Neural precursors of future liking and reciprocity

Submitted to Proceedings of the National Academy of Sciences of the United States of America

Why do certain group members end up especially liking each other more than others? The prediction of interpersonal attraction has been a longstanding pursuit in the social sciences. We combine functional MRI and longitudinal social network data to test whether newly acquainted group members’ reward-related neural responses to one another predict their future attractions after completing a summer program together. We find that one’s own (actor’s) future liking of a particular group member (partner) is predicted jointly by actor’s neural valuation of partner and by that partner’s neural valuation of actor. These actor and partner effects exhibited equivalent predictive strength and were robust to each other, both individuals’ initial liking, and other potential drivers of tie formation. Behavioral findings indicated that actor’s relational attraction (to partner) and partner’s relational attraction (to actor) were initially independent (unreciprocated) at T1 yet became predominantly interdependent (reciprocated) by T2. This emergence of dyadic reciprocity was partly explained by the reciprocal pathways linking dyad members’ T1 neural data both to their own and to each other’s T2 liking outcomes. In sum, these findings elucidate interpersonal brain mechanisms that define how we ultimately end up liking (and being liked by) particular interaction partners, how group members’ initially idiosyncratic attractions become mutually reciprocated, and more broadly, how dyads evolve from the bonding of individuals. This study advances a flexible framework for researching the neural foundations of interpersonal sentiments and social relations that—conceptually, methodologically, and statistically—emphasizes group members’ relational interdependence.

Introduction

In all known human groups, members of the group end up liking each other to varying degrees. Some of the variation in liking is due to group members’ individual differences. Some group members tend to (not) like most everyone, and likewise some individuals are generally more (or less) liked relative to their peers. But the vast majority of variation in liking is due to relational effects, that is, group members having unique attractions to one another (1). Individuals’ ultimate liking ratings of particular group members are only modestly associated with their initial preferences, which evolve substantially over weeks of sustained interaction (2). Group members’ unique liking sentiments thus develop interactively—in relation to each other—in the natural course of socializing, bonding, and forming relationships. Ultimately, in fact, a fundamental feature of interacting group members’ liking is its dyadic reciprocity (1-6), which occurs when individuals we (dis)like also (dis)like us. This study leverages neuroimaging advancements to predict such changes in group members’ unique attractions and elucidate how these personal sentiments become coupled into mutually reciprocated bonds of (dis)liking.

Social scientists have long sought to understand the interpersonal forces that attract group members to one another, generate dyadic ties of mutual affection, and shape how their social-affective networks evolve over time. For decades, this line of research has been pursued primarily within a framework that emphasizes social-structural phenomena. One critical element of this research program has rested on the assumption that social relations tend towards affective reciprocity (1-6). But this assumption, like the axiom that reciprocity is normative (4), prevents us from asking and answering deeply powerful questions, specifically: Why do we end up liking certain group members more than others (even if we initially did not)? To what extent are such changes in idiosyncratic attractions predictable in advance? How do mutually reciprocal affective ties arise (i.e., by what mechanism do dyads—the fundamental units of social relations—emerge from individuals)? Predicting group members’ liking sentiments—and by extension, their emergent reciprocation—is our key focus.

Over the same period, psychologists have emphasized intrapersonal processes undergirding our interpersonal sentiments, affective ties, and social behaviors. Freud and others posited that individuals’ attractions and relationships may be foreshadowed—or even critically shaped—by intrapersonal processes of which they are not necessarily consciously aware (7). Building on reward-reinforcement research, social psychologists have theorized about interpersonal attraction determined by reward value individuals attribute to and elicit from one another (3, 8) and affective reciprocity as emerging from the mutual reinforcement of this reward value between interacting dyad members (2, 3). In this way, a social-structural phenomenon like affective reciprocity can be understood in regard to the intrapersonal processes through which it emerges.

This article extends and integrates both the intrapersonal and interpersonal lines of inquiry by testing a theoretically driven neural predictor of group members’ future attractions. Specifically, we test an a priori hypothesis involving interpersonal engagement of the brain’s reward valuation system in order to identify the neural precursors of relational liking and its reciprocation in human groups. To anticipate the main findings of this research, we show that (i) one’s own (actor’s) future liking of another group member is our key focus.

Significance

When joining a new group, we may initially like some individuals more than others. Likewise, certain group members may be particularly drawn to us. Over weeks and months of interaction, these attractions inevitably change a lot and also typically become reciprocated. This study uses fMRI to predict such changes in liking. Specifically, we measure newly acquainted group members’ unique reward system responses to one another. We find that these neural measures predict group members’ future attractions, both how much they will participate and be liked by each peer. Moreover, this brain-based mechanism helps explain how group members’ liking sentiments—which are initially unreciprocated—become mutually reciprocated. Overall, this study reveals how our brains may shape interpersonal attractions and relationships.

Reserved for Publication Footnotes

www.pnas.org — —

PNAS | Issue Date | Volume | Issue Number | 1–77
**Fig. 1.** Comparison of two conceptual paradigms for predicting future (T2) explicit liking based on initial (T1) explicit liking and implicit neural measure of valuation. The intrapersonal model conceptualizes actor’s outcome (i.e., T2 liking of a given partner) as predicted solely by actor’s inputs at T1: (A) actor’s implicit neural valuation of partner, and (B) actor’s explicit liking of partner. More generally, individual group members’ T2 liking outcomes are assumed to be independent of one another. (C) and (D) By contrast, the interpersonal model allows for and quantifies such interdependence of outcomes between the two individuals—actor and partner—comprising each dyadic pairing. This paradigm treats each predictor variable as potentially capable of exerting both intra- and inter-personal effects (i.e., by predicting both actor-to-partner and partner-to-actor liking at T2, respectively). By the same token, this model necessarily implies that T2 liking can have both intra- and inter-personal predictors. These intra- and inter-personal pathways are represented by straight arrows colored blue/red and purple, respectively. Straight paths with only one arrowhead depict directional paths from T1 predictor to T2 outcome; curved paths with two arrowheads depict symmetric correlations without specified directionality (including dyad members’ correlated error terms, ε₁ and ε₂). Note that, for visual clarity, the (two) neural predictors in(A) and (C) are illustrated separately from the (two) initial liking covariates in(B) and (D); however, both sets of predictor variables were simultaneously modeled in our analyses.

member (partner) at T2 can be *intrapersonally* predicted from actor’s neural valuation of partner measured months earlier (T1); (ii) actor’s future (T2) liking of a partner can be *interpersonally* predicted by that partner’s (T1) reward system response to actor; (iii) these actor and partner forecasting effects are robust to each other, both individuals’ initial attractions, and other potential predictors of affiliation; (iv) these reciprocal predictive effects also help explain how actor’s and partner’s liking of one another—which are initially unrelated—become mutually reciprocated. These results offer insight into the neural precursors of interpersonal attraction and its emergent reciprocation, that is, fundamental ingredients of human sociality from pair-bonding to group cohesion. More broadly, this study advances a paradigm for researching the links between the inter- and intra-personal mechanisms undergirding the formation of social preferences, social ties, and their consequent social network structure.

**Reward value as a precursor of interpersonal attraction.** Psychologists have long theorized interpersonal reward as an antecedent of liking and reciprocity (2, 3, 8). Their rationale is based on principles of positive reinforcement extended to social relations, which we will consider with two hypothetical group members A (Anita) and B (Buddy): if Anita experiences reward during social encounters with Buddy, it will positively bias (i.e., motivate) Anita to approach and affiliate with Buddy such that she increasingly anticipates and experiences positive reward in their future interactions. This positive reinforcement cycle, operating at the individual level, perpetuates Anita’s liking of Buddy (and a parallel intrapersonal process occurring independently for Buddy likewise perpetuates his liking of Anita). Moreover, because Anita’s interactions with Buddy are intrinsically linked to Buddy’s interactions with Anita, the positive feedback loop could play out at the dyadic level too (i.e., unfolding independently between Anita and Buddy). Based on this reward-reinforcement
The psychological literature reviewed above posits reward value as an antecedent of interpersonal attraction, and the neuroscience literature suggests this interpersonal reward value could be implicitly measured and operationalized by neural activity in targeted regions of interest (ROIs) underlying reward valuation, namely, vmPFC and VS. We integrate the social psychological theories and neuroimaging methods in order to test whether these valuation ROIs’ interpersonal activations (i.e., neural reward responses elicited by seeing another participant's face) can be leveraged to prospectively predict how group members’ interpersonal attractions develop over time and become reciprocated. Because this study focuses on relational phenomena in which participants are inherently interdependent—liking, being liked, and forming mutually reciprocated bonds—we embed the brain-as-predictor approach within a dyadic framework such that one’s outcomes can be predicted by one’s own and others’ neural data.

**Analytical Approach.** As our paradigm emphasizes group members’ relational interdependence, it differs from previous brain-as-predictor studies in several respects. First, our study population consists of an interacting group whose members formed organic relationships. Second, the fMRI task models social encounters between participants by presenting each group member’s face to each group member being scanned. Thus, each presentation corresponds to a particular dyadic relationship and the resulting neural data are inherently relational, inextricably linked to the person being scanned and the person whose face is presented. Third, the primary outcome we seek to predict—group members’ unique attractions after months of interaction—consists of interdependent observations. If Anita's liking of Buddy and Buddy’s liking of Anita are correlated at T2, their individual outcomes will exhibit dyadic linkage that should not be ignored for both conceptual and statistical reasons (24). In this vein, our sociological phenomenon of interest—mutually reciprocated attraction—is not a characteristic of individuals, but rather of their dyadic relations. If Anita’s and Buddy’s attractions are mutually reciprocated at T2, this interdependence suggests that their liking outcomes are shaped (at least in part) by interpersonal processes. In practical terms, this means that when we seek to predict an actor’s outcome (i.e., unique attraction to partner at T2), we consider as potential predictors both actor’s inputs and partner’s inputs (corresponding to actor and partner effects, respectively). We thus sociologically extend the brain-as-predictor approach—which conventionally uses our own neural responses to predict our own behavior—to consider how our own behavior could be reciprocally predicted by others’ neural responses to us.

These reflections are captured in Fig. 1. Panel A depicts the intrapersonal (i.e., conventional) brain-as-predictor approach, in which actor’s reward system activity (in response to viewing partner’s face) at T1 predicts actor’s future liking (of partner) at T2. Of course, one critical predictor of actor’s T2 liking is actor’s T1 liking: if we (dis)like someone at one time, we tend to (dis)like him or her at a later time (2). Panel B, still within an intrapersonal paradigm, illustrates the same brain-as-predictor model including T1 liking as a covariate (specifically, one that is tantamount to the baseline measure of the outcome variable). Panels C and D shift our focus from intrapersonal processes to interpersonal dynamics. In Panel D, we consider the fact that an actor’s liking of partner at T2 may be related to being liked by that partner at T1. In Panel C, we consider how others’ neural responses (to us) predict our own future attraction to them, and because the system is symmetrical, how our neural responses (to them) predict their future attraction to us. We tested these hypothesized predictors of future liking using the Actor-Partner Interdependence Model (APIM) (24), which conceptualizes relational dyads—each consisting of two interdependent individuals—as the fundamental units of analysis. It therefore allows for the possibility of correlated outcomes between these two individuals (for every possible pairing of participants). For each predictor variable, APIM simultaneously estimates both its intra-personal and inter-personal...
predictive effects on the outcome variable (referred to as actor effects and partner effects, respectively).

The analysis of liking is complicated by the fact that individuals differ with respect to how much they generally like others in their group, and similarly, how much other group members generally like them. To analyze the evolution of liking and emergence of reciprocity as dyadic relationship processes, however, we need to capture the uniquely relational component of liking that is specific to each dyadic relationship—rather than to each individual—in the group (1, 24). In other words, we want to isolate how much Anita uniquely likes Buddy (i.e., taking into account Anita’s overall tendency to explicitly like others’ explicit liking). For neural valuation, this means that our relational parameter needs to capture how much Anita’s neural reward system uniquely responds to Buddy (i.e., taking into account Anita’s overall neural responsiveness and how others generally respond to Buddy). We used TripleR (25) to isolate unique relationship effects (i.e., disentangled from confounding individual-level effects) for both neural valuation measures and (T1 and T2) explicit liking measures (1)(see SI Text). We then incorporate these uniquely relational variables into models to specifically analyze associations between relationship-specific valuation activity and relationship-specific future liking. These analyses allow us to test a primary hypothesis that relational processes link neural valuation (at T1) to future liking (at T2).

The study aimed to prospectively predict T2 relational liking, that is, specific actors’ unique attractions to particular partners. The study population consisted of an interacting group of 16 college-age students involved in an intense summer of labor organizing (see Methods and SI Text for details on participants). Over the course of the nine weeks, participants spent time in smaller groups as well as in the larger collective. At the beginning of the program (T1), they viewed faces of every other social network member while fMRI data were collected (of specific interest, activation of reward system ROIs in vmPFC and VS which were independently defined; see Methods). Group members were thus implicated as both the sources and targets of one another’s neural valuations. fMRI data were analyzed to predict participants’ unique liking of each other at T2, controlling for their initial affinities (i.e., T1 liking) and social-structural factors that have been shown to be crucial drivers of tie formation (e.g., homophily).

Results

Actor Effects: Intrapersonal Predictors of T2 Liking. Focusing on the intrapersonal precursors of future liking (i.e., actor effects), we asked: do group members’ initial reward responses to one another predict their future attractions? In other words, does Anita’s reward system activity while viewing Buddy’s picture at T1 predict how much Anita will ultimately like Buddy at T2? In support of our primary hypothesis, the AIM analysis demonstrated that actors’ unique neural valuations of partners at T1 predicted their unique liking sentiments at T2 (see Fig. 2B and SI Text; β = 0.119; P < 0.05).

To ensure that the association between neural activity and T2 liking was not merely due to both variables’ association with T1 liking, our model includes a baseline control measure of initial liking at T1 (see Fig. 1D and Fig. 2A). One can interpret the intrapersonal path from T1 liking to T2 liking (β = 0.264; P < 0.001) as measuring relational attractions’ temporal consistency or stability over the course of the program. Critical to our primary hypothesis, actor’s neural valuation of partner remained a significant predictor of future liking even after controlling for T1 liking, indicating this actor effect is not merely an artifact driven by initial liking. On the contrary, explicit (self-reported liking) and implicit (neural marker of valuation) T1 measures were found to be distinct predictors of future liking. Considered together, these actor effects indicate that Anita’s neural valuation of Buddy at T1 predicted how much she would ultimately like Buddy at T2, even taking into account her initial T1 liking of him. This neural predictor thus explains the evolution of—or change in—interpersonal attraction above and beyond its temporal stability.

Partner Effects: Interpersonal Predictors of T2 Liking. In addition to actor effects of neural valuation and initial liking at T1, the respective partner effects of both variables were also examined in this model. These partner effects correspond to predicting Anita’s outcome (liking Buddy at T2) using Buddy’s—rather than her own—T1 liking and fMRI data. As visualized in Fig. 2A, the partner effect of T1 liking was positive and significant (β = 0.159; P < 0.01), meaning that Anita’s ultimate liking of Buddy was predicted by Buddy’s initial liking of Anita. This is consistent with the intuition that we often come to like people who like us. Actor’s T2 liking of partner was likewise predicted by partner’s T1 neural reward response to that actor (β = 0.201; P < .005). In relation to our primary hypothesis (i.e., Anita’s neural valuation of Buddy at T1 predicts how much she will ultimately like him at T2), this finding presents evidence in support of the reciprocal phenomenon (i.e., Buddy’s neural valuation of Anita predicts how much the latter likes him). The partner effect demonstrates how our initial neural responses to individual group members can predict how much each of them will particularly like us at T2. Equivalently, how much we ultimately like particular individuals at T2 can be predicted by each of their unique neural valuations of us at T1 (i.e., the neural reward responses we specifically activate in each of them).

Robustness checks. It is important to note that actor and partner effects of neural valuation are robust to each other, as well as to actor and partner effects of T1 liking. Yet is possible that other mechanisms are at play, specifically, sociological predictors of tie formation. We conducted a series of robustness checks to test these alternative explanations. Extending the AIM analyses described above, we incorporated additional covariates to control for other potential predictors of liking (e.g., homophily on demographic and personality attributes). The results of these robustness checks demonstrated that, even when controlling for each of these potential confounds, both actor and partner effects of T1 neural responses consistently remained significant predictors of T2 liking (all Ps < 0.05; see SI Text for additional details).

Correlations among predictor variables. Although the AIM analysis is primarily intended for regressing an outcome variable (T2 liking) against various T1 predictors, its implementation using SEM also quantifies interrelations among these predictor variables. Two of these correlational pathways are depicted as curved, double-sided arrows in Fig. 2A and 2B: actor’s and partner’s unique liking of each other at T1 were not significantly correlated (β = 0.089; P > .4), nor were their T1 neural valuations of each other (β = 0.060; P > .5). In addition, actor’s neural reward response to partner did not track with actor’s own T1 liking of partner (β = 0.079; P > .3); however, it did correlate with that partner’s T1 liking of actor (β = 0.167; P < .05). Critically, we insured that our brain-as-predictor findings were robust to any such correlation by incorporating all four of these T1 predictors (i.e., actor’s and partner’s T1 liking ratings and neural responses) in the AIM analysis described above and depicted in Fig. 2. The emergence of reciprocity. Between T1 and T2, participants’ relational liking sentiments nearly doubled in variance and became predominantly dyadic as opposed to idiosyncratic (see Fig. 3A). This pattern of results indicates that actors’ and partners’ unique attractions to each other became statistically coupled and—together in pairs—spread out from the distribution’s mean toward its tails. In other words, liking variance increased as dyads became differentiated from one another on the basis of dyad members’ mutual (dis)liking. As depicted in Figs. 3B and 3C, these data also reveal how...
the mutual reciprocation of relational liking dramatically increased—in fact, arose into existence—over the course of the summer program: at T1, dyad members' unique attractions shared only 5% (co)variance and were not significantly correlated (β = 0.089; P > 4), compared to 52% shared (co)variance by T2 (β = 0.52; P < .005). Such strong linkage of actor's and partner's T2 liking also empirically validates our conceptual rationale (and statistical need) for modeling this outcome measure within the dyadic APIM framework (24). Moreover, the APIM analysis estimates that 27% of this actor-partner T2 liking correlation (reciprocation) is explained by the interpersonal brain-as-predictor model depicted in Fig. 2 (i.e., with T1 liking and neural predictors); crucially, even in its rudimentary form (i.e., based solely on dyad members' neural valuations of each other but not their initial liking ratings), the model still explains 14% of the dyadic interdependence in T2 liking.

Discussion

We set out to test a hypothesized neural precursor of relational liking and its reciprocation in human groups. At T1, when this group was just forming, how much one group member (actor) particularly liked a specific peer (partner) was unrelated to how much that actor was particularly liked by that partner. Relational liking sentiments were at first unreciprocated, yet ultimately, these initially personal liking sentiments became dyadically bonded—coupled within pairs of individuals. After months of interaction (T2), approximately half of interpersonal attraction variance was attributable to its dyadic linkage, that is, covariance shared by actor and partner. This empirical reality precluded modeling individuals' outcomes as if they were independent of each other (24), the norm in fMRI and psychological research. Therefore, we incorporated an analytic framework that allowed us to conceptually highlight and statistically model the dyadic interdependence of group members' ultimate (T2) liking.

Future liking predicted by one's own and partner's neural reward responses. A consequence of adopting APIM's dyadic framework is that it enabled us to model an actor's future liking of a particular partner as potentially predicted by both the actor's and the partner's neural responses to each other. Thus, while this framework allowed us to test our original hypothesis—that relational engagement of the brain's reward system could serve as a neural predictor of interpersonal attraction—embedding this predictive pathway within a dyadic context greatly expanded the range of processes which could be considered as precursors of liking ties and their reciprocation. In a narrow sense, our straightforward brain-as-predictor hypothesis was indeed supported by the study findings: an actor's unique neural valuation of particular partners at the beginning of the summer program did in fact predict how much that actor would uniquely like each of them after completing the program, even controlling for initial liking.

In a broader sense, however, this individualistic actor-oriented hypothesis could not anticipate the possibility of partner effects and therefore precluded their predictive potential. By incorporating the dyadic APIM framework, we could conceptually explore and statistically model neural reward responses as both intra- and inter-personal predictors of future liking. This led us to discover that an actor's outcome (i.e., unique liking of partner at T2) could be prospectively predicted from partner's neural reward activity; moreover, the predictive power of this partner effect was distinct from (i.e., non-overlapping with) that of the actor effect and of equivalent magnitude. Our neural partner effect findings thus represent a new utility with untapped potential for researchers' growing usage of neural reward measures to predict individuals' unique preferences among various objects (21-23).

By extending the brain-as-predictor approach to interpersonal preferences (i.e., sentiments about fellow study participants as opposed to, for instance, consumer products), we demonstrate how individuals' preferences can be predicted by their neural valuation of particular targets (as in previous neuroeconomic studies cited above) as well as the reciprocal reward response they elicit from each target.

Both the actor and partner neural effects can be deemed predictive but not necessarily causal since brain function was measured rather than manipulated (21); hence, we ground these results and their interpretations in the broader neuroscience literature. Many fMRI studies have shown vmPFC and VS to activate for depicted individuals whom we like or who like us in the present (9, 10, 13, 17-20), and our study further demonstrates that these regions' activity prospectively predicts both outcomes months later (even controlling for their initial levels). These results are consistent with psychological theories of interpersonal attraction based on the self-reinforcing reward value that group members attribute to one another (3, 8), particularly given extensive neuroscientific evidence implicating our ROIs in processing intrinsic value, anticipating reward, and reinforcing approach behaviors associated with those rewards (9, 10, 12, 15). We also found that the confluence of actor and partner neural effects helps explain how individuals' interpersonal attractions—which were initially unreciprocated at T1—became dyadically coupled by T2. This finding dovetails with a recent fMRI speed-dating study in which vmPFC and VS tracked one's own desires, being desired, and—above all—reciprocal of romantic interest (18). More broadly, neuroscience studies of wide-ranging dyadic relations (e.g., romantic love, sexual partnership, long-term pair-bonding, and mother-infant attachment) have consistently implied these reward regions in humans (26) and other animals (27, 28). In sum, the mechanisms we identify are consistent with neuroscience literature on vmPFC and VS, particularly their roles in encoding value, anticipating reward, and perpetuating—that is, forming, maintaining, and reinforcing—the mutually reciprocated bonds most valuable to our species.

Future liking predicted by one's own and partner's initial liking. Our finding that T1 liking predicted T2 liking is consistent with social psychological research on temporal stability of interpersonal attraction (2). It also underscores the importance of testing whether T2 liking was predicted by (implicit) neural measures above and beyond (explicit) self-report measures of T1 liking (21). By controlling for T1 liking as a covariate—specifically, one that indexed baseline measurements of our outcome variable—we could model the evolution of interpersonal attraction, estimating how well each predictor variable forecasts future changes in liking. These changes in liking were profound: although T2 liking evidences statistically significant traces of its "initial condition" at T1, this accounts for less than 7% of T2 liking.

In addition to an actor effect of T1 liking, we also found a corresponding partner effect of comparable magnitude, suggesting that our unique attractions to particular individuals depend both on initially liking and being liked by them. These findings dovetail with the intuition articulated by Newcomb that "attraction breeds attraction" (3), p. 577, both in the sense that attraction is self-reinforcing and—as evoked by the metaphor of breeding—that both members of the dyad contribute to its reproduction.

Conclusion. Our neural findings suggest that our future liking of group members can be jointly predicted by how our neural reward system uniquely responds to them and how theirs uniquely respond to us. Moreover, these implicit measures of neural activity in reward ROIs mutually predict both dyad members' future liking above and beyond predictive effects of explicit measures collected at the same time (i.e., both actor's and partner's initial self-reported liking of each other) as well as sociological antecedents of liking. It is worth noting that we observe these neural measures' long-term prognostic effects in spite of an experimental context rife with unpredictability; specifically, as young adults both working and living together in small groups for an entire
summer, their relationships were multifaceted and complicated by intense interactions across domains.

Considered together, our findings suggest that neural reward systems may interdependently shape future liking and moreover facilitate their mutual reciprocation. As such, this study offers insight into the mechanisms underlying how we ultimately end up liking (and being liked by) particular individuals, how affective reciprocity emerges, and more broadly, how dyads evolve from the bonding of individuals. Finally, we advance a framework for researching the neural foundations of interpersonal sentiments and social relations that—conceptually, methodologically, and statistically—emphasizes group members’ relational interdependence.

Methods

Participants. Participants were 16 students who volunteered to spend nine weeks together to organize workers and collect oral histories. All participants received monetary compensation and provided informed consent following the standards of the Columbia University Institutional Review Board. See SI Text for additional details.

Procedure and design. The T1 component of the study was comprised of two sessions. In a preliminary session, sociometric instruments (described below) and self-report questionnaires were administered, and photographs were taken of participants’ faces. In a second session, participants underwent fMRI scanning while completing the face-viewing task described below. For all computerized tasks in both T1 and T2 sessions, stimulus presentation and behavioral data acquisition were compiled using E-Prime 2.0 (Psychology Software Tools, Inc.). The T2 wave of data collection included sociometric assessments and was administered via Qualtrics online survey software following conclusion of the nine-week summer program. For both T1 and T2, sociometric assessments were conducted via a computerized peer-rating paradigm for additional details.

Round-robin fMRI face-viewing task. Methods relating to various aspects of this fMRI face-viewing task (e.g., round-robin experimental design, stimulus preparation, and participant procedures) were developed and described in our previous work (14). To prepare task stimuli, participants were photographed with affectively neutral facial expression and gaze directed straight at the camera. These photographs were cropped and converted to grayscale images with equal luminance. The face-viewing task implemented a rapid event-related design that included 10 repetitions of each stimulus face presented in pseudorandomized order. Participants were instructed to press one button each time a group member’s face was presented and to press a different button each time a “ghost face” (superimposition of all face stimuli) was presented for additional details.

Results and analysis. Whole-brain fMRI data were acquired on a 3T GE system. High-resolution anatomical images with 1 mm × 1 mm × 1 mm resolution were acquired with a T1-sensitive SPGR sequence at the end of the scan session. Functional images were acquired with a T2*-sensitive EPI blood oxygenation level dependent (BOLD) sequence. Functional images were preprocessed using SPM8 software (Wellcome Department of Cognitive Neurology, UCL), including slice timing correction, motion correction, realignment, coregistration between each participant’s functional and anatomical data, normalization to a standard MNI template using segmentation parameters, 3 mm isotropic voxels, and spatial smoothing using a Gaussian kernel (full width at half-maximum = 6 mm). fMRI data contain their associated time course (i.e., representing the 10 repetitions of each), created by convolving the canonical hemodynamic response function with a series of boxcars representing segment parameters, linear detrending, and conversion to grayscale images with equal luminance. The face-viewing task included a priori ROIs underling valuation and reward processes in a separate participant sample (these data were published previously in [14]). Following the protocol of prior studies (29), we used an established functional localizer task (30) to identify ROIs engaged in anticipating and receiving monetary reward; specifically, we defined spherical ROIs with 8 mm radius surrounding activation peaks in vmPFC and VS, constrained using an anatomical mask for VS. Parameter estimates extracted from vmPFC and VS ROIs were averaged together for a follow-up measure of reward valuation (14).

Imaging acquisition and analysis. Whole-brain fMRI data were acquired on a 3T GE system. High-resolution anatomical images with 1 mm × 1 mm × 1 mm resolution were acquired with a T1-sensitive SPGR sequence at the end of the scan session. Functional images were acquired with a T2*-sensitive EPI blood oxygenation level dependent (BOLD) sequence. Functional images were preprocessed using SPM8 software (Wellcome Department of Cognitive Neurology, UCL), including slice timing correction, motion correction, realignment, coregistration between each participant’s functional and anatomical data, normalization to a standard MNI template using segmentation parameters, 3 mm isotropic voxels, and spatial smoothing using a Gaussian kernel (full width at half-maximum = 6 mm). fMRI data contain their associated time course (i.e., representing the 10 repetitions of each), created by convolving the canonical hemodynamic response function with a series of boxcars representing the 1000 ms intervals during which a particular face was presented. In addition, the GLM included 6 motion parameters as estimated during realignment as well as a DCT-based basis set covering low-frequency up to 1/8 Hz to account for signal variability introduced by head motion and temporal drifts.

Please review all the figures in this paginated PDF and check if the figure size is appropriate to allow reading of the text in the figure.

If readability needs to be improved then resize the figure again in 'Figure sizing' interface of Article Sizing Tool.