}$ ) from that option. Before being added to the new EV of an option, prediction errors were multiplied by a learning rate (i.e.,  $\alpha^{\text{POS}}$  for positive and  $\alpha^{\text{NEG}}$  for negative prediction errors). EV's of each of the four choice options at each trial were translated to selection probabilities using a softmax selection rule (with temperature  $\tau$ ), such that options with a higher EV had a higher chance of being selected. We estimated the values of the free parameters ( $\alpha^{\text{POS}}$ ,  $\alpha^{\text{NEG}}$ ,  $\tau$ ) for the social and nonsocial conditions separately by using the MATLAB `fmincon` function which finds, in this case, the negative log-likelihood of the Reinforcement Learning model by varying the set of parameters of the model within a set of predetermined bounds (i.e., learning rates were constrained between 0 and 1 and the softmax temperature was constrained between 0 and infinity). Multiple starting values for the free parameters were used to avoid the `fmincon` function reporting the local rather than global minima. To additionally explore potential differences in learning between social and nonsocial conditions, we performed paired-sample t-tests to compare fit of the model and the parameter estimates between social and nonsocial condition (for a similar approach see Behrens, Woolrich, Walton, & Rushworth, 2007).

### **Imaging analyses**

With regards to the neural mechanisms of stay/leave decision-making, we predicted that the EV of staying – across

social and nonsocial conditions – would be represented in specific parts of the neural valuation network (e.g., vmPFC and striatum). Therefore, we first used the best-fitting parameter estimates of our modeling analyses to compute the relative EV of staying for each option within each trial for each participant. The relative EV of staying was indicated by the model-predicted probability of choosing each option over all other options on each trial.

We then used a parametric General Linear Model (GLM) to regress trial-by-trial variations in relative EV of chosen options against Blood-Oxygen-Level-Dependent (BOLD) signal during the four-second decision phase. The model (GLM1) included a boxcar function delineating each decision phase, a parametric modulator indicating the relative EV of the chosen option, six motion parameters, and one constant for each of the four scan runs.

Our second key objective was to explore differential neural activation for social and nonsocial stay and leave decisions across the whole brain, as well as in specific areas of interest (e.g., vmPFC, striatum, septo-hypothalamic region, AI, TPJ and mPFC). To this end, we performed a non-parametric GLM in which we contrasted neural activation for stay versus leave decisions during the four-second decision phase. The model (GLM2) consisted of one boxcar function indicating stay decisions, one boxcar function indicating leave decisions, six motion parameters and one constant for each of the four scan runs.

All fMRI results were initially thresholded at  $P < .001$  uncorrected and were subsequently thresholded at  $P < .05$  FWE corrected. We performed small volume corrections for regions of interest (ROIs; see Supplemental Materials) for which we had strong a priori predictions. Our ROIs within the valuation network (e.g., vmPFC, striatum and AI) were based upon a coordinate-based meta-analysis of the neural valuation network by Bartra and colleagues (Bartra et al., 2013). Specifically, for vmPFC, we built a 10 mm sphere around peak coordinates [2, 46, -8]; for striatum, we combined two 10 mm spheres around peak coordinates [-12, 12, 6] and [12, 10, -6] for left and right striatum respectively; and for AI we combined two 10 mm spheres around peak coordinates [-36, 20, -6] and [40, 22, -6] for left and right AI respectively. The ROIs within the social cognition network were based on the meta-analytic resource Neurosynth (Yarkoni, Poldrack, Nickols, Van Essen, & Wager, 2011) and were defined as a 10 mm sphere around peak coordinates [60, -52, 18] for right TPJ; and a 10 mm sphere around peak coordinates [6, 62, 20] for mPFC. Notably, as mPFC is a very large region, specific peak coordinates based on the search term "ToM" (e.g., Theory of Mind) which fell within

the mPFC and did not overlap with our ROI for vmPFC. Finally, our ROI for septo-hypothalamic region was directly derived from an independent study (Moll et al., 2012) that investigated the neural signature of affiliative or social attachment.

## Results

### Behavioral results

Our first key objective was to demonstrate that stay/leave decisions in both social and nonsocial contexts are affected by value-considerations. In line with this, our mixed model analyses demonstrates that the EV of chosen options significantly ( $F(1, 4) = 672.00, p < .001, \beta = -1.16$ ) predicted participants' decisions to stay or leave, with a higher likelihood of leaving for lower EV's. Stay/leave decision was not impacted by condition per se ( $F(1, 4) = 3.64, p = .483$ ) so our prediction that participants would be more likely to stay in social condition was not supported. However, we found a significant interaction effect ( $F(1, 4) = 28.11, p < .001, \beta = -0.51$ ) that demonstrated that EV was a stronger predictor of stay/leave decision-making in nonsocial rather than social condition.

### Trial-by-trial results

We hypothesized that the EV of staying with each option would be computed via RL mechanisms. As expected, our trial-by-trial analyses demonstrated that our RL model with separate learning rates for positive and negative prediction errors predicted participants' actual choices in both social ( $M = 95.01, SEM = 4.32$ ) and nonsocial ( $M = 100.07, SEM = 3.21$ ) condition better than chance (e.g., 138.67 which is the result of 100 trials multiplied by the log of the probability of choosing one of four options). Our model predicted actual choices equally well in social and nonsocial conditions ( $t(1, 24) = -1.47, p = .155, M_{\text{SOCIAL}} = 95.01, SEM_{\text{SOCIAL}} = 4.32, M_{\text{NONSOCIAL}} = 100.07, SEM_{\text{NONSOCIAL}} = 3.21$ ). Moreover, parameter estimates for  $\alpha\text{POS}$  ( $t(1, 24) = 0.33, p = .747$ ;

$M_{\text{SOCIAL}} = 0.95, SEM_{\text{SOCIAL}} = 0.02, M_{\text{NONSOCIAL}} = 0.94, SEM_{\text{NONSOCIAL}} = 0.03$ ) and  $\alpha\text{NEG}$  ( $t(1, 24) = -0.35, p = .727$ ;  $M_{\text{SOCIAL}} = 0.65, SEM_{\text{SOCIAL}} = 0.04, M_{\text{NONSOCIAL}} = 0.67, SEM_{\text{NONSOCIAL}} = 0.04$ ) and the softmax temperature ( $t(1, 24) = 0.91, p = .347$ ;  $M_{\text{SOCIAL}} = 0.19, SEM_{\text{SOCIAL}} = 0.01, M_{\text{NONSOCIAL}} = 0.36, SEM_{\text{NONSOCIAL}} = 0.19$ ) were not significantly different between social and nonsocial condition. Additionally, parameter estimations indicated that participants learned significantly faster ( $t(1, 24) = 10.32, p < .001$ ) from negative ( $M = 0.95, SEM = 0.01$ ) than positive ( $M = 0.66, SEM = 0.03$ ) prediction errors overall.

### Imaging results

#### Neural correlates of EV

On a neural level, we then predicted that the relative EV of a chosen option was represented across specific parts of the neural valuation network. After small volume corrections, neural activity within vmPFC corresponded significantly ( $P = .013$  FWE cluster level) to the relative EV of chosen options across social and nonsocial conditions (see Figure 2).

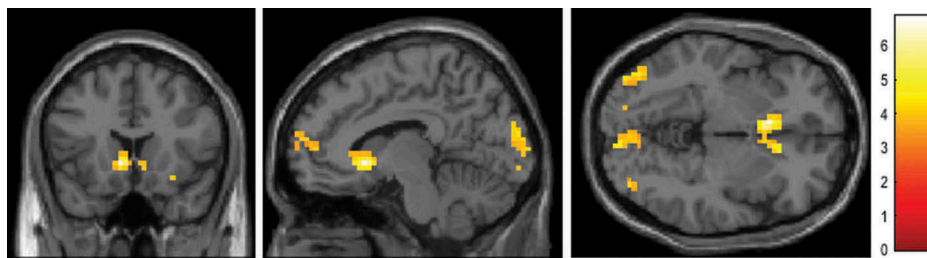
#### Neural correlates of stay/leave DM

Secondly, we examined whether and how a need to belong impacts neural mechanisms of stay/leave decision-making. We proposed four possible mechanisms of how a need to belong could impact stay/leave decision-making. First, we hypothesized increased neural activation within striatum and vmPFC for social rather than nonsocial decisions to stay. Secondly, we proposed that social versus nonsocial "stay" decisions were associated with increased neural activity in septo-hypothalamic region. Thirdly, we proposed that social rather than nonsocial "leave" decisions would be associated with increased neural activity in AI. Fourthly, we proposed that social rather than nonsocial overall would be associated with increased neural activity in TPJ and/or mPFC.

Consistent with our first hypothesis, results demonstrated increased activation ( $P < .001$  FWE corrected) in



**Figure 2.** Neural correlates of EV. EV of chosen options corresponded with neural activity in vmPFC ( $P = .018$ ). Activation map ( $P < .001$  uncorrected) is superimposed on MNI template. Peak coordinates of activated area are  $[-5, 35, -7]$ .



**Figure 3.** Deciding to stay with a social partner. Contrasting neural activity for decisions to stay in social versus nonsocial condition revealed significant ( $P < .05$  FWE corrected) clusters of activation in striatum, vmPFC and septo-hypothalamic region. Activation maps ( $P < .001$  uncorrected;) are superimposed on an MNI template. Peak coordinates of activated areas are  $[-8, 18, -4]$  for striatum,  $[-1, 63, 7]$  for vmPFC and  $[-5, 7, 0]$  for septo-hypothalamic region.

**Table 1.** Results. Differential neural activation for social (S) and non-social (N) stay decisions; and for neural activation corresponding to EV ( $P < .05$  FWE corrected).

		voxels	Z	x	y	z	P
Stay (S > N)	Left caudate nucleus	94	5.06	-8	18	-4	.003
	Left calcarine sulcus	283	4.37	6	-95	0	.000
	Left superior medial frontal gyrus	59	3.75	-1	63	7	.021
	Septo-hypothalamic region (SVC)	7	3.58	-5	7	0	.019
EV	vmPFC (SVC)	12	3.96	-5	35	-7	

bilateral caudate nucleus and vmPFC for social versus nonsocial decisions to stay, even at the whole-brain level. In support for our second hypothesis, after small volume correction, we observed increased activation ( $P = .019$ ) in septo-hypothalamic region for social versus nonsocial “stay” decisions (see Figure 3 and Table 1).

We then contrasted neural activity for social versus nonsocial “leave” decisions, finding no voxels that survived the  $P < .001$  uncorrected threshold within AI. Also, we contrasted neural activity for social and nonsocial stay/leave decision-making overall and found no significant clusters of activation within TPJ or mPFC that survived the  $P < .001$  uncorrected threshold. Thus, our third and fourth hypotheses are not supported.

### Post-hoc analysis & result

To make sure that differential neural activation for social versus nonsocial condition was purely due to social versus nonsocial context and not, for example, due to higher EV of staying in social versus nonsocial condition, we ran a post-hoc analysis. Specifically, we built a mixed model with the main effects and interaction term and of decision (stay, leave) and condition (social, nonsocial) to predict the EV of the chosen option at each trial. To account for the repeated measures design of the study, we included a fixed intercept and a participant-specific adjustment to that model intercept.

This analysis demonstrated that the EV of chosen options was not significantly different ( $F(1, 5) = 10.18$ ,  $p = 0.074$ ) between social and nonsocial conditions. In line with prior results, the EV of chosen options was significantly different ( $F(1, 5) = 832.81$ ,  $p < .001$ ) between stay ( $M = 29.79$ ,  $SEM = 0.78$ ) and leave ( $M = 21.89$ ,  $SEM = 0.60$ ) decisions. The interaction effect of condition by stay/leave decision was not significant ( $F(1, 5) = 0.00$ ,  $p = .958$ ).

### Discussion

The goal of the present paper was two-fold. Firstly, we investigated whether the decision to either stay with or leave a social partner fits within a framework of value-based decision-making (Rangel et al., 2008); and secondly, we explored how decisions to stay with, and also leave, a social partner may be different, on a neural level, than stay/leave decision-making for nonsocial resources.

Using a broad approach, we provided behavioral, computational, and neural evidence that stay/leave decisions can indeed be usefully considered in a general framework of value-based decision-making. That is, we first demonstrated that when in a context where participants could decide freely between staying with or leaving an interaction partner, decisions were based upon the expected value (EV) of staying – or, the expected generosity – of those partners. Next, participants’ choices revealed that EV of specific partners appeared to be updated via Reinforcement Learning mechanisms. This claim was additionally supported by the finding that the model-predicted relative EV of interaction partners was represented in vmPFC.

Crucially, we also explored neural differences between stay/leave decision-making in social versus nonsocial contexts. Hypothesizing a bias towards staying with rather than leaving social partners specifically,



we investigated four possible ways as to how such bias could be implemented in the brain. First, deciding to stay with social partners could be intrinsically valuable, potentially evident as increased neural activity in vmPFC and/or striatum when deciding to stay with social partners specifically. Secondly, attachment mechanisms could be associated with a bias to stay with social partners which could be manifested as increased neural activity in septo-hypothalamic region for social versus nonsocial “stay” decisions. Thirdly, we hypothesized that stay/leave decision-making could be related to a psychological aversion to the breaking of social bonds, and therefore could be associated with differential neural activity in AI in social compared to nonsocial “leave” decisions. Finally, we hypothesized the involvement of socio-cognitive processes in social stay/leave decision-making which would be evident from increased neural activity in right TPJ and/or mPFC for social versus nonsocial stay/leave decision-making overall.

Our results suggest that our first and second hypotheses are useful mechanistic accounts of the social bias we observe in decision-making. Specifically, our results demonstrate that increased activation in vmPFC and striatum and in septo-hypothalamic region underlies a greater tendency to stay with social partners specifically. Importantly, by comparing neural activity for stay decisions across objectively identical social and nonsocial conditions, we can attribute the differential neural activity to the social context, rather than to any potential differences in actual EV between these conditions. In this way, this study provides evidence of an increased reward signal when staying with other, human, partners above and beyond the objective, economic, value of staying.

Our results are in line with previous research investigating neural correlates of social reward-processing and decision-making. That is, previous studies have consistently demonstrated that neural pathways underlying social reward-processing and decision-making engage the reward-circuit (Behrens et al., 2008; De Quervain et al., 2004; Fareri et al., 2012; Harris & Fiske, 2010; Hare et al., 2010; Jones et al., 2001; Moll et al., 2006; Phan et al., 2010; Rilling & Sanfey, 2011; Zaki & Mitchell, 2011) and that Reinforcement Learning models can be applied to social learning (Fareri et al., 2012; Fouragnan et al., 2013; Jones et al., 2001; Lin et al., 2012; Poore et al., 2012; Xiang, Lohrenz, & Montague, 2013).

Moreover, it has been demonstrated that social context can modulate neural reward signals (i.e., Bault, Pelloux, Fahrenfour, Ridderinckhof, & van Winden, 2015; Fareri, Chang, & Delgado, 2015; Fareri &

Delgado, 2014; Fareri, Niznikiewicz et al., 2012; Inagaki et al., 2015) and neural representations of decision value (Strombach et al., 2015). Interpretations of these findings rely thus far on a theorized psychological preference for social connection (e.g., need to belong; Baumeister & Leary, 1995; Bowlby, 1969). That is, experiences that indicate social belongingness are deemed valuable and, thus, elicit neural value signals. The current study provides concrete neural evidence for such need to belong by demonstrating that *actual decisions* to stay with social partners specifically correspond to increased neural activity in the valuation network and septo-hypothalamic region; and are less strongly impacted by the EV of staying with these partners.

Our findings also add to existing psychological theories on social relationships. First, these results are initial demonstrations of a specific biological basis to theories on social relationships (Thibaut & Kelley, 1959) and relationship maintenance (Rusbult, 1980, 1983). Specifically, these theories state that the value of a relationship is a function of relationship rewards and costs (Thibaut & Kelley, 1959) and that relationship commitment is a function of quasi-economic terms, namely (a) what people get from their relationship (i.e., relationship satisfaction or benefits); (b) what people have invested in their relationship (i.e., relationship investments or sunk costs); and (c) what they think they gain or lose by not being in the relationship (e.g., alternatives or opportunity costs). Our results indicate that this economic representation of relationships and relationship commitment matches neurobiological mechanisms of stay/leave decision-making. Secondly, we translated existing psychological theories and data on relationship maintenance to a framework of *actual* decision-making. That is, rather than relying on questionnaire or hypothetical data, the current study used a paradigm in which participants’ decisions to either keep interacting with a partner or not were immediately effective and consequential. Therefore, we were able to study the mechanisms of stay/leave decision-making at the time that the actual decision was being made. Thirdly, we provided a mathematical formalism to the study of social stay/leave decision-making, namely the framework of Reinforcement Learning, which allows for more testable hypotheses about the underlying neural computations of the decision to stay or leave.

One of the major advantages of the present study is the fact that social and nonsocial condition were controlled in such a way that they only differed in terms of the nature of choice options – being social or nonsocial – and not, for example, in terms of the types of reward received, the complexity of the interaction, objective value and/or cost of leaving and

etcetera. We mention these features specifically, because by choosing a design with maximal experimental control between social and nonsocial condition we, at the same time, naturally sacrifice some ecological validity. While this was a necessary limitation of the present design, the result was that the social interactions participants had in the task were rather minimally “social” and not particularly naturalistic. Importantly though, it is exactly in this way that the design and findings of this study complements previous research regarding relationship maintenance and commitment that did have high ecological validity but low experimental control (see Le & Agnew, 2003; Le, Dove, Agnew, Korn, & Mutso, 2010; Rusbult & Farrel, 1983; Rusbult & Johnson, 1986; VanderDrift & Agnew, 2012). Moreover, finding neural differences between social and nonsocial conditions in such a minimally social paradigm supports the robustness of the results.

A possible limitation of the present paper is that neural differences in social versus nonsocial condition could reflect the attribution of intentionality in social condition versus randomness in nonsocial condition. However, prior studies that investigate neural differences in decision-making about intentional versus unintentional agents typically demonstrate differential neural activity in TPJ (Lee & Harris, 2013), but we did not find differential neural activity in this region.

One important aim for future research on social decision-making is to investigate how the neural computations underlying social stay/leave decision-making change when social interactions do become more naturalistic. For example, when monetary rewards are replaced by social rewards such as a smile or an approving gesture (Jones et al., 2001; Lin et al., 2012) or when interactions become more complex. These insights could eventually help explain why people often do decide to stay in relationships with low expected outcomes (Edwards, Gidycz, & Murphy, 2010; Lacey, 2010; Rusbult & Martz, 1995; Slotter & Finkel, 2009).

## Conclusion

The present paper investigated the psychological and neural mechanisms underlying the decision to either stay with or leave a social partner. Despite the complexity of such a decision, our study can provide a theoretical framework for this type of decision-making with a concrete biological basis. Specifically, we demonstrated that decisions to stay or leave are based upon expected outcomes; and that decisions to stay with a social partner specifically are associated with increased neural

activity in caudate nucleus, vmPFC and septo-hypothalamic region.

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