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Higher subjective socioeconomic status is linked to increased charitable giving and mentalizing-related neural value coding

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ABSTRACT

Socioeconomic status (SES), a concept related to an individual's economic and social position relative to others, can shape social interactions like altruistic behaviors. However, little is known about the exact neurocognitive mechanisms that link SES with altruism. Our study aimed to provide a comprehensive account of the socio-cognitive *and* neural mechanisms through which SES affects charitable giving – an important variant of human altruism. To this end, participants completed a charitable donation task while their brain activity was measured using functional magnetic resonance imaging (fMRI). We also assessed participants' socio-cognitive ability to infer other people's mental states (i.e., mentalizing) – a driver of prosocial behavior – in an independent social task. Behaviorally, we found that both charitable giving and social cognition were status-dependent, as subjective SES positively predicted donations and mentalizing capacity. Moreover, the link between SES and charitable giving was mediated by individuals' mentalizing capacity. At the neural level, a multivariate pattern analysis of fMRI data revealed that higher subjective SES was associated with stronger value coding in the right temporoparietal junction (rTPJ). The strength of this value representation predicted charitable giving and was linked to mentalizing. Furthermore, we observed an increased negative functional coupling between rTPJ and left putamen with higher SES. Together, increased charitable giving in higher-status individuals could be explained by status-dependent recruitment of mentalizing-related value coding and altered functional connectivity in the brain. Our findings provide insights into the socio- and neurocognitive mechanisms explaining *why* and *when* higher SES leads to prosociality, which might ultimately inform targeted interventions to promote prosocial behavior in human societies.

1. Introduction

Social hierarchies are a principal feature of human societies and animal groups. An individual's position within a hierarchy, also referred to as social rank or status, reflects an individual's social influence and access to resources (Vogel, 2005). While human social hierarchies can be based on multiple distinctive features (Redhead and Power, 2022), socioeconomic status (SES) represents a key dimension. For instance, decades of research have shown that objective indicators of SES such as income, wealth, education, and neighborhood predict a large array of consequential outcomes, including physical and mental health (Adler and Ostrove, 1999; Kivimäki et al., 2020; Sapolsky, 2005). However, subjective perceptions of social rank (i.e., subjective SES) often outperform more objective measures in predicting health (Operario et al., 2004; Singh-Manoux et al., 2005) and other outcomes such as cognitive function (Kobayashi et al., 2022). An individual's position in a social hierarchy, and particularly its subjective perception, thus have a significant impact on quality of life.

This impact extends to our social life and the social functioning of groups or even whole societies. Altruism, defined as costly other-regarding behavior, is one important domain in which social status may affect social behaviors (Burkart et al., 2014). Common popular beliefs hold that more affluent people may act less considerate of others (Christopher and Schlenker, 2000; but see Almås et al., 2022). In line with this lay belief, initial behavioral findings reported a negative relationship between SES and prosocial behavior (e.g., Guinote et al.

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2015; Piff et al. 2010). However, the replicability of some of these reports has been questioned (e.g., Balakrishnan et al., 2017; Stamos et al., 2020). Instead, a growing body of evidence points to a *positive* association between SES and altruism, with higher-status individuals behaving more prosocially (e.g., Andreoni et al. 2021; Benenson et al. 2007; Korndörfer et al. 2015; Kosse et al. 2020).

Irrespective of the direction of the association, a more fundamental question concerns how a link between SES and altruism might be explained mechanistically. Understanding the cognitive and neural mechanisms behind this link might also provide insights into the inconsistent findings of prior work. One important determinant of altruistic behavior that has received a lot of attention in the past decade is social cognition, including inferring others' thoughts and feelings (mentalizing, also termed Theory of Mind; Lehmann et al., 2022; Tusche and Bas, 2021). Initial empirical evidence found that SES predicted neural activity associated with mentalizing (Muscatell et al., 2012). However, to date, it is unclear whether SES also modulates brain activity related to altruistic decisions – either directly or mediated via mentalizing. Previous studies have examined SES-effects on social cognition or prosocial choice in isolation (e.g., Korndörfer et al. 2015; Muscatell et al. 2012), or failed to provide evidence of a mediating role of mentalizing in the SES-altruism link or an underlying neural mechanism (e.g., Cowell et al. 2017; Liu et al. 2023). Hence, we combined assessments of charitable giving – an important variant of human altruism (Milinski et al., 2002; Tusche et al., 2016) – with measurements of associated brain activity and mentalizing. This allowed us to examine if variation in mentalizing capacity and mentalizing-related brain activity during altruistic choice can explain the link between subjective SES and charitable giving.

Participants reported their subjective SES before they made charitable donations while their brain activity was measured with functional magnetic resonance imaging (fMRI). We focused on *subjective* SES, given the particular importance of subjective perceptions of social rank in predicting real-world outcomes like health (Operario et al., 2004; Singh-Manoux et al., 2005). Mentalizing capacity was measured in the following ways: first, following donation decisions, participants reported the degree of mentalizing (i.e., how much did they take the perspective of the beneficiaries of the charities?). Second, to go beyond retrospective self-reports of mentalizing, participants completed an independent task including a performance-based assessment of participants' mentalizing capacity (EmpaToM; Kanske et al., 2015). We hypothesized that subjective SES would be positively associated with altruistic behavior (e.g., Andreoni et al. 2021; Korndörfer et al. 2015), mediated via SES-related increases in mentalizing capacity. Taking advantage of neurocomputational models and multivariate-decoding techniques developed in the field of decision neuroscience (e.g., Kahnt et al. 2014; Tusche et al. 2016), we used trial-wise donations as an indicator of the subjective value participants placed on specific charities and to reveal brain regions that code for this value. We hypothesized that the SES-donation link could be explained at the neural level by status-related value coding in mentalizing-related brain regions like the temporoparietal junction and dorsomedial prefrontal cortex (Schurz et al., 2021, 2014; Tusche and Bas, 2021). Insights into the precise sociocognitive and neurocomputational mechanisms will elucidate the functional link between SES and prosociality, potentially also shedding light on contradictory prior results.

2. Materials and methods

2.1. Participants

A total of 50 healthy, right-handed volunteers [24 women, 26 men, none identified as other than female or male; mean (M) age ± standard deviation (SD): 23.90 ± 4.03 years] were recruited via flyers at the university, social media (e.g., Facebook student groups), and a student job portal, and participated in this fMRI experiment. This sample is part of a larger project on factors modulating charitable giving and its neural underpinnings (see Schulreich et al. 2022). Ten participants had to be excluded for the following reasons: having not completed the subjective SES measure ($N = 1$); repeatedly exceeding the maximum reading duration in the charity description phase, indicating potentially incomplete task processing ($N = 1$); clinically relevant depression scores ($N = 1$, Beck Depression Inventory score > 30); and lack of variability in donations ($N = 7$; with five participants choosing the maximum donation amount in every single trial, and two participants choosing the maximum amount across at least one block). Sufficient variability is a prerequisite to fit the multivariate model examining value coding during altruistic decision-making on the neural level (see below). Thus, the final sample comprised 40 participants (19 women, 21 men; 23.73 ± 4.21 years; 82.5% students; educational level: 67.5% high-school diploma and 25% academic degree). An a-priori power analysis (G*Power 3.1.; Faul et al., 2009) showed that this sample size was sufficient to detect a medium-sized effect of Cohen's $f^2 = 0.21$ for a single regressor with a statistical power of 80% and α at $P = 0.05$.

All participants gave written informed consent before the experiment and received a compensation of €30 for participating in the study, plus a possible monetary bonus in the donation task (see below). The study protocol was in line with the Declaration of Helsinki and approved by the ethics committee of the Faculty of Psychology and Human Movement Science at Universität Hamburg.

2.2. Experimental design

Participants completed a series of tasks and measures in the lab. Variance in individuals' altruism was captured using a charitable donation task (adapted from Böckler et al., 2018; Tusche et al., 2016; see below) while their brain activity was measured via fMRI. The donation task was performed twice – before and after an experimental stress manipulation. The effect of stress on charitable giving and its neural correlates is reported elsewhere (Schulreich et al., 2022). Here, we focus on the baseline donation task prior to the stress manipulation, thus ruling out any potential stress effects. Participants were informed beforehand that they would undergo either a stress or control condition (the exact condition and task components, however, were only revealed during the procedure). However, this prior information did not result in an increase of stress parameters before the stress/control manipulation (as reported in Schulreich et al. 2022), and a strong influence on donation-task performance and neural activity in the analyzed pre-stress phase is therefore unlikely. Participants were also informed that they would perform the donation task twice. To obtain a behavioral measure of participants' mentalizing capacity, participants completed an established social cognition task (EmpaToM task; Kanske et al., 2015; see below) before the donation task.

Prior to the experiment, participants also completed an online survey at home (implemented via the SoSci Survey platform; Leiner 2020) to measure subjective SES (see below). On average, participants completed the survey 3.84 days prior to the donation-task session (minimum: 77 min) and the SES measure was accompanied by other unrelated measures [including demographic questions, the Beck Depression Inventory (Hautzinger et al., 2006), and the Trier Inventory of Chronic Stress (Schulz and Schlotz, 1999)], minimizing potential priming effects of the SES measure on task performance and neural activity. The length of the time interval between SES measure and experiment was not significantly correlated with charitable giving and subjective SES ($Ps > 0.179$).

2.3. Donation task

Altruistic behavior was measured using a charitable donation task (as also described in Schulreich et al. 2022; adapted from Böckler et al. 2018; Tusche et al. 2016) while simultaneously collecting fMRI data. The relevant task phase consisted of 40 trials, arranged in four functional runs (blocks) of ten trials each.

As illustrated in Fig. 1, each trial started with a short description of a real-world charitable organization (reading phase; terminated by button press with a maximum of up to 25 s; for the complete set of charity descriptions [in German], see OSF project page: https://osf.io/b3kmg/). Participants then decided how much to donate to the respective charity (range of €0 to €20 in steps of €1) (decision phase; up to 8 s). After a variable inter-stimulus interval [ISI] from 2 to 6 s, three rating questions were presented in a randomized order. Participants rated their experienced (1) *mentalizing* ("Took the perspective of others?" [i.e., of the beneficiaries of the charity]), (2) *empathy* ("Felt with others?", in the sense of sharing an affective state), and (3) *compassion* ("Compassion for others?", in the sense of warm, tender feelings towards others) (rating on a 9-point scale ranging from "not at all" to "very strong"; up to 8 s per rating; for complete instructions, see https://osf.io/b3kmg/). Trials were separated by another variable interval (2 to 6 s). The charities were selected and allocated to blocks such that average donations were comparable (i.e., not significantly different) across task blocks and that a broad range of giving behavior was elicited across the ten charities of each task block. The latter was crucial as sufficient variance in giving behaviors is a prerequisite for the *Multivariate Pattern Analysis* described below. The order of charities within a task block and the block order were randomized across participants. Averaged donation amounts (across the four blocks) varied between €2.11 and €19.50 (M = €11.82, SD = €4.64; see Fig. 1B – left violin plot), indicating substantial variability in charitable giving across participants. In addition to the main task blocks, participants completed one block of 10 trials outside the scanner before the main experiment. This block did not contain mentalizing-, compassion- and empathy-rating questions and served both as a training block and as a control for the potential influence of the rating task on charitable giving. Mean donations did not differ significantly between the control block and the fMRI blocks (including the ratings), $P = 0.561$ (paired-samples *t*-test). Moreover, across participants, charitable giving in control and test blocks were highly correlated, $r_{(38)} = 0.823$, $P < 0.001$, and mentalizing predicted charitable giving in both kinds of blocks very similarly [EmpaToM measure: $r_{(38)} = 0.46$, $P = 0.003$ (control block), $r_{(38)} = 0.467$, $P = 0.002$ (fMRI blocks); fMRI ratings: $r_{(38)} = 0.584$, $P < 0.001$ (control block), $r_{(38)} = 0.649$, $P < 0.001$ (fMRI blocks)], suggesting very similar underlying processes. In line with this evidence, a previous study with retrospective instead of within-task ratings found a similar engagement of mentalizing that also predicted prosocial choice (Tusche et al., 2016). Hence, a rating-induced alteration of mentalizing that could have influenced decisions, or a stronger coupling between mentalizing-related brain activity and decisions due to the inclusion of the ratings, is rather unlikely.

Before the donation task, participants were informed that one trial would be randomly selected at the end of the experiment and implemented. The charity would receive the total amount donated in that trial, and participants could keep 25% of the amount not donated. For example, if a participant donated €12 of their €20 endowment, then €12 was transferred to the charity after the experiment, and €2 [25% of the amount not donated (€8)] was added to the participant's compensation. Thus, choices in the donation task were costly (as they reduce personal gains) and had real consequences, ensuring that donations were consistent with participants' preferences. A partial (instead of full) payout of the non-donated amount was implemented not to override other-regarding preferences and to provide a moderate donation incentive (Tusche et al., 2016).

2.4. EmpaToM task

To assess participants' mentalizing capacity in naturalistic social settings, we administered an independent behavioral task prior to the donation task – the EmpaToM task (Hildebrandt et al., 2021; Kanske et al., 2015; Tholen et al., 2020). This well-established instrument also assessed socio-affective responses (empathy, compassion), allowing us to examine the specificity of socio-cognitive (i.e., mentalizing-related) effects. Each of the 24 trials started with a fixation cross (1–3 s), after which the name of a person appeared (1 s), followed by a short video in which one of six actors (3 females, 3 males) recounts an autobiographical episode (∼ 15 s). The videos differed in emotionality (neutral vs.

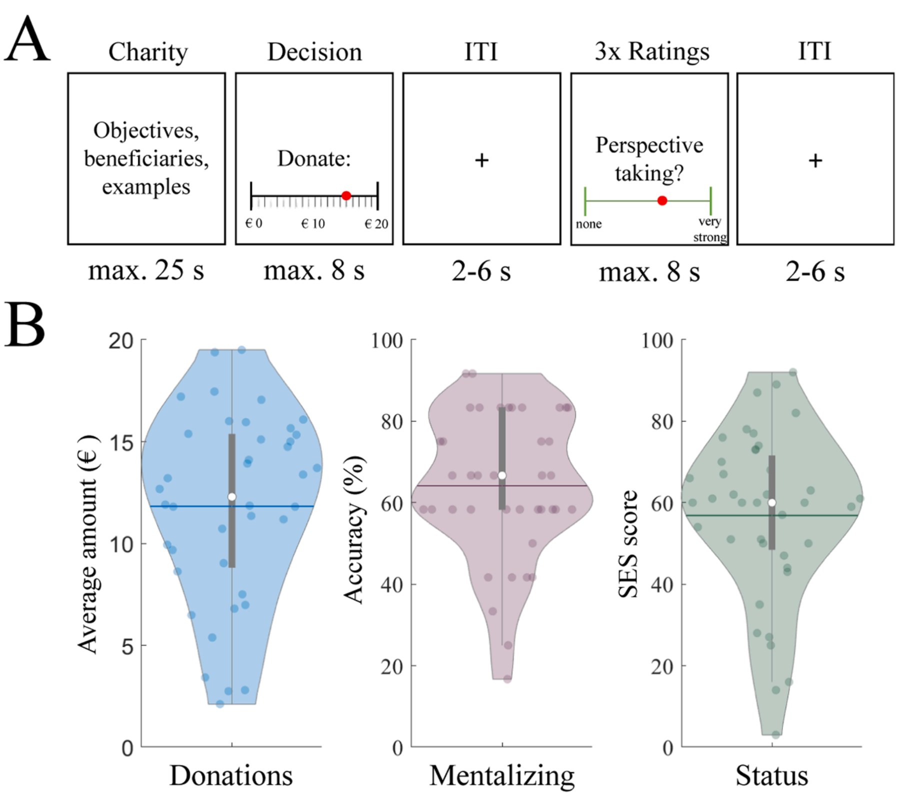

Fig. 1. (A) Trial sequence of the fMRI donation task. Each trial included a charity description phase, followed by the decision phase, and ratings of experienced mentalizing, empathy and compassion. (B) Violin distribution plots of participants' average donations (left), mentalizing capacity in the separate EmpaToM task (middle), and subjective socioeconomic status (SES, right). Horizontal colored lines = mean across participants; white data point = median; vertical: boxplot with gray box ranging from lower quartile (25th percentile) to upper quartile (75th percentile) and whiskers extending to 1.5 × interquartile range.

negative) and in whether their content was mentalizing-related (e.g., beliefs, deception) or not (yielding a 2 × 2 factorial design; 6 actors x 4 conditions = 24 trials). After each video, participants rated their emotional state on a rating scale from negative to positive (ranging from −3 to 3). Following previous approaches (e.g., Kanske et al., 2015), we derived a measure for the tendency to share others' affect (i.e., empathy) by creating a difference score (ratings for negative minus neutral videos). Participants then rated their compassion for the person in the video (on a scale from 0 to 6) (4 s per rating). The mean rating across all videos served as our measure of compassion. The ratings were followed by a multiple-choice question with three response options. The question either demanded mentalizing (e.g., "Anna thinks that […]" [12 trials]) or factual reasoning (e.g., "It is correct that […]" [12 trials]) on the contents of the previous video. Participants responded by pressing one of three buttons assigned to the three choice options (up to 15 s). The rate of correct responses (accuracy) in the mentalizing-related questions served as our measure of *mentalizing capacity*. Accuracy ranged from 16.67% to 91.67% ($M = 64.17\%$, SD = 18.02%; also see Fig. 1B – middle violin plot), indicating considerable variation in mentalizing capacity in our sample.

2.5. Subjective socioeconomic status

To measure subjective SES, participants completed a variant of the MacArthur Subjective Social Status Scale (Adler et al., 2000), an established SES measure in the field (Muscatell et al., 2012; Operario et al., 2004; Singh-Manoux et al., 2005). Participants were instructed to indicate where they stand in society on a scale ranging from 0 to 100 in increments of one. The upper end represents the people who are the best off (most wealth and income, highest education, and best jobs); the lower end represents the people who are worst off (least wealth and income, lowest education, and worst jobs). Notably, subjective perceptions of SES have previously been found to predict certain variables like health outcomes even better than more objective measures of SES (Operario et al., 2004; Singh-Manoux et al., 2005) and show adequate stability over time (Spearman's rho = 0.62 for a 6-month test-retest interval; Operario et al., 2004). Subjective SES scores ranged from 3 to 92 (out of a possible 100; $M = 56.88$, SD = 20.721; also see Fig 1B – right violin plot), indicating that participants showed considerable variation in their perceptions of their status within society.

2.6. Behavioral data analysis

2.6.1. Relationship between subjective SES and charitable giving

To investigate whether subjective SES predicts charitable giving, we set up a Generalized Linear Model (*Model 1*) with the participant-wise average donation amount in the baseline donation task (i.e., across four pre-stress blocks) as the dependent variable, and participants' reported subjective SES as the predictor variable. In addition, we compared this model to an extended model with age and gender as additional predictors (*Model 1_{EXT}*). This extended model also included the level of salivary cortisol immediately before the start of the donation task as a predictor variable to account for the significant positive correlation between subjective SES and baseline cortisol levels ($r_{(38)} = 0.327$, $P = 0.039$) (for details on cortisol assessment, see Schulreich et al. 2022). Notably, this effect is in line with previous research demonstrating blunted diurnal cortisol dynamics (e.g., awakening response) in lower-SES individuals (Desantis et al., 2015; Raffington et al., 2018) (all pre-task cortisol measurements took place between 8:30 and 11:00 AM). However, extending the simple model with these additional predictors decreased the model fit (BIC_{SIMPLE}: 241.567 vs. BIC_{EXT}: 244.591). Nevertheless, we also report the extended model results to demonstrate the robustness of the link between subjective SES and charitable giving.

2.6.2. Relationship between subjective SES and mentalizing

Next, we assessed whether subjective SES is associated with mentalizing capacity. In this model (*Model 2*), we defined subjective SES as the dependent variable, and mentalizing capacity, empathy, and compassion, as measured in the independent EmpaToM task, as the predictors. This allowed assessing the unique contribution of mentalizing capacity beyond a potential role of socio-affective processes such as empathy or compassion. In a similar vein, we tested if participants' average mentalizing ratings (i.e., perceived degree of taking the perspective of the charities' beneficiaries), empathy and compassion ratings obtained in the donation task predicted subjective SES (*Model 3*).

2.6.3. Mediation model

To investigate whether the relationship between subjective SES and charitable giving can be explained via variation in mentalizing capacity, we used the PROCESS toolbox v. 3.4.1. (Hayes, 2018) to set up a mediation model (*Model 4*). The model used individuals' average donations as the dependent variable, subjective SES as the independent variable, and mentalizing capacity measured in the EmpaToM task as the mediator variable.

Behavioral data were preprocessed and analyzed using Matlab R2019a (Mathworks) and SPSS 26 (IBM). The significance level was set at $P \leq 0.05$. All reported P-values are two-tailed unless indicated otherwise. Since SPSS does not provide (adjusted) R^2 values for Generalized Linear Models, we report adjusted R^2 derived from the standard regression function.

2.7. MRI acquisition and preprocessing

Functional imaging was conducted using a 3 T Magnetom Prisma MRI scanner (Siemens, Erlangen, Germany) equipped with a 64-channel head coil. We acquired gradient-echo T_2*-weighted echo-planar-images (EPI). In each of the four functional runs (corresponding to the four task blocks of the donation task), we collected a series of volumes using a slice thickness of 2 mm and isotropic voxel size of 2 mm^2, 60 slices aligned to the anterior commissure-posterior commissure (AC-PC) line and acquired in descending order, repetition time (TR) = 2000 ms, echo time (TE) = 30 ms, flip angle = 60%, and field of view (FOV) = 224 × 224. After the four functional runs, we obtained a static field map for offline image distortion correction of the EPI scans. After the donation task, an additional magnetization-prepared rapid gradient-echo (MPRAGE) sequence was employed to acquire high-resolution (0.8 × 0.8 × 0.9 mm) T_1-weighted structural images for each participant (TR = 2.5 s, TE = 2.12 ms, 256 slices).

Preprocessing of functional images was performed using SPM12 (http://www.fil.ion.ucl.ac.uk/spm/) implemented in Matlab (Mathworks). For each run, the first five functional images were discarded from the analysis to avoid T_1 saturation effects. The remaining functional images were spatially realigned and distortion-corrected using the field map, slice-time corrected, co-registered to the structural image, followed by spatial normalization to the Montreal Neurological Institute (MNI) stereotaxic standard space. The resulting (unsmoothed) images were used as inputs to our multivariate decoding analysis (the decoding maps were later smoothed for a whole-brain analysis, see below). Only for the complementary univariate analysis, preprocessing also included spatial smoothing using an 8 mm full-width half-maximum (FWHM) Gaussian kernel.

2.8. fMRI analysis

For each subject, we estimated a General Linear Model (*Model 5*) to obtain trial-wise measures of blood-oxygenation-level-dependent (BOLD) responses during the donation task. In line with previous implementations of the task (Schulreich et al., 2022; Tusche et al., 2016), the model included a regressor for each of the 40 decision phases of the baseline donation task (R1-R40 for the 40 donation choices). The estimated regressors of the altruistic decision phases served as inputs for our multivariate analysis to examine trial-by-trial variations in neural activity coding donation values (see below). Matching previous approaches, *Model 5* also included two additional regressors of no interest, modeling the reading phases (R41) and the rating phases (R42), and six motion regressors accounted for residual motion-related signal changes (R43-R48). Task-related regressors were modeled as boxcar functions with a duration of the associated trial phase (e.g., decision phase) and convolved with a canonical hemodynamic response function. We applied a 128 s high-pass cutoff filter to eliminate low-frequency drifts in the data.

2.9. Brain regions of interest (ROIs)

Our fMRI analyses focused on the dorsomedial prefrontal cortex (dmPFC), and the right and left temporoparietal junction (TPJ) as regions of interest (ROIs) that emerged as a core network of mentalizing across a range of tasks in meta-analyses (Molenberghs et al., 2016; Schurz et al., 2014). Specifically, we constructed spherical ROIs (10 mm radius) around the previously identified cluster peaks of a permutation-based conjunction analysis (Schurz et al., 2014; MNI coordinates [x, y, z]: dmPFC: −1, 54, 25 [Brodmann area / BA 10]; right TPJ: 51, −60, 20 [BA 39]; left TPJ, −55, −59, 19 [BA 21]). We chose a radius of 10 mm as the resulting spheres cover a large proportion of the meta-analytic clusters (Schurz et al., 2014), are centered at their peak effects, are fully consistent across regions, and consist of continuous voxels, in contrast to the partially patchy meta-analytic clusters. Moreover, a 10 mm radius ensures a balance between sensitivity regarding neurally distributed information (that may be only detectable with a larger voxel space) and a certain degree of spatial specificity. An ROI-radius of 10 mm is also widely used in the literature (e.g., Guterstam et al., 2021; Majerus et al., 2016; Tusche et al., 2014). Furthermore, we included the right and left striatum as well as the ventromedial prefrontal cortex (vmPFC) as three additional ROIs, given their role in value processing and (prosocial) decision making (Bartra et al., 2013; Bellucci et al., 2020; Saulin et al., 2022; Spaans et al., 2019). For the vmPFC, we constructed a spherical ROI (10 mm radius) around the peak coordinate of a meta-analysis of neural correlates of prosocial behavior (MNI coordinates [x, y, z]: 0, 46, −8 [BA 10]; Bellucci et al., 2020). Notably, this ROI overlaps with the vmPFC cluster associated with decision-related positive value coding reported in another fMRI meta-analysis on value processing across choice domains (Bartra et al., 2013). We delineated the bilateral striatum using the Harvard-Oxford Subcortical Atlas (tissue-probability threshold 25%). ROI masks are provided at https://osf.io/b3kmg/). Thus, ROIs were defined entirely independently of the current fMRI data and subject sample, effectively reducing the risk of circular analysis (Kriegeskorte et al., 2009).

2.10. ROI-based multivariate pattern analysis (MVPA)

To test whether participants' subjective SES modulates neural value coding (of trial-wise donations) during altruistic choices in mentalizing- and value-related brain regions, we performed a multivariate pattern analysis (MVPA). In line with previous implementations of this analytical approach (Schulreich et al., 2022; Tusche et al., 2016), this decoding analysis was performed for each of the a-priori ROIs using the following steps: For each of the N voxels within a particular ROI, we extracted trial-wise parameter estimates of *Model 5* representing the neural response patterns during each individual donation decision (R1-R40) (Fig. 1A). Extracted neural activation patterns were transformed into N-dimensional pattern vectors. This was done separately for each of the four runs (à 10 trials). Pattern vectors of all runs but one ("training data") were used to train a support vector regression (SVR) model (*Model 6*), as implemented in LIBSVM (http://www.csie.ntu.edu.tw/~cjlin/libsvm; Chang and Lin, 2011) using a linear kernel (nu-SVR) and a fixed regularization parameter ($c = 1$). This provided the basis for the following prediction of the donation amounts of the remaining run ("test data") solely based on their trial-wise neural response patterns. The procedure was repeated four times, always using data of a different run (block of the donation task) as a test dataset (4-fold leave-one-run-out cross-validation). Splitting the dataset into training and test datasets and run-wise cross-validation is a measure to control for potential problems of overfitting (Poldrack et al., 2020). The amount of predictive information on generosity was defined as the average Fisher's Z-transformed correlation coefficient between the donations predicted by the SVR model and the participant's actual donations in these trials (Kahnt et al., 2014; Tusche et al., 2016). Trial-wise donations served as an indicator of the value people place on specific charities; thus, this decoding procedure served to detect neural value coding.

To examine which of our brain regions of interest displayed value coding, we performed ROI-wise permutation tests to assess the statistical significance of the ROI-wise predictions. These tests determine how likely ROI-based decoding accuracies were achieved by chance by comparing observed prediction accuracies with empirical permutation-based null distributions. Specifically, for each participant, null distributions were created by breaking up the mapping of observed donations and neural response pattern vectors (10,000-fold). We then compared the average "real" decoding accuracies (i.e., ROI-wise mean across participants) to the sampled null distribution obtained by chance. If the "real" decoding accuracies were unlikely to have resulted by chance, this indicated that neural activation patterns in the respective brain region code for value. To statistically control for multiple comparisons across a-priori ROIs, we only consider p-values of the permutation test that survived a family-wise error (FWE) correction as significant for value coding.

2.11. MVPA of SES-related effects

To examine whether subjective SES is linked to neural value coding, we set up another Generalized Linear Model (*Model 7*). The model used subjective SES scores as the dependent variable and the ROI-wise predictive information on donations as the predictor variable (i.e., neural value coding reflected in the Z-transformed correlation coefficient between the donations predicted by the SVR model and the participant's actual donations in these trials). We repeated this model separately for each ROI that significantly coded donation values: the three mentalizing-related ROIs (i.e., dmPFC, right and left TPJ) and the vmPFC, whereas the striatum did not display significant value coding and, consequently, was omitted (see *Results*). In addition, we compared this model to an extended model with age, gender, and baseline cortisol as additional predictors (*Model* 7_{EXT}), to provide further evidence for the robustness of the link between subjective SES and neural value coding.

Furthermore, for the rTPJ ROI that showed a relationship with subjective SES, we also assessed whether the strength of neural value coding in the rTPJ also predicts charitable giving (*Model 8*) and whether rTPJ value coding is uniquely predicted by mentalizing capacity, but not empathy and compassion in the EmpaToM task (multiple regression; *Model 9*). One participant was removed from these two analyses for being an outlier in both bivariate relationships (Cook's Distance = 0.546 and 1.243, respectively; standardized residuals $Z = -2.178$ and -3.286, respectively).

2.12. Exploratory whole-brain MVPA

We complemented our ROI-based decoding analyses with an exploratory whole-brain MVPA approach. Specifically, we applied a searchlight decoding approach that does not depend on a priori assumptions about informative brain regions and ensures unbiased information mapping throughout the whole brain (Haynes et al., 2007; Kriegeskorte et al., 2006). For each participant, we defined a sphere (radius = 5 voxels) around a given voxel v_i of the acquired brain volume

(Libby et al., 2014; Solanas et al., 2020). For each of the N voxels within this sphere, we then performed an identical support vector regression as described above. The resulting predictive-accuracy value was then assigned to the central voxel of the searchlight cluster, and the procedure was repeated for every voxel of the acquired brain volume, resulting in a 3D map of average predictive accuracies for trial-by-trial donations (value) for each participant. These subject-specific, whole-brain decoding maps were smoothed with a Gaussian kernel (8 mm FWHM) and submitted to a random-effects group analysis (*Model 10*) to identify brain regions that encode trial-wise donations across participants (simple *t*-test against baseline as implemented in SPM12). To also test whether value coding is related to subjective SES, this model also included the subjective SES as a between-subject covariate. For this whole-brain analysis, we applied a cluster-forming threshold of $P \leq 0.001$, FWE-corrected for multiple comparisons at the cluster level ($P_{FWE} \leq 0.05$).

2.13. Univariate fMRI analysis

We complemented our main multivariate analyses of the fMRI data with a univariate analysis by estimating a further GLM (*Model 11*) based on smoothed brain data (8 mm FWHM), which included a regressor denoting the decision phases per session (R1) and a parametric regressor denoting donation amounts (R2). Furthermore, two additional regressors of no interest modeled the reading phases (R3) and the rating phases (R4). Six movement parameters were again included as nuisance regressors (R5-R10). Similar to the MVPA approach, we performed an ROI-based analysis on the extracted donation-encoding parameter estimates (R2, average over all voxels within a particular ROI). First, we used a one-sample *t*-test to assess whether brain activity within each ROI was parametrically modulated by donation values (i.e., whether they display positive value coding). However, in contrast to the more sensitive multivariate analysis, none of the ROIs displayed value coding in this univariate analysis (see *Results*). Hence, we refrained from setting up further ROI-based models assessing potential effects of subjective SES on value coding. However, we performed an exploratory group-level whole-brain analysis (*Model 12*) to identify potential other regions that encode trial-wise donations (R2) across participants (one-sample *t*-test against baseline as implemented in SPM12). This model also included the subjective SES as a between-subject covariate. For this univariate whole-brain analysis, we applied a cluster-forming threshold of $P \leq 0.001$, FWE-corrected for multiple comparisons at the cluster level ($P_{FWE} \leq 0.05$).

2.14. Psychophysiological interaction (PPI) analysis

We performed a PPI analysis to identify brain regions for which subjective SES predicted functional connectivity with the right TPJ as our seed region, given the observed link between subjective SES and multivariate neural value coding in this region. This analysis was performed in several steps. First, we used our rTPJ sphere (10 mm radius) as an outer sphere (bounding region) in which we centered a smaller subject-specific inner sphere (5 mm radius) at their individualized peak in the decision-phase contrast (i.e., decision phase > baseline) to account for inter-subject heterogeneity in brain activation (Martin et al., 2022; Reicherts et al., 2017). Second, the activation of the seed region was obtained by extracting the principal eigenvariate of the BOLD signal time series from the subject-specific sphere. Third, for each participant, we estimated a GLM (*Model 13*) with the following three regressors: (R1) a psychological regressor denoting donation phases convolved with a canonical HRF; (R2) a physiological regressor denoting the activation time course of the subject-specific rTPJ seed region, and (R3) a PPI regressor denoting the element-by-element product of the previous two (i.e., the PPI term). Individual contrast images (R3 > baseline) were submitted to a higher-level group analysis (one-sample *t*-test), which included subjective SES as a between-subject covariate. In an ROI-based analysis, we identified whether the strength of functional connectivity between the rTPJ and our other ROIs (i.e., lTPJ, dmPFC, vmPFC, right and left striatum) was significantly associated with subjective SES, using a small-volume correction for multiple comparisons with an FWE-corrected ($P_{FWE} \leq 0.05$) peak activation. This ROI-based analysis was complemented by a whole-brain analysis in which we applied a cluster-forming threshold of $P \leq 0.001$, FWE-corrected for multiple comparisons at the cluster level ($P_{FWE} \leq 0.05$).

3. Results

3.1. Subjective SES predicts generosity

In line with our hypothesis, we observed that higher subjective SES predicted increased charitable giving ($B_{SES} = 0.075$ [SE = 0.033], $P = 0.025$, Fig. 2A) (*Model 1:* $R^2_{adjusted} = 0.088$). This positive association was also observed ($B_{SES} = 0.074$ [SE = 0.034], $P = 0.029$), when controlling for age, gender, and pre-task cortisol levels (*Model 1*$_{EXT}$: $R^2_{adjusted} = 0.191$). In this extended model, we also found that male participants were more generous than female participants ($B_{GENDER} = 2.884$ [SE = 1.209], $P = 0.017$), while age and cortisol did not significantly predict charitable giving (both $P > 0.731$). Notably, the effect remains robust to the inclusion of those participants that were excluded due to insufficient variability in choices ($B_{SES} = 0.08$ [SE = 0.035], $P = 0.022$). The effect also remains significant when we included (i.e., controlled for) self-reported chronic stress and depression ($B_{SES} = 0.078$ [SE = 0.034], $P = 0.022$). Chronic stress and depression were not significantly correlated with charitable giving (both $Ps > 0.384$), and only self-reported chronic stress was trend-wise negatively correlated with subjective SES ($r_{(38)} = -0.277$, $P = 0.084$), indicating higher chronic stress in lower-status individuals. Hence, chronic stress and depression, as measured in our study, could not explain the link between subjective SES and charitable giving.

3.2. Subjective SES is positively associated with mentalizing

Higher subjective SES was linked to an increased mentalizing capacity, as assessed in the independent EmpaToM task ($B_{MENT} = 0.423$ [SE = 0.176], $P = 0.016$; Fig. 2B), but not with empathy ($B_{EMP} = 1.356$ [SE = 3.973], $P = 0.733$) and compassion ($B_{COMP} = -2.134$ [SE = 4.967], $P = 0.667$) (*Model 2:* $R^2_{adjusted} = 0.063$). This pattern of results was confirmed by a supplemental model using ratings of mentalizing, empathy and compassion obtained in the donation task (instead of performance-based scores of the independent EmpaToM task): Matching findings of the main model, higher subjective SES was linked to an increased degree of self-reported mentalizing ($B_{MENT} = 7.452$ [SE = 2.93], $P = 0.011$; Fig. 2C), but not self-reported empathy ($B_{EMP} = -3.136$ [SE = 2.895], $P = 0.279$) or compassion ($B_{COMP} = -2.594$ [SE = 3.23], $P = 0.422$) (*Model 3:* $R^2_{adjusted} = 0.085$).

Notably, mentalizing capacity captured in the EmpaToM task was positively related to mentalizing ratings in the donation task ($r_{(38)} = 0.396$, $P = 0.011$). This indicates that participants with higher mentalizing performance in the EmpaToM (free from charitable giving) also tended to recruit mentalizing more strongly during donation decisions. Moreover, both mentalizing capacity ($r_{(38)} = 0.467$, $P = 0.002$) and self-reported mentalizing ($r_{(38)} = 0.649$, $P < 0.001$) were positively related to charitable giving.

3.3. The relationship between subjective SES and charitable giving is mediated by mentalizing capacity

So far, we reported that higher subjective SES was associated with more generous choice and indicators of mentalizing, an important contributor to altruism. This raises the question of whether the positive association between subjective SES and charitable giving can be explained by variation in mentalizing capacity. A mediation model

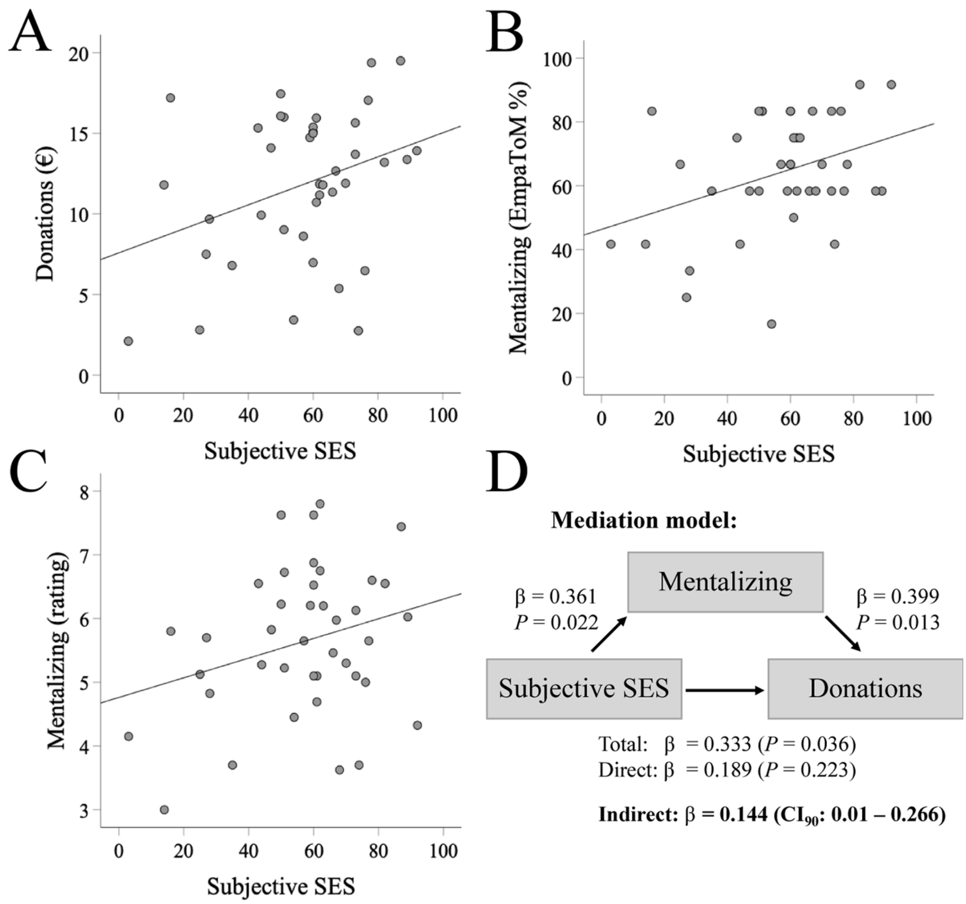

Fig. 2. Higher subjective SES was associated with (A) increased charitable giving, (B) increased mentalizing capacity in the EmpaToM task, and (C) increased self-reported mentalizing during donation decisions. Panels A-C depict scatter plots and simple regression slopes for descriptive purposes only (models presented in the *Results* section partly differ in complexity; hence no inference statistics are provided in the Figure). (D) Mediation model: Mentalizing capacity, as assessed in the EmpaToM task, mediated the positive relationship between subjective SES and charitable giving. The mediation model illustrates total, direct, and indirect effects of subjective SES on charitable giving. β coefficients represent standardized regression coefficients. β_{total} is the total effect of subjective SES on charitable giving, β_{direct} is the direct effect after the mediator (i.e., mentalizing capacity) had been taken into account, and $\beta_{indirect}$ is the indirect effect, that is, the effect of subjective SES on charitable giving that was mediated by mentalizing capacity. For the indirect effect, bias-corrected bootstrapping (50,000 bootstrap samples) provided a 90% confidence interval that did not span 0 (corresponding to one-tailed $P < 0.05$), indicating a significant mediation.

(*Model 4)* showed an indirect effect of subjective SES on charitable giving via mentalizing capacity ($\beta_{indirect} = 0.1438$) using a more liberal 90% confidence interval that excludes zero (CI_{90}: 0.01 – 0.266). Notably, this corresponds to a significant effect for a one-sided 95% confidence interval [or, alternatively, $P < 0.05$ (one-tailed), matching an established approach in the literature, see e.g., Hogeveen et al. 2017; Murphy et al. 2018], in line with our directional hypothesis that *higher* mentalizing capacity would explain the positive SES-donation link. In other words, the positive link between subjective SES and charitable giving can be partly explained by increased mentalizing capacity in high-status individuals (Fig. 2D).

3.4. Neural decoding of trial-by-trial variations in donations

As a first step in our fMRI analysis, we used a multivariate pattern analysis to test whether neural activity in our a-priori ROIs related to mentalizing (dmPFC, right and left TPJ) and reward processing (vmPFC, right and left striatum) predicts charitable donations (*Model 6*). Permutation-based testing revealed significant value coding in all three mentalizing-related regions (dmPFC: $P_{FWE} = 0.006$; right TPJ: $P_{FWE} = 0.002$; left TPJ: $P_{FWE} = 0.006$) in line with previous findings (e.g., Spaans et al. 2020; Tusche et al. 2016; Waytz et al. 2012) as well as in the vmPFC ($P_{FWE} = 0.025$), in line with its role in value-based and prosocial decision making (e.g., Bartra et al. 2013; Bellucci et al. 2020; Hare et al. 2010). In contrast to previous work that found the striatum involved in prosocial decisions (e.g., Saulin et al. 2022; Spaans et al. 2019) but in line with a previous study using the donation task (Tusche et al. 2016), we did not observe significant value coding in the bilateral striatum (both $P_{FWE} > 0.999$, $P_{uncorrected} > 0.172$). For distribution plots of ROI-based decoding accuracies, see Fig. 3.

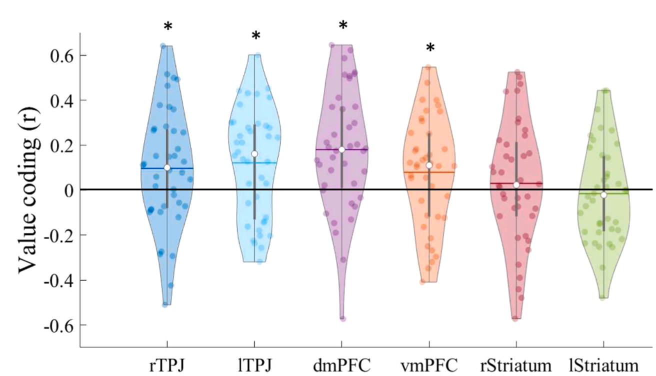

Fig. 3. Violin distribution plots of SVR decoding accuracies (i.e., neural value coding; here expressed as Pearson correlation coefficients r between predicted and observed donations). Permutation tests revealed significant value coding in the bilateral TPJ, dmPFC, and vmPFC (* indicate $P_{FWE} < 0.025$). Horizontal colored lines = mean across participants; white data point = median; vertical: boxplot with gray box ranging from lower quartile (25th percentile) to upper quartile (75th percentile) and whiskers extending to 1.5 × interquartile range.

3.5. Subjective SES is associated with neural value coding in the right TPJ

In a next step, we examined whether subjective SES was associated with neural value coding (i.e., predictive neural information about upcoming donations) in our three mentalizing-related ROIs and the vmPFC. We found that decoding accuracies in the rTPJ were positively linked to subjective SES scores. In other words, we observed stronger value coding in the rTPJ in higher-status compared to lower-status individuals (B_{VALUE}: 20.161 [9.251], $P = 0.029$; Fig. 4A) (*Model 7:* $R^2_{adjusted}$

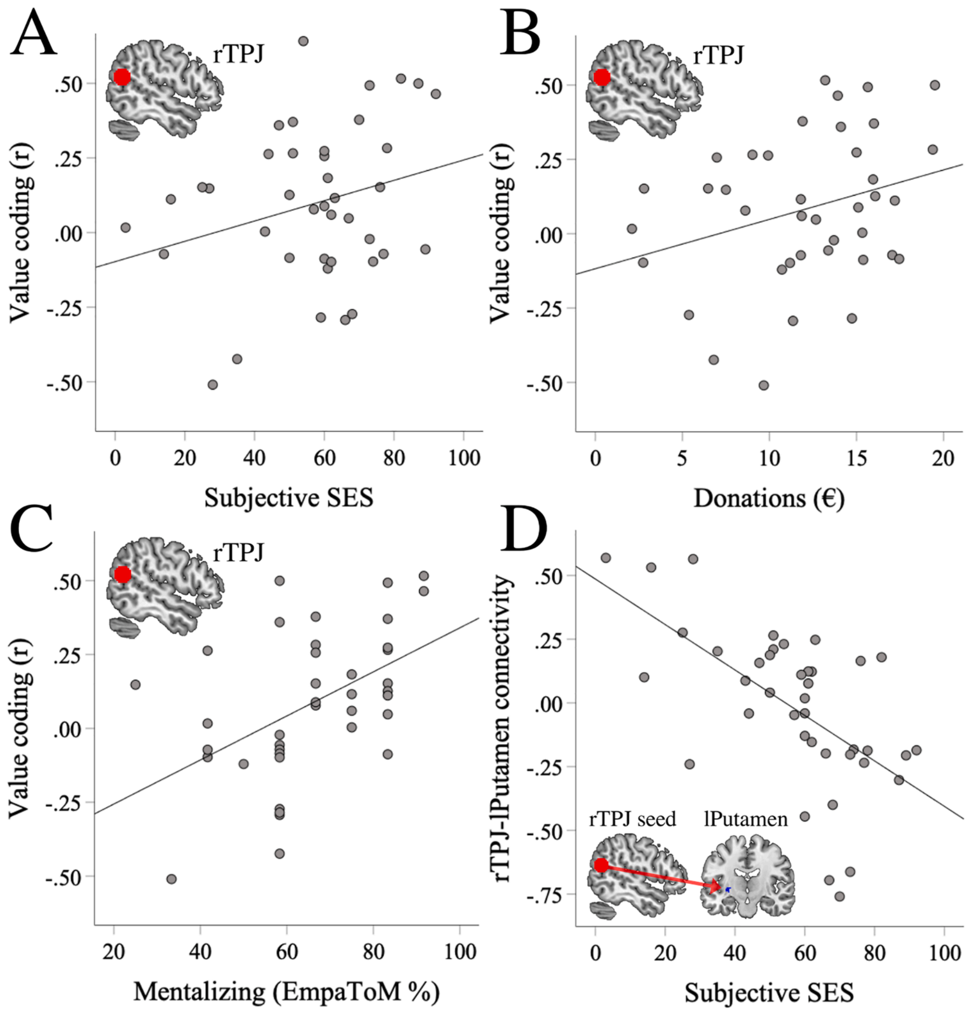

Fig. 4. (A) Subjective SES was positively associated with the strength of value coding in the rTPJ (expressed as Pearson correlation coefficients r of predicted and observed donations). (B) The strength of value coding in the rTPJ was also positively associated with the monetary amount given to charity in the donation task. (C) rTPJ value coding was associated with mentalizing capacity in the EmpaToM task (but not with empathy and compassion). (D) Higher subjective SES was associated with a more negative functional connectivity between the rTPJ and left putamen in the decision phase (peak activation with $P_{FWE} = 0.023$; The blue cluster contained 57 voxels using a cluster-defining threshold of $P \leq 0.005$).

= 0.052). As a robustness test, we repeated this analysis in an extended model that also controlled for age, gender, and pre-task cortisol. Results of the extended model confirmed the positive association between subjective SES and value coding in the rTPJ (B_{VALUE}: 19.481 [7.652], $P = 0.011$) (*Model 7*$_{EXT}$: $R^2_{adjusted} = 0.162$). Importantly, this effect also survives a Bonferroni correction for the number of ROIs tested ($P_{FWE} = 0.044$). As in the previously mentioned bivariate correlation, we observed that increased cortisol levels predicted higher subjective SES in this multiple regression (B_{CORT}: 1.621 [0.532], $P = 0.002$). Age ($P = 0.147$) and gender ($P = 0.974$) did not emerge as significant predictors. We found no significant link between subjective SES and value coding in the left TPJ ($P = 0.18$), dmPFC ($P = 0.739$), and vmPFC ($P = 0.76$). Hence, the rTPJ was the only ROI that displayed SES-dependent value coding.

In line with our ROI-based approach, an exploratory whole-brain searchlight analysis revealed several regions that showed activity predictive of donations (i.e., value coding). We found an extended cluster spanning occipital, parietal, dorsomedial and lateral prefrontal cortex, among others (cluster peak [x, y, z]: −2, −86, 2; see decoding map provided on https://osf.io/b3kmg/), and which partly overlaps with our dmPFC-, vmPFC- and TPJ-ROIs. Another cluster included the right amygdala (cluster peak [x, y, z]: 18, 6, −26). However, this whole-brain analysis did not reveal any additional regions showing a significant link between subjective SES and neural value coding. In contrast to our MVPA, we did not observe any regions that significantly coded value in our exploratory univariate analysis (*Ps* > 0.111 in our ROI-based analysis and no brain area significant at $P < 0.001$ at the voxel-level that survived FWE-correction [$P_{FWE} < 0.05$] at the cluster-level in the whole-brain analysis). Hence, we did not test for SES-dependent modulations of value coding in this analysis.

3.6. *The strength of neural value coding is linked to charitable giving and mentalizing*

The strength of value coding in the right TPJ also positively predicted charitable giving: individuals with stronger value representations donated more money ($B_{VALUE} = 5.093$ [1.879], $P = 0.007$; Fig. 4B) (*Model 8:* $R^2_{adjusted} = 0.067$). In line with the well-documented role of the rTPJ in mentalizing (Schurz et al., 2014), neural value coding was also positively associated with mentalizing capacity in the EmpaToM task ($B_{MENT} = 0.008$ [0.003], $P = 0.003$, Fig. 4C), but not with empathy and compassion (Ps > 0.457) (*Model 9:* $R^2_{adjusted} = 0.187$). Together, these results suggest that higher-status individuals show stronger representations of value in the rTPJ, which are linked to mentalizing capacity, and which also predict more charitable giving, compared to lower-status individuals.

3.7. *Higher subjective SES is linked to decreased functional connectivity between rTPJ and left putamen*

In a final analysis, we explored whether there are changes in the functional coupling of decision-related activity between the rTPJ and other brain regions with increasing or decreasing subjective SES (*Model 13*). To this end, we performed a psycho-physiological interaction analysis (PPI) with the rTPJ as seed region. When focusing on our a-priori ROIs, we identified an SES-dependent change in the coupling of decision-related activity of the rTPJ and left putamen, which is a part of the striatum ROI (MNI coordinates [x, y, z]: −30, −16, 0; small-volume corrected $P_{FWE} = 0.023$). Specifically, negative functional connectivity between these two regions increased with increasing subjective SES (Fig. 4D). Our exploratory whole-brain PPI analysis revealed no additional significant clusters.

4. Discussion

An individual's position in a social hierarchy determines a range of consequential outcomes, including proximate ones like access to social and material resources (Vogel, 2005) as well as more distal and long-term ones like health and mortality (Adler and Ostrove, 1999; Sapolsky 2005). Socioeconomic status also governs altruistic behavior – a fundamental building block of human societies – but there is a debate about whether higher or lower SES is associated with increased prosocial behavior (e.g., Andreoni et al., 2021; Piff et al. 2010). Here we found a significant *positive* relationship between subjective SES and charitable giving, an important instance of human altruism. This finding is in line with previous research suggesting that higher SES is associated with more prosocial behavior (e.g., Andreoni et al. 2021; Benenson et al., 2007; Korndörfer et al. 2015; Kosse et al. 2020).

Our findings significantly extend prior work in two important ways: First, our study provides a sociocognitive account of this functional link, showing that SES-related differences in mentalizing mediate the positive SES-donation association. Second, we provide insights into the neuro-computational mechanisms of this relationship, pointing towards variance in mentalizing-related value coding in the brain as a core component of the link between SES and charitable giving. Deciphering the socio-neurocognitive mechanisms can provide insights into why and when the link between SES and charitable giving can be observed.

Behaviorally, subjective SES was linked to increased mentalizing capacity as captured in an independent task (EmpaToM; Kanske et al. 2015) and via self-reports following donation decisions, consistent with previous reports linking higher SES to enhanced mentalizing (e.g., Cutting and Dunn 1999; Sun et al. 2020). Importantly, an individual's ability to mentalize mediated the positive relationship between perceived SES and charitable giving. At the neural level, higher-status individuals displayed an increased strength of value coding in the right temporoparietal junction (rTPJ) relative to lower-status individuals. In other words, higher-status individuals showed a tighter coupling between patterns of neural activity in the rTPJ and their decision to donate (or not), reflecting a decision-relevant neural process. The strength of value coding also predicted the size of donations given to charity across participants. Moreover, rTPJ value coding was uniquely associated with mentalizing capacity in the EmpaToM task, but not with empathy and compassion. These findings are in line with the well-documented involvement of this region in mentalizing (for meta-analyses, see e.g., Molenberghs et al., 2016; Schurz et al., 2021, 2014) and in altruistic choice (Morishima et al. 2012; Obeso et al. 2018; Park et al., 2017; Tusche and Bas 2021). Specifically, the observed links might reflect the neural integration of mentalizing in the social decision process, consistent with previous fMRI and neurocomputational studies. For instance, mentalizing-related rTPJ activity has been found to predict charitable giving (Tusche et al., 2016), an effect that may be explained neurocomputationally by the integration of others' benefits in the evidence accumulation process towards a decision (Hutcherson et al., 2015; Tusche and Bas, 2021; Tusche and Hutcherson, 2018). Theoretically, such signals could also reflect more domain-general processes related to self-other distinction or attentional processes, which have also been related to the TPJ (Lamm et al., 2016). In any case, our current findings suggest that mentalizing-related neural value coding is deployed in an SES-dependent manner, as higher-status individuals displayed increased value coding in the rTPJ and more charitable giving relative to lower-status individuals.

In an exploratory PPI analysis, we also observed an SES-dependent increase in negative functional coupling between the rTPJ and left putamen during choice. Activity in the putamen has been associated with the trade-off between monetary costs and moral benefits of altruistic choice (Qu et al., 2019), and rTPJ-putamen connectivity has been suggested to reflect the influence of other-regarding preferences on valuation (Ou et al., 2021). In this regard, an increased *negative* – instead of positive – connectivity in more altruistic higher-status individuals might be surprising. Increased negative connectivity might instead suggest a down-regulation of the processing of rewards to the self, which is also processed in striatal areas (Moll et al., 2006; Morelli et al., 2015). Alternatively, it might reflect a shift from a trade-off between personal costs and moral benefits to a decision process driven mainly by other-regarding preferences, which could be further explored in future research.

The observed positive link between subjective SES and charitable giving is inconsistent with some earlier reports showing more prosociality in lower-status relative to higher-status individuals (e.g., Guinote et al., 2015; Piff et al., 2010), although some of these findings did not replicate (Balakrishnan et al., 2017; Stamos et al., 2020). These inconsistencies indicate that moderating factors need to be considered when studying this relationship. One such factor might be the costliness of prosocial behaviors. For instance, individuals lacking monetary resources might be prone or even need to keep more money for themselves in charitable transfers, whereas donations are less costly for the more affluent individuals. A recent study found that while higher-status individuals were more generous in the monetary domain, but they were less generous when distributing time, which presumably is more costly to them (Liebe et al., 2022). Apart from differences in costliness, this pattern could also be explained by norms of redistribution, requiring those in the upper strata of society to take social responsibility ("noblesse oblige"; Fiddick and Cummins, 2007), and which are more salient when considering differences in monetary (but not time) endowments. Individuals share more resources with lower-status recipients (Liebe et al., 2022). Although a considerable degree of the beneficiaries included in the present task may have been perceived as lower-status individuals, the exact (trial-wise) relative ranking was not assessed. Future studies might benefit from such a measurement to allow for the detection of potential interactions between the social positions of the donor and recipient. While norms guide behavior, normative generosity, in turn, can also help to establish and maintain one's high social status (Hardy and van Vugt, 2006; Smith and Bird, 2000), which represents a potential alternative causal mechanism underlying the observed relationship (i.e., rather than SES determining charitable giving, more charitable giving leads to increased SES). Future research could investigate the role of norm-based behavior and its underlying neural processes (Ruff et al., 2013; Spitzer et al., 2007; Zinchenko and Arsalidou, 2017) in shaping the status-mentalizing-altruism relationship. While we cannot be sure whether status-related norms also influenced our observed effects in the context of anonymous donations, it is important to note that, if present, these norms did not overwrite mentalizing. Instead, mentalizing might be a downstream process engaged by social norms. Given the correlational nature of our data, we cannot rule out that other factors than costliness and norms might explain the link between SES and charitable giving, including differences in cognitive ability, physical and mental health (though self-reported chronic stress and depression could not explain the link in the present data), childhood adversity, stereotype threat, and differences in social roles and motives. In any case, the identification of mentalizing-related value coding as an involved mechanism provides a possible answer to the question *why* we observe the link between SES and charitable giving: higher-status individuals mentalize more, promoting charitable giving. It might also help to better understand which other factors shape the direction of the SES-altruism link, through their effects on mentalizing (e.g., costliness/effort; Contreras-Huerta et al., 2020), possibly providing an answer to the question *when* this link can be observed: when mentalizing is enhanced or attenuated, thereby helping to resolve empirical inconsistencies in the field.

In the present study, we focused on a *subjective* measure of SES. Relative to the general population, our sample consisted mainly of young-adult students. Thus, our sample was less heterogeneous with respect to certain *objective* variables associated with differences in SES, such as age, education, and occupational prestige, and might not generalize beyond the population studied (i.e., young-adult, educated). Notably, despite this reduced heterogeneity, we observed substantial variation in the subjective perception of SES. Some of that variation may still be related to unmeasured objective factors (e.g., parental income and education), which future studies might aim to examine further. However, subjective perceptions of one's socioeconomic status might be considered an integrated measure or "cognitive average" of such objective indicators (Andersson, 2015; Singh-Manoux et al., 2003) and measuring individual objective factors might thus not be of such high importance. Moreover, perceived SES also goes beyond objective indicators of SES, given that it predicts a range of consequential outcomes better than more objective measures (e.g., Operario et al., 2004; Singh-Manoux et al., 2005). Together, this emphasizes the importance of subjective perceptions of SES.

In sum, the present study provided evidence for a positive association between subjective perceptions of SES and charitable giving. Moreover, by showing that this positive link could be explained by mentalizing-related neural value coding in the rTPJ, we provide a socio-neurocognitive account of this effect. Furthermore, we observed an increased negative functional coupling of the rTPJ and the left putamen while participants decided whether to donate. Our findings suggest that subjective SES is an important predictor of charitable giving and that this link can be explained by the engagement of mentalizing- and decision-related neural mechanisms. Future studies may assess the generalizability of these mechanisms to other domains of altruistic behavior, including non-monetary (e.g., volunteering) and non-person-centric forms (e.g., environmentalism), and test potential interventions to promote prosocial behavior via enhanced mentalizing (Böckler et al., 2018; Trautwein et al., 2020; Valk et al., 2017).

CRediT authorship contribution statement

Stefan Schulreich: Conceptualization, Investigation, Project administration, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Anita Tusche:** Conceptualization, Resources, Writing – review & editing. **Philipp Kanske:** Resources, Writing – review & editing. **Lars Schwabe:** Conceptualization, Project administration, Funding acquisition, Resources, Writing – review & editing.

Declaration of Competing Interest

None.

Data availability

Behavioral and (aggregated) fMRI data, group-level decoding maps, ROI masks, and task material (instructions, charity descriptions) are publicly available on the project's Open Science Framework (OSF) page (https://osf.io/b3kmg/). The open source code for the SVR decoding analysis is available at the "The Decoding Toolbox" (TDT; Hebart et al., 2015) and the LIBSVM website (http://www.csie.ntu.edu.tw/~cjlin/libsvm; Chang and Lin, 2011) (both are implemented in Matlab R2019a, Mathworks).

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