

Social Decisions from Description Compared to Experience Rely on Different Cognitive and Neural Processes

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Abstract

Social decisions reveal the degree to which people consider societal needs relative to their own desires. Although many studies showed how social decisions are taken when the consequences of actions are given as explicit information, little is known about how social choices are made when the relevant information was learned through repeated experience. Here, we compared how these two different ways of learning about the value of alternatives (description versus experience) impact social decisions in 147 healthy young adult humans. Using diffusion decision models, we show that, although participants chose similar outcomes across the learning conditions, they sampled and processed information differently. During description decisions, information sampling depended on both chosen and foregone rewards for self and society, while during experience decisions sampling was proportional to chosen outcomes only. Our behavioral data indicate that description choices involved the active processing of more information. Additionally, neuroimaging data from 40 participants showed that the brain activity was more closely associated with the information sampling process during description relative to experience decisions. Overall, our work indicates that the cognitive and neural mechanisms of social decision making depend strongly on how the values of alternatives were learned in addition to individual social preferences.

Introduction

Social preferences reflect how much individuals care about others relative to themselves¹⁻⁷. These preferences are important at the individual, organization, and societal levels. For example, they may influence local acts to help one's neighbor as well as global efforts to reduce carbon emissions or decrease societal inequality. However, there is still much to discover about how social preferences are learned and how they are shaped by the decision context.

Previous work examining human social decisions has focused mostly on how explicitly described tradeoffs between selfishness and prosociality are represented and resolved at the behavioral and neural levels⁸⁻¹⁰. This line of work has examined how factors such as cognitive load, time pressure or delays, priming and nudging, age, training, competition/cooperation, or social value orientation influence the neural representation of social information and outcomes of social decisions¹¹⁻¹⁸. These previous studies of human social preferences have focused almost exclusively on decisions made on the basis of explicit information given at the time of choice, about the costs and benefits to self or others¹⁹⁻²⁴. However, experiments in non-human animals have shown that social factors also influence choices between highly trained stimuli that were learned through repeated experience^{25,26}. Thus far, the potential behavioral and neural distinctions between social choices based on information learned through experience versus concurrent descriptions are unknown.

Decisions from experience and description differ in the way individuals learn about the value or utility the options. As the names indicate, in description decisions the information about potential outcomes is displayed and described explicitly at or near the time of choice, while in experience decisions stimulus-outcome associations were learned through past experience in the absence of explicit descriptions of

potential outcomes^{27,28}. Humans often learn about the world through experience, without ever receiving any explicit instructions or descriptions²⁹⁻³². The way humans learn about the choice options can influence the decisions they make. For example, risk preferences are expressed differently in description relative to experience-based decisions, specifically individuals underweight rare outcomes when decisions are made based on past experience relative to description^{29,33}. In addition, two functional magnetic resonance imaging (fMRI) studies have shown that decisions over individual rewards whose subjective values were previously learned through extensive training compared to decisions based on planning of the potential outcomes show different BOLD activity patterns in the caudate versus putamen and medial versus more lateral regions of ventral prefrontal cortex^{34,35}. However, other work using rewards learned through experience (e.g., familiar snack foods or conditioned stimuli) has shown very similar BOLD activity patterns in the striatum, prefrontal cortex, and posterior cingulate cortex between familiar, experienced stimuli and decisions based on concurrently described alternatives within and across participants³⁶⁻⁴¹. Thus, it is not yet clear how and when behavior and/or brain activity during social decision making differs between experience and description contexts. Therefore, it is important to understand how the processes underlying social decisions may differ as a function of the ways in which the values of the rewards for self and others were learned.

In this study, we used a social decision task together with fMRI to investigate individuals' behavior and brain activity in description and experience-based choices. The participants made decisions involving tradeoffs between monetary rewards for the self and a charity of their choosing (i.e., society). The amounts available for self and society were learned through either concurrent description or over three days of experience training (Description or Experience trials). The social tradeoffs underlying each decision problem were matched across the description and experience trials. We fit hierarchical diffusion decision models (HDDM)⁴² to the description and experience decisions to determine how information about individual and social rewards was used during the decision process. Our hypothesis was that the evaluation and accumulation of subjective option values and value differences would differ when the information about rewards was learned from description relative to experience. Lastly, we used fMRI to test if activity in the striatum, prefrontal cortex, posterior cingulate cortex or other key decision-related brain regions differed in description versus experience trials.

We found that, even though participants chose the same outcomes in the two conditions, the information that individuals used to make decisions from experience or description, differed. Evidence accumulation in description decisions was based on the chosen and foregone payoffs to self and society. In contrast, experience decisions were based only the chosen self-payoff and societal payoffs. Furthermore, description decisions exhibited increased brain activity in many regions compared to experience decisions, consistent with more extensive information processing of both chosen and unchosen outcome in description trials. Overall, we found that behavioral and neural mechanisms underlying social choices depend on how the value of the decisions was learned.

Results

We tested behavior and brain activity during a social decision task in which individuals faced the same underlying tradeoffs between options, but learned about these tradeoffs through past experience or concurrent description. In each condition, individuals made tradeoff decisions between either maximization of self-profits or societal-benefits (FIGURE 1). We define self-profit (society-benefit) maximizing decisions as those in which the individual receives more (less) points than society. In addition to the decision task, we also measured social preferences using the Social Value Orientation scale (SVO), which gives the degree of a person's prosociality angle with lower values indicating more selfish preferences⁴⁶.

Prosocial choices in description and experience trials

We first tested the outcomes of social decisions as a function of prosocial preferences. We computed a hierarchical Bayesian beta regression model that sought to explain the proportion of prosocial choices each participant made as a function of the condition (either description (DE) or experience (EX) trials), controlling for their prosociality, as determined by the SVO scale. Prosocial choices in the description and experience trials did not differ (Bayes Factor₁₀ = 0.06; regression coefficient = -0.02 95% credible interval (CI) = [-0.13, 0.08]; see Equation 1). According to scores on the independent SVO scale, most participants had moderately selfish preferences, but there was considerable variability in prosocial preferences across participants (FIGURE 2B). As expected prosocial choices in the decision task increased significantly as a function of SVO across both conditions (coef = 0.57, 95% CI = [0.46, 0.68], $PP_{mcmc} > 0.999$; FIGURE 2C). However, the relationship between SVO and prosocial choices did not differ between description and experience choices (Bayes Factor in favor of a regression model without an SVO*condition = 18). In summary, the regression results indicate that decision outcomes did not differ between description and experience trials in the specific sets of social tradeoffs we tested here.

Response times in experience versus description decisions

We also compared response times across conditions and found that they were faster in experience relative to description trials. A hierarchical Bayesian linear regression explaining the natural logarithm of response times as a function of condition and SVO showed that the mean response times were faster in experience than description trials (EX mean = 0.98 ± 0.54 ms; DE mean = 1.53 ± 0.66 ms; coef = -0.5, 95% CI = [-0.51, -0.48], $PP_{mcmc} > 0.999$; see FIGURE 2A and Equation 2). In addition, there was a main effect of SVO; response times increased as a function of SVO in both decision conditions (coef = 0.08, 95% CI = [0.04, 0.12], $PP_{mcmc} > 0.999$). In other words, more prosocial individuals made their choices more slowly. However, there was also an interaction between SVO and condition such that response times were less strongly related to SVO in experience compared to description trials (coef = -0.05, 95% CI = [-0.07, -0.03], $PP_{mcmc} > 0.999$). These results indicate that highly prosocial participants required more time than less prosocial participants to resolve the tradeoffs between self-profit and society benefits they faced in this task, especially if the tradeoffs were presented as explicit descriptions rather than learned through experience.

Information sampling in description and experience decisions

We fit hierarchical diffusion decision models (HDDM)⁴⁷⁻⁴⁹ to test how the chosen and foregone payoffs to self and society influenced the decision process in description relative to experience trials. We fit and compared two types of models that differed in how the chosen and unchosen payoffs to self and society influenced the evidence accumulation or drift rate (see Methods section on HDDM). The best-fitting HDDM parameters were able to explain the distributions of response times for prosocial and selfish choices in both the description and experience trials and (FIGURE 3).

Behavior during the description trials was explained by HDDM1, in which the mean drift rate was proportional to the chosen payoffs for self and society as well as the differences between chosen and unchosen payoffs for self and society (HDDM1 Description, DIC = 27419; TABLE 1). This is consistent with a large body of past literature reporting that evidence accumulation rates are proportional to the difference in (subjective) values between options during description decisions^{42,50-54}. In contrast, including the differences between self and society payoffs did not improve the model fits to experience decisions. Instead, behavior on experience trials was slightly better fit by the simpler model, HDDM2, in which the mean drift rate was proportional to the chosen payoffs for self and society only (HDDM1 Experience, DIC = 11397; HDDM2 Experience, DIC = 11392; TABLE 1). Although, the model comparison results did not provide strong evidence in favor of either HDDM for experience trials, the posterior estimates of the drift weighting parameters from both HDDM1 and HDDM2 show that the evidence accumulation rates during experience trials are more strongly related to chosen outcomes than differences between chosen and unchosen outcomes.

TABLE 1. Posterior estimates and model fit for HDDM Models.

Parameter	HDDM1 Description		HDDM1 Experience		HDDM2 Experience	
	Mean	SD	Mean	SD	Mean	SD
Drift (b0), Intercept	0.065	0.026	0.260	0.044	0.214	0.037
Drift (b1), Payoff Outcome Society	0.120	0.016	0.108	0.023	0.089	0.018
Drift (b2), Payoff Outcome Self	0.285	0.018	0.414	0.026	0.428	0.020
Drift (b3), Payoff Difference Society	0.053	0.026	-0.105	0.044	-	-
Drift (b4), Payoff Difference Self	0.197	0.032	-0.041	0.045	-	-
Non-decision time (theta)	0.413	0.016	0.336	0.009	0.337	0.009
Boundary separation (alpha)	4.173	0.094	2.759	0.052	2.735	0.051
Starting Point Bias (bias)	0.480	0.007	0.458	0.009	0.457	0.009
DIC	27419.43		11397.05		11392.22	

We used hierarchical drift diffusion models (HDDM) fit to the response time data from description and experience decisions. In HDDM 1 (see Equation 3 in the Methods section), we modeled the evidence accumulation rate as a function of both payoff outcomes (b1, b2) and payoff differences (b3, b4). In HDDM2 (see Equation 4 in the Methods section), we modeled the evidence accumulation rate only as a function of payoff outcomes (b1, b2). Additionally, we included the following free parameters at the group and subject levels: boundary separation (i.e., the evidence threshold for making a response), starting point bias for evidence accumulation and non-decision times. We list the mean and standard deviation (SD) for all parameter estimates. A lower DIC indicates better model fit.

Thus, the information upon which description and experience choices are based appears to differ, with experience choices being less sensitive to tradeoffs between chosen and unchosen outcomes for self and society. This decrease in sensitivity to unchosen outcomes during experience relative to description trials may explain why response times show a weaker relationship to social preferences (i.e., SVO) in experience compared to description decisions.

BOLD activity during description and experience social choices

To investigate how brain activity differed in social decisions made from description and experience, we analyzed the BOLD signal during each type of choice. We fit a generalized linear model that included regressors for the mean level of activity during description and experience trials as well as parametric regressors for the mean HDDM evidence accumulation rate on each trial. We report results that survive correction for multiple comparisons at the whole-brain level using non-parametric permutation tests with 5000 permutations for each contrast.

We found significant differences in mean BOLD activity during social decisions in description compared to experience trials. There was greater average activity during description than experience trials in several brain regions including the caudate, middle frontal gyrus, paracingulate and cingulate gyrus, frontal pole and dorsal precuneus (FIGURE 4A and Supplementary Table S1A). In contrast, average activity was significantly greater in more ventral portions of the precuneus and posterior cingulate during experience than description trials (FIGURE 4A and Supplementary Table S1B). Note that these contrasts testing for differences in mean activity across trial types included the participants' SVO angles as a continuous covariate (z-scored across participants) to account for variation in social preferences.

Next, we investigated whether brain activation patterns during experience and description trials differed in participants who were more versus less prosocial. We divided our participants into two groups based on the median SVO in our sample (45.30 points). Previous fMRI studies investigating how BOLD activity during social decisions relates to SVO reported greater activity in medial orbitofrontal cortex (mOFC) and dorsal medial prefrontal cortex (dmPFC) for more selfish (i.e., low SVO) relative to prosocial individuals during a social choice task using the typical choices from description²². We found a similar difference in the mOFC (MNI: -8, 44, -14; TFCE t-stat: 5.00), with low SVO individuals showing greater BOLD activity during description choices than high SVO participants. However, there were no significant differences in dmPFC activity in our sample after correcting for multiple comparisons. In contrast to description trials, we did not find any significant differences between high and low SVO participants' BOLD responses during experience choices. A direct comparison between description and experience choices showed that there were significant interactions in the association between mean activity and SVO between experience and description trials within the set of brain regions listed in Supplementary Table S2, including the occipital cortex, posterior cingulate gyrus, posterior insula and the posterior portion of the temporoparietal junction (pTPJ, as defined by the Mars et al., atlas⁵⁵; FIGURE 4B). In general, this interaction was driven by low SVO individuals showing greater activity during description than experience trials, while, in contrast, high SVO individuals showed more activity in experience than description trials. FIGURE 4C shows the patterns of BOLD responses underlying the interactions between decision type and social value orientation in the set of voxels that partially overlap with the posterior TPJ.

Trial-wise levels of BOLD activity were more closely associated with HDDM evidence accumulation rates in description than experience trials. Note that our DDM model was specified such that positive evidence accumulation rates promoted prosocial choices while negative rates promoted selfish choices, and that the evidence accumulation rates on each trial were participant-specific and thus incorporated participants' social preferences. During description choices, the evidence accumulation rate was positively correlated with BOLD activity in regions including the caudate, dorsolateral prefrontal cortex, insula, putamen, and thalamus (Supplementary Table S3). No regions showed significant negative correlations with trial-wise mean evidence accumulation rates during description trials, and there were no significant positive or negative correlations in any regions during experience trials after correcting for multiple comparisons. Furthermore, the association between evidence accumulation rates and BOLD

activity was significantly more positive during description than experience trials in the caudate nucleus, cerebellum, cingulate cortex, middle temporal and frontal gyri, and thalamus (Supplementary Table S4).

Discussion

Individuals and organizations frequently face tradeoffs between benefits for themselves and others when considering actions that reduce climate change or inequalities in education, healthcare, employment, or wages. It is important for both basic and applied sciences to understand the formation and expression of the social preferences that drive these decisions. For example, within organizations, social preferences are associated with support for interdepartmental goals and problem solving⁵⁶. Most studies of social preferences have investigated decision contexts in which choice options and parameters are explicitly described to the decision makers^{19,20}. However, it is often the case that individuals and organizations can only learn about the consequences of their actions through experiencing the outcomes of different options²⁸. Far less is known about this type of social decision.

We studied differences in the cognitive and neural processes underlying experience versus description choices in a set of social tradeoffs that were matched in terms of the probability of making a prosocial choice in each context. Thus, any differences in the cognitive processing or neural activity we observe between experience and description trials are due to the decision processes rather than the decision outcomes. We find that decisions taken from novel, explicit descriptions of the potential outcomes are slower and involve more overall brain activity than decisions based on extensive experience with the options and outcomes. The finding that mean response times decrease in experience relative to description trials is consistent with previous results^{34,57}, and suggests that the experience decisions may have become more reflexive or automated.

Previous work has shown that differences in SVO are related to response times as well as information search and utilization patterns during decisions from description^{58,59}. In general, response times are proportional to the difference in subjective values in descriptive binary choice problems, and the subjective value difference in social decisions is determined by the decision maker's social preferences⁶⁰⁻⁶². Chen and Fischbacher⁵⁸ have shown that more prosocial individuals, who weight self and other payoffs more equally, take longer to decide between the alternatives on each trial of the widely used SVO Slider Measure designed by Murphy and colleagues⁴⁶. Using eye-tracking, Fiedler and colleagues⁵⁹ showed that, in addition to responding more slowly to decisions involving social tradeoffs, prosocial, relative to selfish, individuals have more total fixations and inspect more of the available information, especially information about others' payoffs. Our results from the description choices replicate the positive correlation between SVO and response times in social decisions.

Interestingly, the association between social value orientation and response times changes across description and experience choices. The positive correlation between the same participants' SVO and

response times was significantly weaker in experience than description decisions even though chosen outcomes (i.e., the proportion of prosocial decisions) did not differ across the two conditions. Assuming that differences in the information search and accumulation processes leading up to a decision drive the correlations between SVO and response times in description trials, our results suggest that these search and accumulation processes differ between description and experience trials. While our current data do not provide direct insights into information search patterns during description or experience choices, we could quantify the evidence accumulation processes during each type of decision.

We used diffusion decision models to examine evidence accumulation processes during social decisions from experience and description. The findings from our drift diffusion model fits and comparisons indicate that description choices are based on differences in the subjective values of the two options. This is consistent with a large body of literature applying sequential sampling models to descriptive decisions^{42,63}. However, including information about unchosen or foregone payoffs for the self and society isn't necessary to explain experience decisions. Experience decisions can be modeled equally accurately with only information about the chosen payoffs. Thus, in the case of binary choices, experience decisions seem to rely on half the information used in description choices. Fiedler and colleagues⁵⁹ showed that longer response times during description choices for higher SVO individuals correspond with those participants making more fixations to different pieces of information on the screen and processing a greater proportion of the total available information. We do not have fixation data in the current experiments, but our DDM results indicate that less information is processed during experience decisions overall. Less information processing during experience choices could result in smaller absolute differences in processing time between people with high and low SVO, and thus more similar response times.

Consistent with the DDM results, comparisons of average BOLD activity during description and experience trials showed that, in many brain regions, there was less activity during decisions from experience. Activity was greater in description than experience choices in the caudate, occipital, parietal, temporal, and prefrontal cortex, whereas voxels spanning the precuneus and posterior cingulate cortex were more active during experience decisions. Many of the regions more active in description trials overlap with those found in meta-analyses of fMRI studies of valuation and choice^{40,64}. Notably, activity in the precuneus and posterior cingulate cortex has been linked to automatic representations of stimulus value⁶⁵⁻⁶⁷. Greater activity in these regions during experience compared to description choices is thus consistent with a more automated or reflexive representation of the typical outcome (i.e., chosen value) associated with the highly familiar stimuli shown on experience trials. In addition to differences in mean activity levels, BOLD activity in striatal, prefrontal, and thalamic regions were more strongly correlated with trial-wise evidence accumulation rates during description compared to experience trials. Once again, this is consistent with more extensive processing of the potential outcomes for self and others during description relative to experience trials. Thus, overall, the behavioral and neuroimaging data indicate that the neurobiological processes underlying social decisions from experience and description are substantially different even when decision makers ultimately select the same outcomes.

Limitations

We wish to acknowledge an important limitation of our study and results. We intentionally used a small number of unique tradeoffs (5-7) so that we could be sure the tradeoffs would be well-learned after the three online training sessions. Moreover, we compared identical tradeoffs across description and experience. The small number of tradeoffs means that we have a limited decision space in which to measure social preferences. At the individual level, we mitigated this limitation by measuring social value orientations with a separate instrument. However, the decision space limits our ability to determine how the different processes underlying experience and decision choices may lead to different outcomes (e.g., more prosocial choices) for specific tradeoffs between self and society-gains. Future studies using either larger or individually tailored sets of social tradeoffs are needed to shed light on the boundary conditions under which prosocial preferences may be expressed differently across description, experience, or other decision contexts.

Conclusion

Our work indicates that the neural mechanisms of social decision making depend strongly on how the value of choices was learned or determined in addition to an individual's social preferences. The results from description choices in our study are generally consistent with this existing body of literature showing that regions such as anterior insula, striatum, temporoparietal junction and the prefrontal cortex contribute to social and charitable decisions^{10, 19–21, 23, 68, 69}. However, the stark differences in brain activity patterns that we observe in experience relative to description choices suggest that the neural mechanisms of social decision making are not fixed, but rather depend on how the potential outcomes for self and others are learned and/or processed at the time of choice. The differences across decision type in average BOLD activity patterns and the relationships between BOLD activity and participants' social value orientation highlight the fact that our understanding of how social preferences are instantiated in the brain remains incomplete. Studying when and how social preferences and decision mechanisms remain generalizable (i.e., remain consistent) or differ between specific learning and decision contexts will be important for furthering our understanding of social decision making and brain mechanisms.

Methods

Participants. A total of 147 individuals, 69 females and 78 males, participated in this study (mean age = 24.04 ± 4.61 s.d. years). All experimental protocols and methods were implemented in accordance with the official guidelines and regulation approved by the Ethics Commission of the Canton of Zurich and every participant provided informed, written consent in accordance with the regulations established. Participants were drawn at random from a database maintained by the University of Zurich Economics Department. Participants were sampled in five waves (mean 29.4 ± 6.23 s.d. participants per wave). During the fifth wave, we collected fMRI data in addition to behavior from forty participants (19 female) while they completed the description-experience decision task (see Supplementary Methods S1 for

inclusion criteria). Participants received a base level of compensation and earnings from their choices in the online training sessions and description-experience decision task. Individuals earned on average \$18 during the online training and \$40 if the description-experience decision task was completed in the behavioral lab or \$61 if it was done in conjunction with MRI scanning.

Description-experience decision task. The description-experience decision task included both the description and experience trials and took place after the online training sessions described in the subsection below. Within both the online training sessions and the description-experience decision task, participants were asked to adopt the mindset of a manager of an independent business taking a decision in favor of profit for the business (paid out as money to the participant) or society-benefits (paid out as money to a charity of the participant's choosing). At the beginning of the study, participants were asked to choose their preferred charitable organization. Participants could choose either from a list of eight well-known charities or could suggest their preferred charity.

The description-experience decision task presented tradeoffs between self-profit and society-benefits. On each trial, participants had to select between two payoff combinations. Individuals made their choice within 3.5 seconds (mean 1.79 ± 1.53 s.d. seconds). One option maximized self-profit and the other maximized societal-benefit. The choice pairs contained two payoff combinations, a payoff to self (business) and a payoff to society (charity): E.g. the payoff pair 60/50 vs. 30/70, which signified the business-/society payoffs for the left payoff combination vs. business-/society payoffs for the right payoff combination. The payoffs ranged between 30-80 points and we used 5-7 pre-selected payoff pairs that were the same for all the participants sampled in a wave, but differed between waves.

Supplementary Table S5 lists all payoff combinations for each wave of data collection. In waves 1-4, participants completed on average 122 (± 14 s.d.) description and 116 (± 16 s.d.) experience trials during the description-experience decision task. In data collection wave 5, participants completed 61 description and 49 experience trials during three runs while undergoing fMRI (Supplementary Table S6).

The description-experience decision task consisted of description (DE) and experience (EX) trials. In the description trials, the payoff combinations for self- and societal profit were displayed directly on novel cue images that were not used during the training sessions or repeated during the description-experience decision task. All cue images were unique fractals taken from the Mandelbrot set, and in description trials the cues showed the payoffs explicitly. Thus, the description trials required participants to acquire and compare the payoffs associated with each option, but there was no need to remember cue-payoff associations from one trial to the next because cues were never repeated. In addition to the 5-7 unique payoff combinations per wave, we added 20% more novel description trials to serve as foils in that condition. The foil trials had similar, but not identical, payoff combinations to the primary trials that were matched between description and experience conditions, and were used to make it less obvious that the payoffs and tradeoff were matched across the two conditions. The foil trials were excluded from behavioral analyses comparing description and experience choices. In the experience trials, payoff combinations were displayed as hash tags (#/#) on the image instead of numbers. One specific cue image was associated with each of the 5-7 unique payoffs for each participant. The image-payoff

pairings were learned during three days of online training before the main experiment session (see Supplementary Table S7 and Supplementary Methods S2), which presented a mix of description and experience choices. Participants accurately remembered and reported the payoff alternatives associated with the learned cues (see Supplementary Results S1). The positioning of the payoff combinations on the left, right, top, or bottom of the fractals was fully randomized across participants to avoid systematic bias. The choices were incentive compatible; two trials were selected at random and the participant's decisions about self- and societal profit on those trials were converted into a cash payment to the participant or a donation to his or her chosen charitable organization, respectively.

Prosociality measure. After completing the online training, the individuals were asked to complete the six primary items of the Social Value Orientation (SVO) scale measuring their level of prosociality⁴⁶, fill in the Cognitive Reflection Test⁷⁰ and respond to a set of demographic questions (see Supplementary Methods S3). For our prosociality measure, we classified individuals on a continuum between selfish and altruistic preferences based on their SVO angle. The SVO measure was fully incentivized and was completed at the end of the online training but before participants came to the lab to complete the main task in order to avoid interference with choices during the main task⁷¹.

Bayesian regressions. See Supplementary Methods S4 for statistical analyses. The Bayesian regression models were run using the brms package⁷² in R⁷³ as an interface to Stan⁷⁴. We used weakly regularizing priors for the intercepts and group-level beta coefficients (normal(0, 1) and a cauchy(0, 5) prior for the standard deviations of group-level effects in our models. We used a hierarchical beta regression with grouping effects for each participant (n = 147) and unique tradeoff (n = 5 or 7 depending on the data collection wave) to test whether the probability of making the self-profit-maximizing (i.e., selfish) choice differed across description and experience trials, or was linearly related to the SVO angle. The dependent variable in this regression was the mean number of selfish choices for each unique tradeoff per condition and participant. We adjusted for choice proportions equal to 0 or 1 according to the procedures outlined in Douma & Weedon (2019)⁷⁵, resulting in proportions of selfish choices ranging from 0.0003 to 0.9997. The SVO angle was z-scored across participants.

Equation 1: Choice $\sim \beta_0 + \beta_1 \text{Trial Type} + \beta_2 \text{Prosociality} + (1 | \text{Individual}) + (1 | \text{Tradeoff}) + \varepsilon$

We also used a hierarchical linear regression with grouping effects for each participant (n = 147) and unique tradeoff (n = 5 or 7 depending on the data collection wave) to test whether the natural logarithm of the response time differed across description and experience trials or was linearly related to SVO angle. The dependent variable in this regression was the mean of the log response times for each unique tradeoff per condition and participant. Once again, the SVO angle was z-scored across participants.

Equation 2: Response Times $\sim \beta_0 + \beta_1 \text{Trial Type} * \beta_2 \text{Prosociality} + (1 | \text{Individual}) + (1 | \text{Tradeoff}) + \varepsilon$

For each regression model we ran three independent MCMC chains in STAN and based our inference off of 1000 (2000 for the RT model) samples from each chain with a thinning step equal to 1 after a warmup

of 1000 samples per chain (2000 for the RT model). We assessed the chains for convergence using the Gelman-Rubin statistic ($psrf < 1.05$).

Hierarchical Drift Diffusion Model (HDDM). We fit hierarchical drift diffusion models to the response time data from description and experience decisions separately. We specified two types of HDDM that differed in which aspects of the decision options could influence the mean evidence accumulation or drift rates. In HDDM1, we modeled the evidence accumulation rate as a function of both payoff differences and chosen payoff outcomes (Equation 3). In HDDM2, only the chosen self and society outcomes had an influence the evidence accumulation rate (Equation 4). In addition to the drift rates, both HDDMs included the following free parameters at the group and subject levels: boundary separation (i.e., the evidence threshold for making a response), starting point bias for evidence accumulation and non-decision times.

Equation 3: $\text{Mean Drift}_{(i)} = b_0 + b_{1(i)} * \text{Payoff Outcome Society}_{(i)} + b_{2(i)} * \text{Payoff Outcome Self}_{(i)} + b_{3(i)} * \text{Payoff Difference Society}_{(i)} + b_{4(i)} * \text{Payoff Difference Self}_{(i)}$

Equation 4: $\text{Mean Drift}_{(i)} = b_0 + b_{1(i)} * \text{Payoff Outcome Society}_{(i)} + b_{2(i)} * \text{Payoff Outcome Self}_{(i)}$

Where Payoff Outcome Society, and Payoff Outcome Self are the chosen payoff amounts for trial i , and Payoff Difference Society, and Payoff Difference Self are the differences between the chosen and unchosen payoff amounts for society and self, respectively. We fit both versions of the HDDM using the runjags package⁷⁶ in R as an interface to the MCMC sampler JAGS. We based our inferences about the posterior distributions of each HDDM parameter on 2000 posterior samples (thinning step = 10) after an initial burn-in of 80,000 samples for each of three independent chains. We assessed the convergence of the chains using the Gelman and Rubin's statistic ($psrf < 1.05$). For the HDDMs, we used weakly regularizing gaussian priors (mean = 0, s.d. = 1) for all group-level parameters related to the drift rate, and uniform priors for boundary (0.001, 6) and non-decision time (0, 6), and a beta distribution (2,2) for the prior on the bias.

fMRI Analyses. See Supplementary Methods S5 for task timing, data acquisition and preprocessing. For fMRI analyses, the regressors of our General Linear Models (GLM) were defined as boxcar functions with durations equal to the reaction time on each trial. To examine the neural correlates of choices we constructed a generalized linear model using the HDDM weights from the behavioral data. Our regressors identify two events, description choices and experience choices. We used the trial-specific mean drift rates from the HDDM as parametric modulator (all parameteric modulators were mean centered). To facilitate the comparison of fMRI responses between description and experience decisions, we used the best-fitting parameters from the drift diffusion model specification that included both payoff differences and outcomes to compute the mean drift rates for both description and experience trials (HDDM1, Equation 3). Note that the mean drift rates on experience trials derived from HDDMs 1 and 2 were highly correlated (mean r across participants = 0.988, s.d. = 0.04), and thus the parametric modulators derived from either HDDM specification yield similar results. Regressors for head motion, cardiac effects, and respiratory effects were included in the GLM to help to control for BOLD signal variability related to those

non-task factors. For the second level analysis as well as for the visualization of images, we used the non-parametric permutation test (n=5000 permutations) with threshold-free cluster enhancement (TFCE) and the randomise function from the FMRIB software Library 5.0.10 (FSL; FMRIB Centre, Oxford, UK, RRID:SCR_002823)). Results are FWE corrected and coordinates are given in Montreal Neurological Institute (MNI) space.

Declarations

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Competing interests

The authors declare no competing interests.

Additional information

Code and behavioral data can be accessed under

https://osf.io/3gffj6/?view_only=afb2289c88fb4fad97957fe762a218ea

Imaging data can be accessed under <https://neurovault.org/collections/LNOGACGC/>

Author contributions

A.D., D.L.M., S.B. and T.A.H., designed research; A.D. performed research and collected the data; A.D. and T.A.H. analyzed the data; A.D. and T.A.H. wrote the paper; and D.L.M. and S.B. commented the paper.

References

1. Fehr, E. & Schmidt, K. M. A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics* **114**, 817–868 (1999).
2. Bolton, G. E. & Ockenfels, A. ERC: A theory of equity, reciprocity, and competition. *American economic review* **90**, 166–193 (2000).
3. Charness, G. & Rabin, M. Understanding Social Preferences with Simple Tests*. *The Quarterly Journal of Economics* **117**, 817–869 (2002).
4. Fehr, E. & Fischbacher, U. The nature of human altruism. *Nature* **425**, 785–791 (2003).
5. Crockett, M. J., Kurth-Nelson, Z., Siegel, J. Z., Dayan, P. & Dolan, R. J. Harm to others outweighs harm to self in moral decision making. *PNAS* **111**, 17320–17325 (2014).

6. Crockett, M. J., Siegel, J. Z., Kurth-Nelson, Z., Dayan, P. & Dolan, R. J. Moral transgressions corrupt neural representations of value. *Nat Neurosci* **20**, 879–885 (2017).
7. Goldstein, A., Turner, W. R., Gladstone, J. & Hole, D. G. The private sector's climate change risk and adaptation blind spots. *Nature Climate Change* **9**, 18–25 (2019).
8. Fehr, E. & Camerer, C. F. Social neuroeconomics: the neural circuitry of social preferences. *Trends in Cognitive Sciences* **11**, 419–427 (2007).
9. Tricomi, E., Rangel, A., Camerer, C. F. & O'Doherty, J. P. Neural evidence for inequality-averse social preferences. *Nature* **463**, 1089–1091 (2010).
10. Ruff, C. C. & Fehr, E. The neurobiology of rewards and values in social decision making. *Nat Rev Neurosci* **15**, 549–562 (2014).
11. Schulz, J. F., Fischbacher, U., Thöni, C. & Utikal, V. Affect and fairness: Dictator games under cognitive load. *Journal of Economic Psychology* **41**, 77–87 (2014).
12. Böckler, A., Tusche, A., Schmidt, P. & Singer, T. Distinct mental trainings differentially affect altruistically motivated, norm motivated, and self-reported prosocial behaviour. *Sci Rep* **8**, 13560 (2018).
13. Chen, F. & Krajbich, I. Biased sequential sampling underlies the effects of time pressure and delay in social decision making. *Nature communications* **9**, 1–10 (2018).
14. Capraro, V., Jagfeld, G., Klein, R., Mul, M. & Van De Pol, I. Increasing altruistic and cooperative behaviour with simple moral nudges. *Scientific reports* **9**, 1–11 (2019).
15. Lockwood, P. L., Apps, M. A. J. & Chang, S. W. C. Is There a 'Social' Brain? Implementations and Algorithms. *Trends in Cognitive Sciences* **24**, 802–813 (2020).
16. Teoh, Y. Y., Yao, Z., Cunningham, W. A. & Hutcherson, C. A. Attentional priorities drive effects of time pressure on altruistic choice. *Nature communications* **11**, 1–13 (2020).
17. Hu, X. & Mai, X. Social value orientation modulates fairness processing during social decision-making: evidence from behavior and brain potentials. *Social Cognitive and Affective Neuroscience* (2021).
18. van Dijk, E. & De Dreu, C. K. Experimental games and social decision making. *Annual Review of Psychology* **72**, 415–438 (2021).
19. Moll, J. *et al.* Human fronto–mesolimbic networks guide decisions about charitable donation. *Proceedings of the National Academy of Sciences* **103**, 15623–15628 (2006).
20. Harbaugh, W. T., Mayr, U. & Burghart, D. R. Neural responses to taxation and voluntary giving reveal motives for charitable donations. *Science* **316**, 1622–1625 (2007).
21. Hare, T. A., Camerer, C. F., Knoepfle, D. T., O'Doherty, J. P. & Rangel, A. Value computations in ventral medial prefrontal cortex during charitable decision making incorporate input from regions involved in social cognition. *Journal of Neuroscience* **30**, 583–590 (2010).
22. Kuss, K. *et al.* Neuronal correlates of social decision making are influenced by social value orientation—an fMRI study. *Front. Behav. Neurosci.* **9**, (2015).

23. Tusche, A., Böckler, A., Kanske, P., Trautwein, F.-M. & Singer, T. Decoding the charitable brain: empathy, perspective taking, and attention shifts differentially predict altruistic giving. *Journal of Neuroscience* **36**, 4719–4732 (2016).
24. Cutler, J. & Campbell-Meiklejohn, D. A comparative fMRI meta-analysis of altruistic and strategic decisions to give. *NeuroImage* **184**, 227–241 (2019).
25. Hernandez-Lallement, J., van Wingerden, M., Schäble, S. & Kalenscher, T. A Social Reinforcement Learning Hypothesis of Mutual Reward Preferences in Rats. in *Social Behavior from Rodents to Humans: Neural Foundations and Clinical Implications* (eds. Wöhr, M. & Krach, S.) 159–176 (Springer International Publishing, 2017). doi:10.1007/7854_2016_436.
26. Tremblay, S., Sharika, K. M. & Platt, M. L. Social decision-making and the brain: A comparative perspective. *Trends in cognitive sciences* **21**, 265–276 (2017).
27. Dolan, R. J. & Dayan, P. Goals and habits in the brain. *Neuron* **80**, 312–325 (2013).
28. Hertwig, R., Hogarth, R. M. & Lejarraga, T. Experience and description: Exploring two paths to knowledge. *Current Directions in Psychological Science* **27**, 123–128 (2018).
29. Hertwig, R. & Erev, I. The description–experience gap in risky choice. *Trends in Cognitive Sciences* **13**, 517–523 (2009).
30. Ludvig, E. A., Madan, C. R. & Spetch, M. L. Extreme outcomes sway risky decisions from experience. *Journal of Behavioral Decision Making* **27**, 146–156 (2014).
31. Botvinick, M. & Braver, T. Motivation and cognitive control: from behavior to neural mechanism. *Annual Review of Psychology* **66**, 83–113 (2015).
32. Denrell, J. & Le Mens, G. Information sampling, belief synchronization, and collective illusions. *Management Science* **63**, 528–547 (2017).
33. Hertwig, R., Barron, G., Weber, E. U. & Erev, I. Decisions from experience and the effect of rare events in risky choice. *Psychological science* **15**, 534–539 (2004).
34. Wunderlich, K., Dayan, P. & Dolan, R. J. Mapping value based planning and extensively trained choice in the human brain. *Nature Neuroscience* **15**, 786 (2012).
35. Bongioanni, A. *et al.* Activation and disruption of a neural mechanism for novel choice in monkeys. *Nature* **591**, 270–274 (2021).
36. Chib, V. S., Rangel, A., Shimojo, S. & O’Doherty, J. P. Evidence for a common representation of decision values for dissimilar goods in human ventromedial prefrontal cortex. *Journal of Neuroscience* **29**, 12315–12320 (2009).
37. Gläscher, J., Hampton, A. N. & O’Doherty, J. P. Determining a Role for Ventromedial Prefrontal Cortex in Encoding Action-Based Value Signals During Reward-Related Decision Making. *Cerebral Cortex* **19**, 483–495 (2009).
38. Hare, T. A., Camerer, C. F. & Rangel, A. Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. *Science* **324**, 646–648 (2009).

39. Levy, D. J. & Glimcher, P. W. The root of all value: a neural common currency for choice. *Current Opinion in Neurobiology* **22**, 1027–1038 (2012).
40. Clithero, J. A. & Rangel, A. Informatic parcellation of the network involved in the computation of subjective value. *Social cognitive and affective neuroscience* **9**, 1289–1302 (2013).
41. Rudolf, S. & Hare, T. A. Interactions between dorsolateral and ventromedial prefrontal cortex underlie context-dependent stimulus valuation in goal-directed choice. *Journal of Neuroscience* **34**, 15988–15996 (2014).
42. Forstmann, B. U., Ratcliff, R. & Wagenmakers, E.-J. Sequential sampling models in cognitive neuroscience: Advantages, applications, and extensions. *Annual review of psychology* **67**, 641–666 (2016).
43. Morishima, Y., Schunk, D., Bruhin, A., Ruff, C. C. & Fehr, E. Linking brain structure and activation in temporoparietal junction to explain the neurobiology of human altruism. *Neuron* **75**, 73–79 (2012).
44. Obeso, I., Moisa, M., Ruff, C. C. & Dreher, J.-C. A causal role for right temporo-parietal junction in signaling moral conflict. *Elife* **7**, e40671 (2018).
45. Holroyd, C. B. & Verguts, T. The best laid plans: Computational principles of anterior cingulate cortex. *Trends in Cognitive Sciences* (2021).
46. Murphy, R. O., Ackermann, K. A. & Handgraaf, M. Measuring social value orientation. *Judgment and Decision Making* **6**, 771–781 (2011).
47. Ratcliff, R. A theory of memory retrieval. *Psychological Review* **85**, 59 (1978).
48. Wiecki, T. V., Sofer, I. & Frank, M. J. HDDM: Hierarchical Bayesian estimation of the drift-diffusion model in Python. *Frontiers in neuroinformatics* **7**, 14 (2013).
49. Lombardi, G. & Hare, T. Piecewise constant averaging methods allow for fast and accurate hierarchical Bayesian estimation of drift diffusion models with time-varying evidence accumulation rates. (2021).
50. Hare, T. A., Schultz, W., Camerer, C. F., O'Doherty, J. P. & Rangel, A. Transformation of stimulus value signals into motor commands during simple choice. *Proceedings of the National Academy of Sciences* **108**, 18120–18125 (2011).
51. Krajbich, I. & Rangel, A. Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences* **108**, 13852–13857 (2011).
52. Milosavljevic, M., Malmaud, J., Huth, A., Koch, C. & Rangel, A. The drift diffusion model can account for value-based choice response times under high and low time pressure. *Judgment and Decision Making* **5**, 437–449 (2010).
53. Clithero, J. A. Improving out-of-sample predictions using response times and a model of the decision process. *Journal of Economic Behavior & Organization* **148**, 344–375 (2018).
54. Fontanesi, L., Gluth, S., Spektor, M. S. & Rieskamp, J. A reinforcement learning diffusion decision model for value-based decisions. *Psychonomic bulletin & review* **26**, 1099–1121 (2019).

55. Mars, R. B. *et al.* Connectivity-Based Subdivisions of the Human Right “Temporoparietal Junction Area”: Evidence for Different Areas Participating in Different Cortical Networks. *Cerebral Cortex* **22**, 1894–1903 (2012).
56. Nauta, A., De Dreu, C. K. W. & van der Vaart, T. Social value orientation, organizational goal concerns and interdepartmental problem-solving behavior. *Journal of Organizational Behavior* **23**, 199–213 (2002).
57. Tricomi, E., Balleine, B. W. & O’Doherty, J. P. A specific role for posterior dorsolateral striatum in human habit learning. *European Journal of Neuroscience* **29**, 2225–2232 (2009).
58. Chen, F. & Fischbacher, U. Response time and click position: Cheap indicators of preferences. *Journal of the Economic Science Association* **2**, 109–126 (2016).
59. Fiedler, S., Glöckner, A., Nicklisch, A. & Dickert, S. Social value orientation and information search in social dilemmas: An eye-tracking analysis. *Organizational Behavior and Human Decision Processes* **120**, 272–284 (2013).
60. Krajbich, I., Bartling, B., Hare, T. & Fehr, E. Rethinking fast and slow based on a critique of reaction-time reverse inference. *Nature communications* **6**, 1–9 (2015).
61. Alós-Ferrer, C., Fehr, E. & Netzer, N. Time will tell: Recovering preferences when choices are noisy. *Journal of Political Economy* **129**, 1828–1877 (2021).
62. Busemeyer, J. R. & Townsend, J. T. Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychological review* **100**, 432 (1993).
63. Wang, Z. J. & Busemeyer, J. R. *Cognitive Choice Modeling*. (MIT Press, 2021).
64. Bartra, O., McGuire, J. T. & Kable, J. W. The valuation system: a coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *Neuroimage* **76**, 412–427 (2013).
65. Grueschow, M., Polania, R., Hare, T. A. & Ruff, C. C. Automatic versus choice-dependent value representations in the human brain. *Neuron* **85**, 874–885 (2015).
66. Lebreton, M., Jorge, S., Michel, V., Thirion, B. & Pessiglione, M. An automatic valuation system in the human brain: evidence from functional neuroimaging. *Neuron* **64**, 431–439 (2009).
67. Levy, I., Lazzaro, S. C., Rutledge, R. B. & Glimcher, P. W. Choice from Non-Choice: Predicting Consumer Preferences from Blood Oxygenation Level-Dependent Signals Obtained during Passive Viewing. *J. Neurosci.* **31**, 118–125 (2011).
68. Lockwood, P. L. & Wittmann, M. K. Ventral anterior cingulate cortex and social decision-making. *Neuroscience & Biobehavioral Reviews* **92**, 187–191 (2018).
69. Zahn, R. *et al.* The neural basis of human social values: evidence from functional MRI. *Cerebral cortex* **19**, 276–283 (2009).
70. Frederick, S. Cognitive reflection and decision making. *Journal of Economic perspectives* **19**, 25–42 (2005).

71. Andersson, O., Huysentruyt, M., Miettinen, T. & Stephan, U. Person–Organization Fit and Incentives: A Causal Test. *Management Science* **63**, 73–96 (2016).
72. Bürkner, P.-C. brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software* **80**, 1–28 (2017).
73. R Team, C. R: A language and environment for statistical computing. (2013).
74. Carpenter, B. *et al.* Stan: A probabilistic programming language. *Journal of Statistical Software* **76**, (2017).
75. Douma, J. C. & Weedon, J. T. Analysing continuous proportions in ecology and evolution: A practical introduction to beta and Dirichlet regression. *Methods in Ecology and Evolution* **10**, 1412–1430 (2019).
76. Denwood, M. J. runjags: An R package providing interface utilities, model templates, parallel computing methods and additional distributions for MCMC models in JAGS. *Journal of statistical software* **71**, 1–25 (2016).

Figures

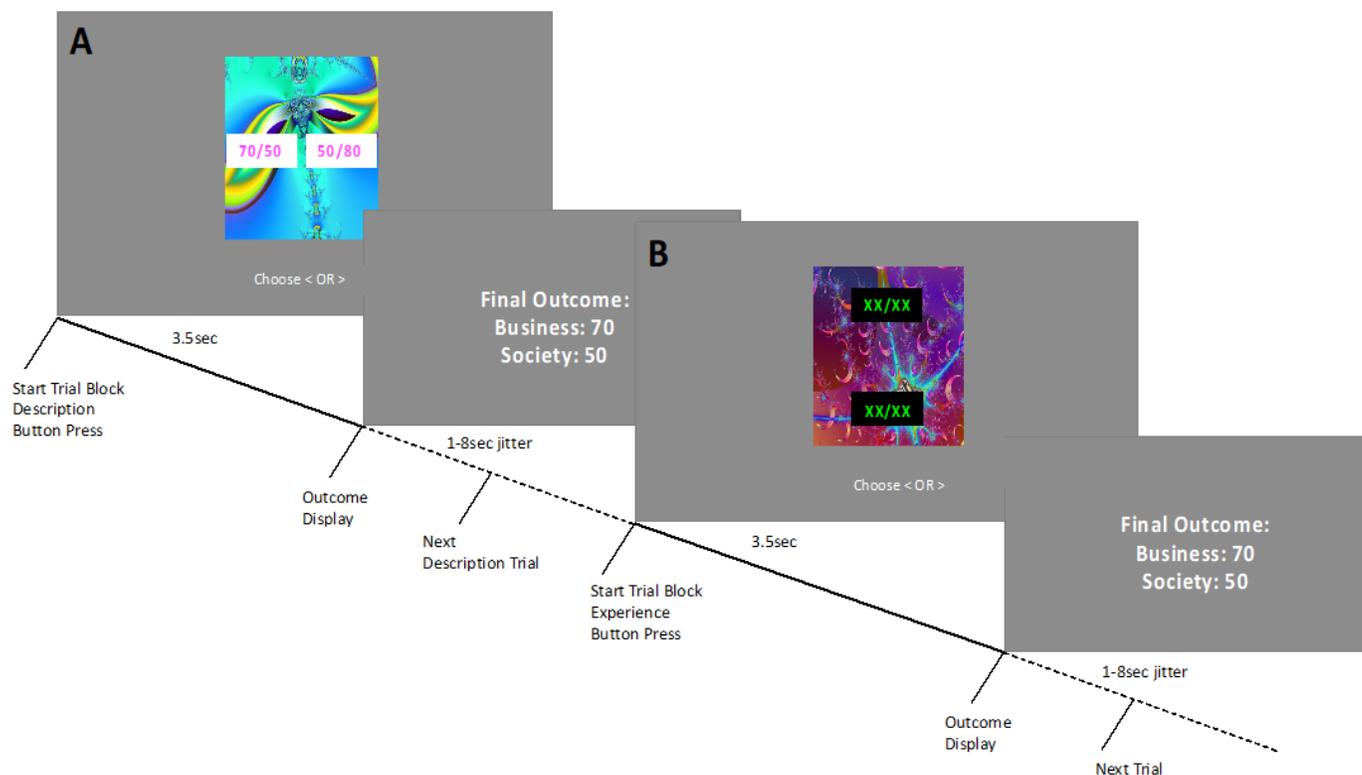


Figure 1

Task structure of the social decision task. Participants chose in 3.5 seconds between two pairs of outcomes for business and society, that represented choices that were paid out to them and a charity of their choice at the end of the experiment. The choice was followed by an outcome screen and 1-8 second jittered inter-trial interval. We compared two different types of trials, description and experience trials were both presented in blocks ranging between 2-10 trials. A) In description trials each pair of outcomes was shown explicitly on the left and right sides or top and bottom of a novel fractal image and participants pressed the left or right button to indicate their preferred outcomes. B) In experience trials, participants were shown a unique fractal image but could not see the outcomes at the time of choice. Instead, they had learned the outcomes for the unique fractal images through extensive training over three days prior to the main experimental session.

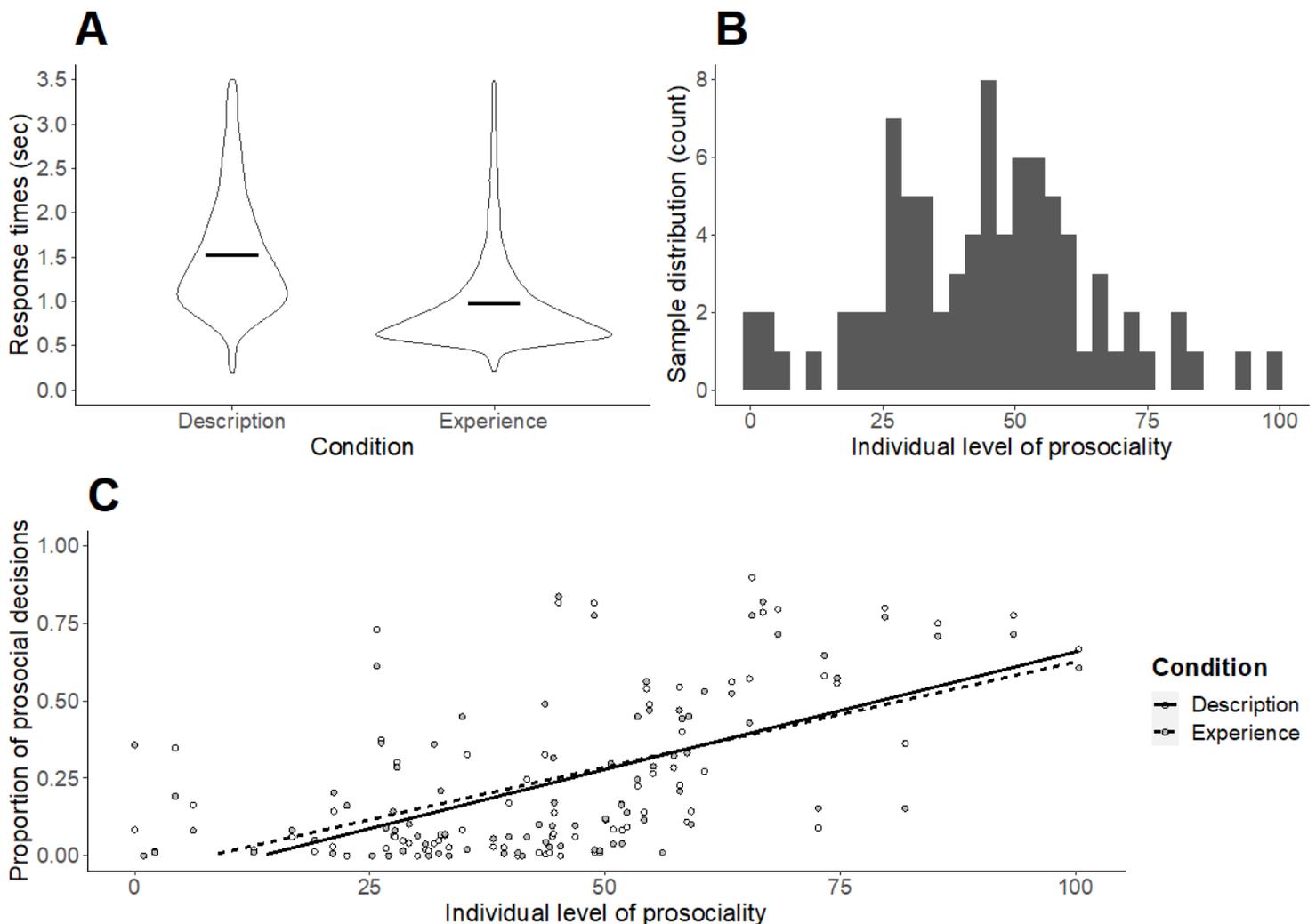


Figure 2

Description and experience in social decisions. A) Mean response times (RTs) considerably varied between description decisions (1.53 ± 0.66 seconds) and experience decisions (0.98 ± 0.54 seconds). The outlines of the violin plots show the distribution of RTs in each choice condition and the horizontal bars

show the group means. B) There was considerable variability in prosocial preferences across the 147 participants in our sample. The x-axis shows the social preference angles from the SVO measure. Prosociality scores near zero indicate selfish preferences whereas higher scores indicate more prosocial preferences. C) More selfish participants made fewer society-benefit maximizing choices compared to prosocial individuals. The y-axis shows the proportion of choices that maximize the benefits to society (i.e., proportion of prosocial decisions) for each individual in description (white dots, solid regression line) and experience (grey dots, dotted regression line) trials. The x-axis shows the individual level of prosociality derived from the SVO measure⁴⁶. The proportion of prosocial decisions across description and experience trials were similar.

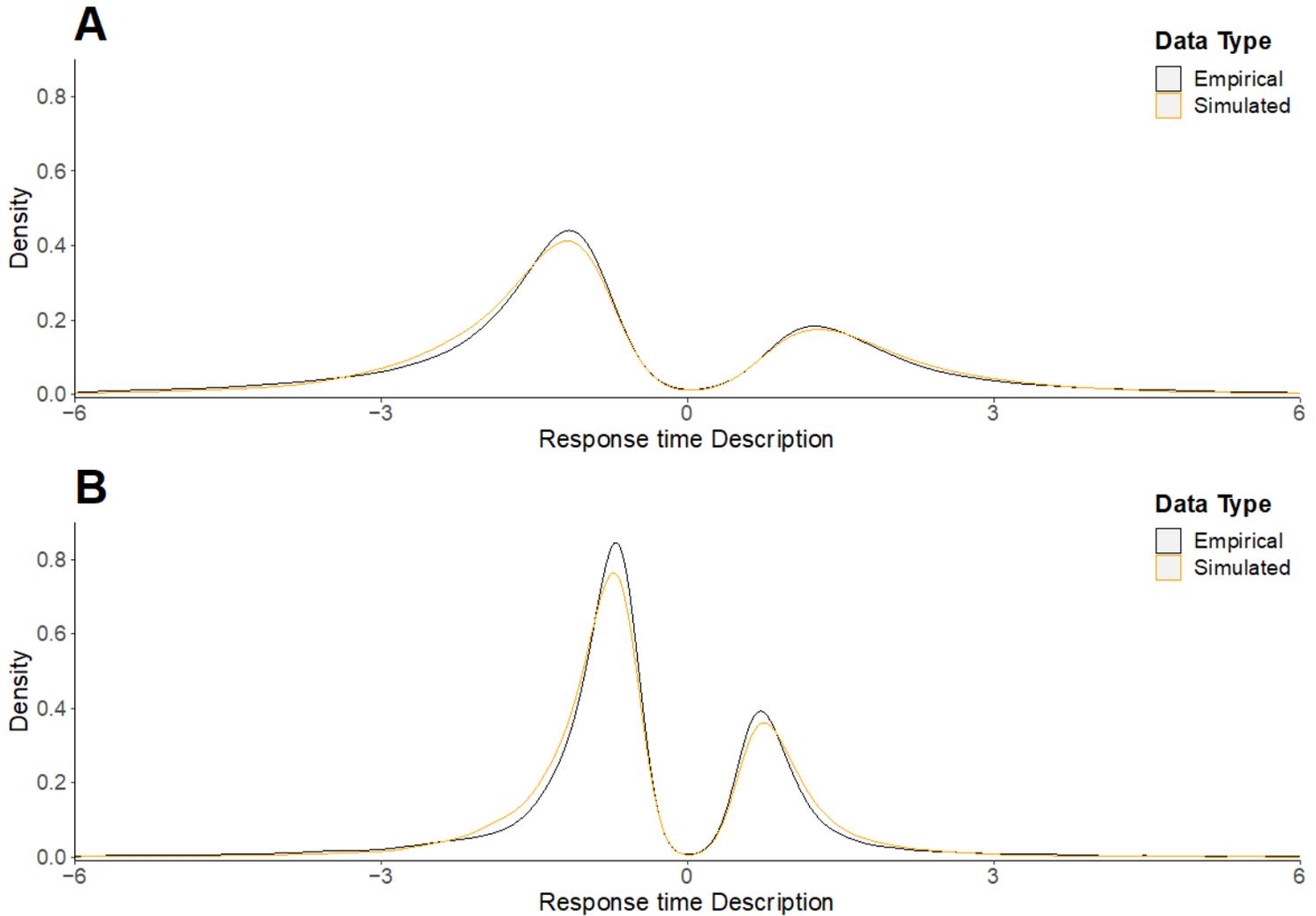


Figure 3

Individual level posterior probability distributions of the mean response times. The values for empirical and simulated response times in description A) and experience B) trials. The black lines indicate the empirical distribution of response times, while the orange lines show the distributions of simulated response times. The data were simulated using the best-fitting participant-level parameters.

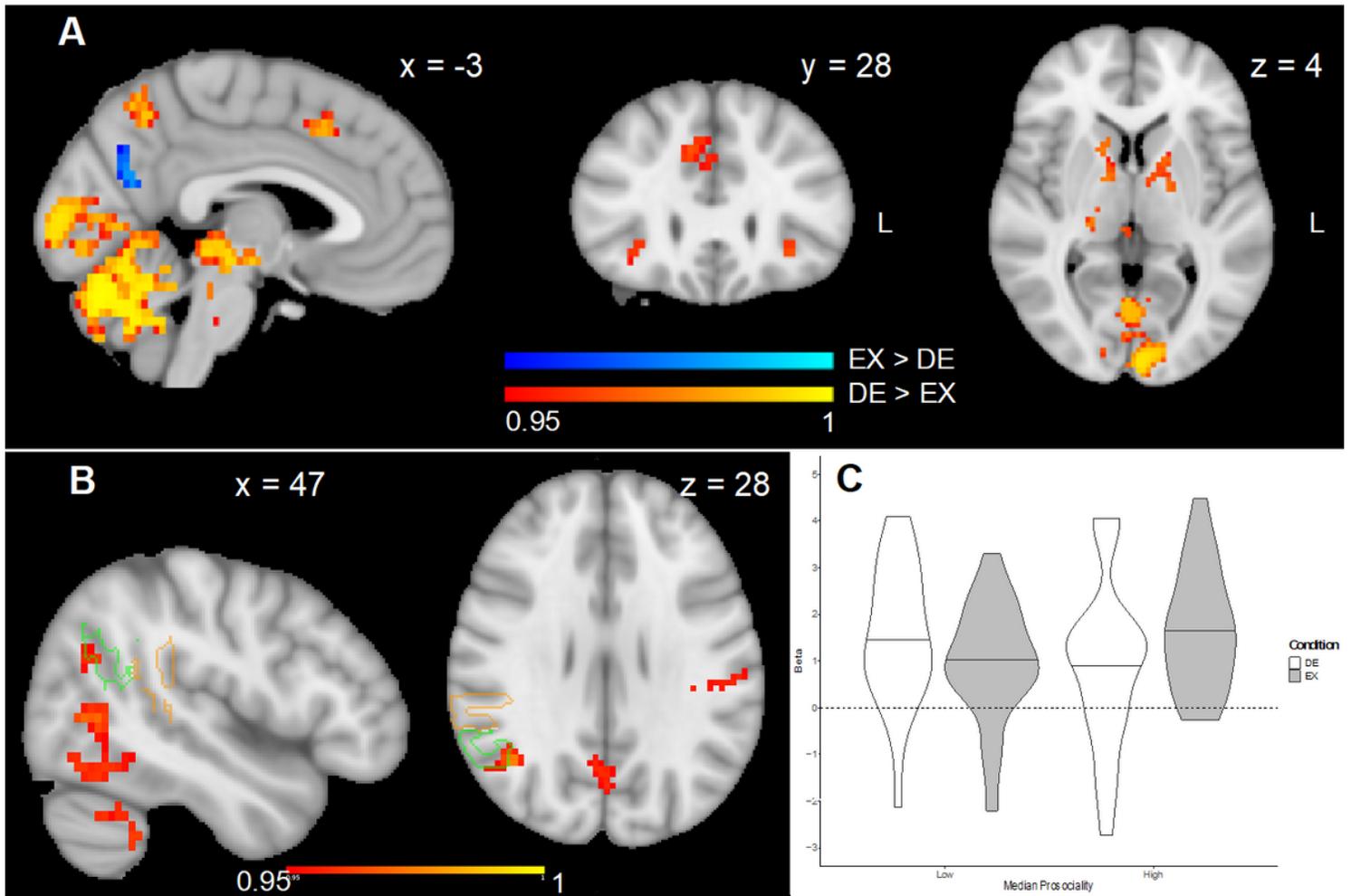


Figure 4

Differences in BOLD activity during description compared to experience social decisions. A) Areas with greater activation during description than experience trials are shown in the red-yellow color scale, while areas with greater activity during experience compared to description decisions are shown in the blue color scale. B) Voxels in red showing an interaction between condition (DE or EX) and Social Value Orientation (SVO) in the partially overlap with the posterior TPJ. The anterior (orange) and posterior (green) TPJ are outlined based on the atlas created by Mars et al.⁵⁵ C) This violin plot shows that the interaction in TPJ voxels is driven by low SVO individuals who show greater activity during description (white) than experience (grey) trials. Participants were split into two groups by the median prosociality resulting in low and high SVO individuals. The statistical parametric map shows significant voxels ($p < 0.05$) and was FWE corrected at the whole brain level.

Supplementary Files

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