Biological Psychiatry: CNNI

# Computational Phenotyping of Effort-Based Decision Making in Unmedicated Adults With Remitted Depression

Manuel Kuhn, Emma H. Palermo, Guillaume Pagnier, Jacob M. Blank, David C. Steinberger, Yinru Long, Genevieve Nowicki, Jessica A. Cooper, Michael T. Treadway, Michael J. Frank, and Diego A. Pizzagalli


## ABSTRACT

**BACKGROUND:** Reduced motivation is a core feature of major depressive disorder (MDD). Yet, the extent to which this deficit persists in remitted MDD (rMDD) remains unclear. Here, we examined effort-based decision making as one aspect of amotivation in rMDD using computational phenotyping to characterize decision-making processes and strategies.

**METHODS:** Unmedicated adults with rMDD ($n$ = 40) and healthy control (HC) participants ($n$ = 68) completed the Effort Expenditure for Rewards Task. Repeated-measures analysis of variance and computational modeling—including hierarchical drift diffusion modeling and subjective value modeling—were applied to quantify decision-making dynamics in effort allocation across different reward magnitudes and probabilities.

**RESULTS:** Relative to HC participants, participants with rMDD made overall fewer hard task choices, with an attenuated effect when accounting for anhedonia. However, specific to high reward, high probability conditions, participants with rMDD chose to expend effort more often than HC participants. This was supported by the drift diffusion model results revealing that participants with rMDD showed a drift rate biased toward selecting the easy task, counteracted by heightened influence of reward probability and magnitude. Probed with the subjective value model, this was not driven by group differences in decision strategies with respect to magnitude and probability information use.

**CONCLUSIONS:** Collectively, these findings suggest that while individuals with rMDD exhibit persistent motivational deficits, they retain a heightened sensitivity to high-value rewards, requiring more substantial or certain rewards to engage in effortful tasks. This pattern may reflect impairments in reward processing and effort-cost computations, contributing to motivational dysfunction. Targeting reward sensitivity and effort allocation could be valuable for interventions aimed at preventing MDD relapse.


https://doi.org/10.1016/j.bpsc.2025.02.006

Major depressive disorder (MDD) is characterized by pervasive mood disturbances, cognitive impairments, and reduced motivation. Anhedonia—the diminished ability to experience pleasure or interest in activities—is a core impairment in MDD, particularly when decisions require balancing effort against potential rewards (1,2). Despite improvements in mood after remission, individuals with remitted MDD (rMDD) continue to exhibit some cognitive and motivational deficits, such as alterations in reward processing (3,4), impairing daily activities and functional recovery (5). However, the extent to which deficits specific to balancing effort against potential rewards persists in rMDD remains unclear.

Effort-based decision-making tasks, which examine how individuals weigh the potential benefits of rewards against the cognitive or physical effort required to obtain them, provide valuable insight into motivational processes underlying MDD. These tasks have largely shown that individuals with elevated depressive symptoms (e.g., anhedonia) or current MDD are characterized by reduced willingness to expend effort for rewards, for example, due to reduced sensitivity to the reward magnitude and reward probability (6–12); inconsistencies exist, however, and some studies have reported no differences in effort allocation in MDD (13). When deficits emerged, dysfunctions in reward-related neural circuitry, which impair the ability to evaluate effort and motivation in pursuit of rewards, have been postulated (14). While most existing research has focused on acute depressive states, less is known about the extent to which these motivational impairments persist into remission. One study found no differences in expenditure of cognitive effort in individuals with partially medicated rMDD (15). Two other studies probing physical effort in medicated individuals reported either no residual impairments (16) or a lower willingness to expend effort in individuals with rMDD, especially for low rewards (17). Using computational modeling,



ISSN: 2451-9022

the latter study (17) identified increased effort sensitivity, but no differences in reward sensitivity in rMDD. Thus, individuals with rMDD may exhibit motivational impairments, potentially requiring greater incentives to engage in effortful activities, which may be linked to altered functioning of the dopaminergic system underlying reward processing and motivation (14). However, participants in these studies were partially or fully medicated, which is an important confound considering that antidepressants can blunt reward-related neural processes (18). As such, the precise nature of motivational impairments in individuals with unmedicated rMDD remains poorly understood. Given the increased risk of relapse among individuals with rMDD (19), understanding the nuanced motivational profiles in rMDD via approaches that tap into latent processes is critical for understanding relapse risk and for developing targeted prevention interventions.

Using the Effort Expenditure for Rewards Task (EEfRT) (7), we examined how individuals with unmedicated rMDD weigh reward magnitude and probability when making decisions about expending effort, using both behavioral and computational modeling approaches. Given the centrality of motivational factors in MDD, we hypothesized that participants with rMDD would exhibit a reduced willingness to engage in effortful tasks compared with healthy control (HC) participants. Additionally, it remains unclear if reward magnitude or probability sensitivity is altered in individuals with unmedicated rMDD. While generally blunted reward sensitivity to reward variables could be expected based on studies in MDD, it can be speculated that, to retain daily functioning in rMDD, increased sensitivity to higher and more likely rewards might be required. Finally, we explored whether alterations in effort allocation may be driven by residual cognitive impairments in integrating reward magnitude and probability information into decision-making strategies.

To evaluate the first 2 hypotheses, we implemented both an analysis of traditional measures of effort expenditure and computational modeling via a hierarchical drift diffusion model (DDM) (20). By analyzing both choices and reaction times, a process model such as the DDM can uncover latent value-based decision-making processes (and thus assess the influence of reward magnitude and probability, respectively) that cannot be evaluated when examining choice behavior via traditional analyses (21–23). As such, the DDM has been successfully applied to effort-based decision making, unveiling the underlying processes that drive cost/benefit decision making (24–26). Finally, to complement DDM analyses, we performed subjective value modeling (27) to probe individual decision-making strategies, which may be reflected in differences in how an individual makes use of the available reward magnitude and probability information.

## METHODS AND MATERIALS

### Participants

Participants comprised 114 adults, including 42 unmedicated participants with rMDD and 72 HC participants ages 18 to 45 years, who were recruited from the greater Boston community. For details of inclusion and exclusion criteria, see the Supplement.

The rMDD and HC groups did not differ on any demographic measures except race. Although scores on clinical scales were well below clinical cutoffs,[a] groups differed on self-report measures of depression and anhedonia (Table 1), which motivated separate control analyses. Participants completed the EEfRT (see Supplement) as part of a larger neuroimaging study, for which the sample size was determined based on the design and objectives of the broader study. Given evidence that antidepressants can blunt reward-related neural processes (18), only unmedicated individuals with rMDD were included to minimize potential confounding effects. Six participants were excluded due to overlapping issues, including inadequate task performance due to not selecting any hard tasks ($n = 1$), failing to complete any of the hard tasks ($n = 5$), or an overall completion rate of less than 50% ($n = 4$). Accordingly, the final sample included 108 participants: 68 HC participants and 40 participants with rMDD. All study procedures were approved by the Mass General Brigham Human Research Committee, which serves as the Institutional Review Board for McLean Hospital. Participants provided written informed consent.

### Statistical Analyses

Trials were excluded if no task was selected or selection reaction times were less than 250 ms (27). Given the central role of anhedonia in MDD, follow-up analyses explored the effects of grand mean-centered Snaith-Hamilton Pleasure Scale (SHAPS) scores using analysis of variance (ANOVA) as well as their associations with model parameters from both computational approaches.

**Repeated-Measures ANOVA.** A repeated-measures ANOVA examined the effects of reward probability, reward magnitude, and group. Independent variables were 3 levels of reward probability (low, 12%; medium, 50%; high, 88%), 3 levels of reward magnitude [following recent work (30), categorized as low, \$1.24–\$2.00; medium, \$2.01–\$3.00; high, \$3.01–\$4.12], and 2 levels of group (HC, rMDD). To dissect a possible 3-way interaction effect, 3 follow-up post hoc ANOVAs examined group differences of proportion of hard task choices under specific probability conditions, with Bonferroni correction of criteria significance values ($p = .0167$ [.05/3]). Interaction

[a]Due to stringent exclusion criteria and clinical screening ensuring that participants had no depressive symptoms, both groups reported extremely low clinical scores (well below clinical cutoffs). Specifically, the mean Beck Depression Inventory (BDI) scores (possible range, 0–63) were 1.85 (rMDD group) and 0.63 (HC group). The lack of range in BDI scores prevented us from entering these values as covariates in control analyses (77% of HC and rMDD participants had a BDI score of 0 or 1). Similarly, the mean Snaith-Hamilton Pleasure Scale (SHAPS) scores [single missing SHAPS items for 2 HC participants were imputed via Multivariate Imputation by Chained Equations using the mice package in R (28)] (possible range, 14–56) were low (participants with rMDD = 22.00, HC participants = 19.47) (see Figure S3 for SHAPS score group distributions) and in agreement with a meta-analysis reporting no overall differences in SHAPS scores between HC participants and participants with rMDD (29).

**Table 1. Demographics and Clinical Measures of Participants**

| Measure | rMDD Group, *n* = 40 | HC Group, *n* = 68 | *p* Value |
|---|---|---|---|
| Age, Years, Mean (SD) | 25.72 (6.25) | 26.50 (5.74) | .51 |
| Sex, Female, % | 87.50% | 75.00% | .19 |
| Race, % | | | .04* |
| American Indian or Alaskan Native | 0.00% | 1.47% | |
| Asian | 20.00% | 29.41% | |
| Black | 0.00% | 10.29% | |
| White | 77.50% | 55.88% | |
| Unknown | 2.50% | 2.94% | |
| Hispanic or Latinx, % | 17.50% | 10.29% | .37 |
| Education, % | | | .24 |
| High school | 0.00% | 4.41% | |
| Some college | 30.00% | 17.65% | |
| 4-Year college | 35.00% | 30.88% | |
| Graduate or professional school | 35.00% | 47.06% | |
| Income, % | | | .32 |
| <$50,000 | 22.50% | 23.53% | |
| $50,000–$100,000 | 52.50% | 39.71% | |
| >$100,000 | 22.50% | 35.29% | |
| Unknown | 2.50% | 1.47% | |
| BDI, Mean (SD) | 1.85 (2.61) | 0.63 (1.47) | .002** |
| SHAPS, Mean (SD)[a] | 22.00 (6.32) | 19.47 (6.06) | .045* |

$\chi^2$ tests were conducted for categorical variables. For categorical variables in which there were cell counts of 0 or 1, Fisher exact test was conducted in place of $\chi^2$ test. Two-sample *t* tests were conducted for continuous variables.

$^*p < .05$, $^{**}p < .01$.

BDI, Beck Depression Inventory; HC, healthy control; rMDD, remitted major depressive disorder; SHAPS, Snaith-Hamilton Pleasure Scale.

[a]Single missing SHAPS items for 2 HC participants, respectively, were imputed via Multivariate Imputation by Chained Equations using the mice package in R (28). See Figure S3 for the groupwise distribution of SHAPS scores.

effects were followed up via marginal means pairwise comparisons. Additionally, condition and group effects were assessed for decision reaction times. For all ANOVAs, a Greenhouse-Geisser correction was used, when applicable. To evaluate the dependency of the observed effects on the categorization of reward magnitude, a generalized linear mixed-effects model was performed treating reward magnitude as a continuous variable (see Supplement). All tests were performed in R (31) using the afex (32), emmeans (33), and lme4 (34) packages.

**Hierarchical Bayesian Drift Diffusion Modeling.** To fit and simulate behavioral choices and response times, we used the Python-based Bayesian hierarchical drift diffusion modeling toolbox (HDDM) (21). DDMs and related evidence accumulation models have been used extensively to study latent processes underlying perceptual and value-based decision making, wherein parameter estimates can be more informative about clinical status than raw choices and reaction times (20,22,35,36). In the context of the EEfRT, the upper decision bound represents selection of the high reward, high effort option. Thus, the decision variable serves as a proxy for evidence accumulation toward the high reward, high effort option, with the drift rate increasing toward the upper boundary parametrically with reward magnitude or reward probability to overcome the effort cost (25). Regressor variables were centered before model fitting. Convergence of Bayesian model parameters was assessed by visually inspecting parameter traces, confirming acceptable levels of mixing with low amounts of autocorrelation. Convergence was formally examined via the Gelman-Rubin statistic; all parameters had $\hat{R}$ below 1.1, suggesting acceptable convergence. Each model included was run with 4 chains and a minimum chain length of 2000 to ensure smooth posteriors. Model comparison was performed by starting with a base DDM with static decision bounds for both the HC and the rMDD groups and systematically determining if there were other DDM variants that improved the fit to the empirical data, based on posterior predictive checks (PPCs) and deviance information criterion, using the likelihood approximation networks extension to the HDDM tool for likelihood-free inference (37,38). The winning model (Weibull model) estimated 2 additional parameters beyond the standard DDM that allows for the decision threshold to collapse nonlinearly over time, with the shape of the collapse determined by the $\alpha$ parameter and the onset by the $\beta$ parameter. We fit separate Weibull models for each group, allowing drift rate to vary as a function of both reward probability and reward magnitude on a trial-by-trial basis (see Supplement), and compared posteriors to estimate how the latent DDM parameters differed between rMDD and HC groups (22). Model validation via PPCs involved generating simulated data from the winning DDM (sampling from the full posterior distribution over parameters) and determining whether these synthetic data successfully recapitulate the qualitative patterns seen in the empirical data.

**Subjective Value Modeling.** The goal of a subjective value model (SVM) of choice behavior during the EEfRT was to specifically allow inferences about the individual's choice strategy characterizing how decisions are made, providing important information beyond a repeated-measures ANOVA, which examines what choices an individual makes (i.e., easy or hard), and the DDM analyses, which examine the trialwise dynamic process of decision making and its latent components. In brief, following the approach by Cooper *et al.* (27), an SVM probed the participant's integration of the 3 presented components of information (reward probability, reward magnitude, and required effort) into the individual's choice strategy (see Supplement for details). Four possible models were tested for each individual separately using maximum likelihood estimation of underlying strategies that best fit the observed trial-by-trial behavior: 1) a full SVM, which assumes that participants consistently incorporate both trialwise reward probability and reward magnitude information when deciding how to allocate effort; 2) a reward-only SVM, which assumes that participants consider only the magnitude of reward; 3) a probability-only SVM, which assumes that participants consider only the probability of reward; and 4) a bias model, which assumes that participants do not consider the reward or probability information at all, representing unsystematic and random effort allocation, highly favoring one option over the other, or make choices that were inconsistent with the assumptions of the SVM (e.g., favoring the hard effort task for low reward/low probability trials).

Finally, following Cooper *et al.* (27), for a subset of participants who had the full SVM as the winning model, we performed follow-up analyses to determine group differences in the 2 model parameters (i.e., $k$, capturing perceived effort, and $h$, capturing probability).

## RESULTS

### Task Performance

The mean (SD) task completion rate across all participants was 93.77% (8.54%) with a mean number of 63.3 (range, 34–84) trials. Mean completion rates for the HC (93.08% [8.93%]) and rMDD (94.93% [7.79%]) groups did not differ ($t_{106}$ = 1.09, $p$ = .280). Similarly, mean selection reaction times (1.624 [0.378] seconds) across all conditions did not differ between the HC (1.634 [0.400] seconds) and rMDD (1.609 [0.342] seconds) groups ($t_{106}$ = 0.33, $p$ = .740).

### Willingness to Expend Effort Across Different Levels of Reward Magnitude and Probability (ANOVAs)

An omnibus repeated-measures ANOVA assessing effects on the proportion of hard task choices revealed the expected main effects of increased hard task selection with increasing reward magnitude and probability and their interaction (Table S1). Importantly, a significant group main effect ($F_{1,106}$ = 4.04, $p$ = .047) emerged, with estimated marginal means averaged across levels of reward probability and reward magnitude showing a reduced willingness to exert effort for participants with rMDD (25.6%, SE = 2.46%) compared with HC participants (31.9%, SE = 1.9%). In addition, the group × reward probability × reward magnitude 3-way interaction was significant ($F_{3.28,347.5}$ = 3.79, $p$ = .009). Post hoc repeated-measures ANOVAs (Table S2) further dissecting this 3-way interaction revealed a significant group effect in the medium probability condition showing decreased expenditure of effort for rMDD in the medium probability condition across all 3 reward magnitude levels ($p$s < .04). In addition, a 2-way interaction of group and reward magnitude was observed in the high probability condition that was driven by a significant difference in the high reward magnitude condition ($p$ = .03) indicating higher reward expenditure for rMDD in this condition (Figure 1). Treating reward magnitude as a continuous variable in a generalized linear mixed-effects model, the 3-way interaction was confirmed, whereas the group effect was not significant (Table S3).

No differences between groups and conditions emerged for selection reaction times (Table S4; Figure S2). Finally, the overall pattern of findings was confirmed when entering SHAPS scores as covariate, although the group effect was reduced to a trend ($p$ = .057) (Table S4). No association with SHAPS emerged.

### Hierarchical Bayesian Drift Diffusion Modeling

The winning Weibull model (Figure 2A) captured qualitative patterns in both HC and rMDD groups well (see PPCs) (Figure 3). Drift rate increased with reward magnitude and reward probability in both HC and rMDD groups. As the HDDM tool is a Bayesian estimation framework, null hypothesis testing can be conducted via directly comparing Bayesian posteriors (21,22,39). Specifically, we can ask statistically meaningful questions by examining the proportion of the posteriors that overlap or are above or below 0 to extract the probability of a hypothesis being true. Notably, the group drift rate intercept (reflecting the overall propensity to select the hard task) was considerably more negative for participants with rMDD than for HC participants, indicating an increased preponderance to accumulate evidence toward the low effort option in participants with rMDD compared with HC participants (Figure 2B), whereas the positive effects of reward probability (Figure 2C, E) and reward magnitude

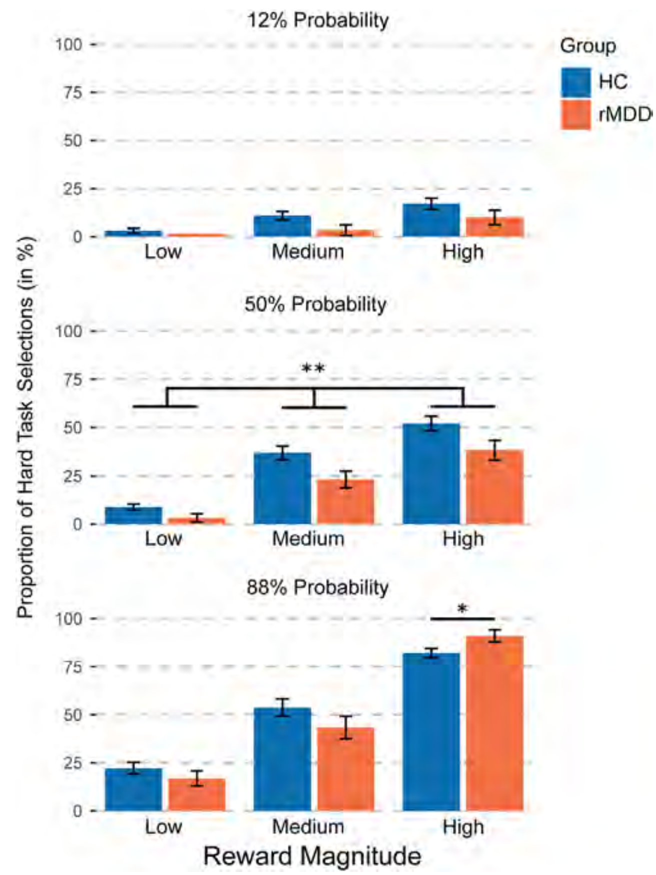


**Figure 1.** Proportion of hard task selections by reward magnitude and probability levels. The proportion of hard task selections (%) for healthy control (HC) and remitted major depressive disorder (rMDD) groups, categorized by different levels of reward magnitude (low, medium, high) and reward probability (12%, 50%, 88%). For illustration, the values are based on estimated marginal means extracted from the full analysis of variance (ANOVA) model (Table S1). Follow-up ANOVAs (Table S2) revealed a significant group effect in the medium probability condition, while a significant group × reward magnitude interaction was observed in the high probability condition driven by a significant group difference in the high reward magnitude condition. Error bars represent the SE of the mean. Note that for the rMDD group at low reward (12% probability), the SE exceeds the mean value, leading to unobservable negative values, and is therefore omitted. *$p$ < .05, **$p$ < .01.

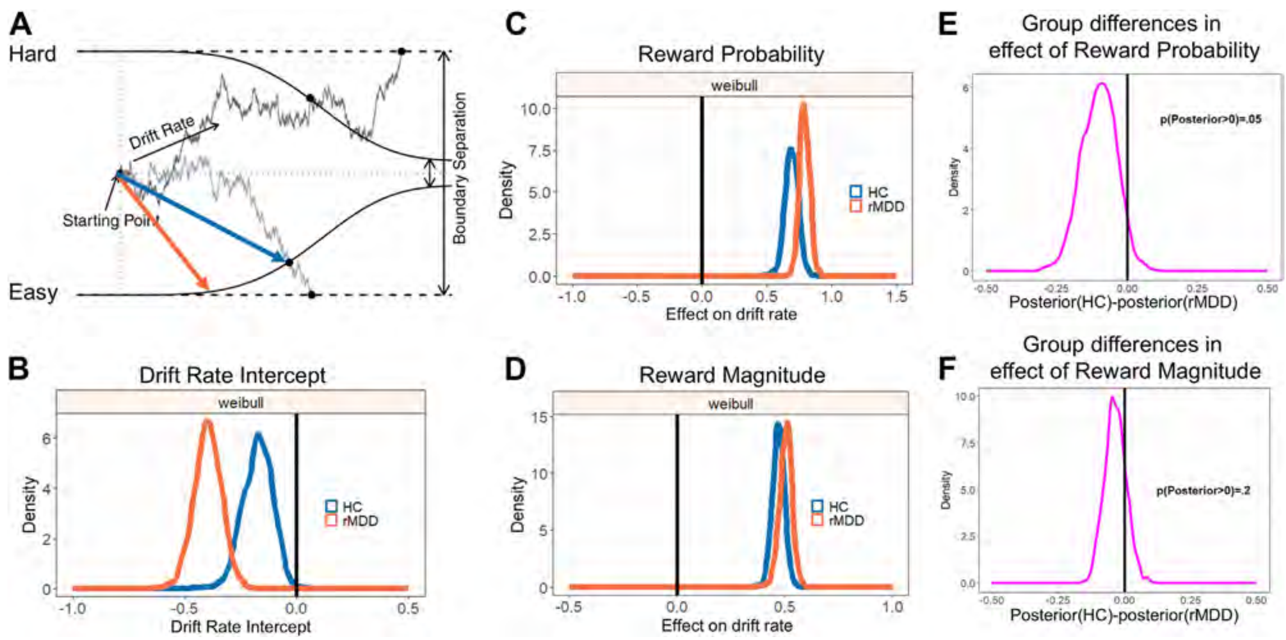


**Figure 2.** Drift diffusion model analysis and group comparisons. Hierarchical Bayesian drift diffusion modeling analysis comparing healthy control (HC) and remitted major depressive disorder (rMDD) groups. **(A)** Schematic of the drift diffusion model illustrating key parameters: drift rate, starting point, and boundary separation (indicators for angle and starting point of boundary collapse are omitted). **(B)** Density plot of the drift rate intercept for HC and rMDD groups, showing the distribution of intercept (i.e., the propensity to choose the hard task). **(C)** Density plot showing the effect of reward probability information on drift rate for HC and rMDD groups. **(D)** Density plot of the effect of reward magnitude information on drift rate for HC and rMDD groups. **(E)** Posterior distribution plot indicating the difference between groups in the reward probability information effect on drift rate. **(F)** Posterior distribution plot showing the difference between groups in the reward magnitude effect on drift rate.

(Figure 2D, F) on drift rate toward the high effort option were increased in participants with rMDD at the population level.

The posteriors of the other DDM parameters (i.e., starting point, boundary separation, or the 2 parameters of start and angle of collapse) did not differ meaningfully between groups (data not shown). A supplementary DDM for binned reward magnitude confirms the observations how drift rate varies as a function of reward probability and magnitude (see Supplement; Figure S4).

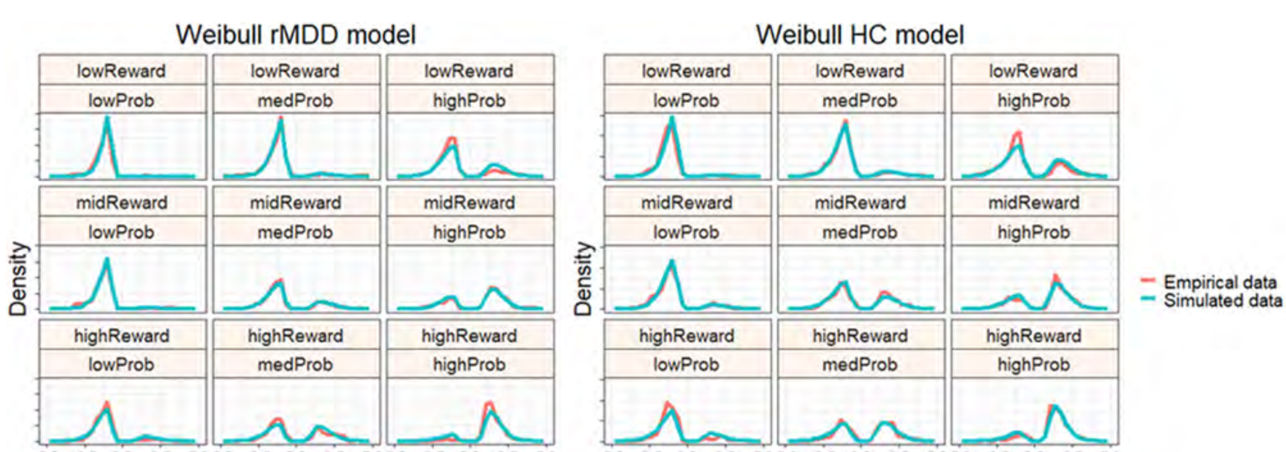


**Figure 3.** Posterior predictive checks (PPCs)—comparison of empirical and simulated data for remitted major depressive disorder (rMDD) and healthy control (HC) groups using Weibull models. PPC density plots comparing empirical data (red) and simulated data (blue) for both rMDD (left panel) and HC (right panel) groups, modeled using Weibull distributions. Each subplot represents combinations of reward magnitude (low, medium, high) and reward probability (low, medium, high). The alignment of empirical and simulated data within each condition indicates a good model fit and the accuracy of the Weibull parameter estimations across different reward probability scenarios for both groups. med, medium; prob, probability.

Notably, there were no significant correlations with the DDM parameters (i.e., drift rate intercept, reward probability sensitivity, reward magnitude sensitivity) and SHAPS.

## Subjective Value Modeling

Across groups, the majority of participants employed a strategy that fully integrated both reward magnitude and probability information (full SVM) ($n$ = 98, 90.7%), while only a few participants chose either a reward-only approach ($n$ = 4, 3.7%) or a probability-only approach ($n$ = 2, 1.9%) or employed no choice strategy based on the task information (bias) ($n$ = 4, 3.7%). A similar pattern was observed within groups (Table 2), and Fisher's exact test indicated that groups did not significantly differ in choice strategy ($p$ = .570).

Follow-up analyses were run to evaluate putative group differences in the 2 model parameters. For $k$, with higher values reflecting higher perceived costs in effort, a multiple regression yielded significant main effects of group, SHAPS, and a group × SHAPS interaction (Table S7). Following up the main effect of group with pairwise comparison of estimated marginal means (corrected for SHAPS) showed no significant difference between HC and rMDD groups (HC emmeans = 1.81, SE = 0.124; rMDD emmeans = 1.70, SE = 0.159; HC-rMDD = 0.117, $p$ = .563). The significant main effect of SHAPS indicated that higher residual anhedonic symptoms are significant predictors of higher perceived costs in effort. For the group × SHAPS interaction effect, simple slope analyses were employed, highlighting a significant difference in the association of $k$ with SHAPS scores between HC and rMDD groups (difference = 0.081, SE = 0.032, $t_{94}$ = 2.55, $p < .012$) (Figure 4A). Specifically, the slope of SHAPS for HC participants was significantly positive ($B$ = 0.047, SE = 0.021, $t_{58}$ = 2.20, $p < .032$), while the slope for participants with rMDD was not significant ($B = -0.034$, SE = 0.022, $t_{36} = -1.55$, $p$ = .129). For $h$, which captures individuals' weighing of the probability information, a significant group difference was observed (2-sample $t$ test: $t_{96}$ = 2.291, $p$ = .024) (Figure 4B), with rMDD demonstrating a higher weight on the probability information. No associations of $h$ emerged with SHAPS.

## Exploration of Convergence Between Modeling Approaches

Because a conceptual convergence between the model parameters from the DDM and the SVM analyses emerged, we explored further targeted hypotheses about parameter convergence. Specifically, exploratory linear regression analyses tested 2 hypotheses: 1) drift rate is negatively predicted by effort discounting ($k$), as higher perceived costs reduce evidence accumulation toward the hard task; and 2) reward probability sensitivity is related to the weight of reward probability in the SVM. Results confirmed that drift rate was significantly negatively predicted by perceived effort cost ($k$), with a trend for a $k$ × group interaction (Table S8). Similarly, individual reward probability weighting ($h$) significantly predicted the probability sensitivity effect on drift rate, with a significant $h$ × group interaction, showing a significant association in the HC group, but not rMDD group (Table S9). See full results in the Supplement.

**Table 2. Distribution of Winning Subjective Value Models by Group**

| Model | HC Group | rMDD Group |
|---|---|---|
| Full SVM | 60 (88.2%) | 38 (95%) |
| Reward-Only | 3 (4.4%) | 1 (2.5%) |
| Probability-Only | 1 (1.5%) | 1 (2.5%) |
| Bias | 4 (5.9%) | 0 (0%) |

Total number (%) of winning subjective value models within each group are reported. Full SVM includes models incorporating both reward and probability; reward-only, models based solely on reward; probability-only, models based solely on probability; and bias, models that include bias without consideration of reward or probability.

HC, healthy control; rMDD, remitted major depressive disorder; SVM, subjective value model.

## DISCUSSION

This study examined motivational and cognitive aspects of decision-making processes underlying effort expenditure in unmedicated individuals with rMDD. While no significant group differences emerged in global task performance metrics (task completion rates, selection reaction times), differences emerged in traditional measures of willingness to expend effort as a function of varying reward probabilities and magnitudes as well as latent decision-making processes identified via computational modeling.

The lack of significant group differences in overall task completion rates and selection reaction times indicate that the cognitive capacity to engage in the task itself was preserved in rMDD. However, this does not imply that motivational factors are equivalent between groups.

Specifically, the group effect in the ANOVA points to a reduced willingness to exert effort in individuals with rMDD, particularly in conditions of ambiguity about receiving the reward. These findings extend prior observations in which medicated individuals with rMDD showed reduced willingness to exert effort, especially when reward is low (17). This blunted response may be driven by residual motivational symptoms (7), although no relation to self-reported levels of anhedonia emerged here (possibly due to a truncated range).

Interestingly, a reduced effort in participants with rMDD was not uniform across reward conditions. While participants with rMDD were less likely to choose hard tasks in the context of moderate reward probability, they showed a higher acceptance rate and greater drift rates in high magnitude/high probability conditions compared with HC participants. This finding suggests that individuals with rMDD retain sensitivity to high value incentives, but require a significantly larger and certain reward to overcome the perceived effort cost, as they may undervalue potential rewards or overvalue the effort required, which could be linked to a persistent blunted sensitivity to reward and diminished motivation (1,3–5,40).

These patterns are supported by the DDM analyses. Both HC participants and participants with rMDD demonstrated increases in drift rate as reward magnitude and probability increased. However, participants with rMDD showed a significantly lower drift rate, indicating a general bias away from selecting the hard task, while the positive effects of reward probability and reward magnitude on drift rate toward the high effort option were increased. While this may seem paradoxical,

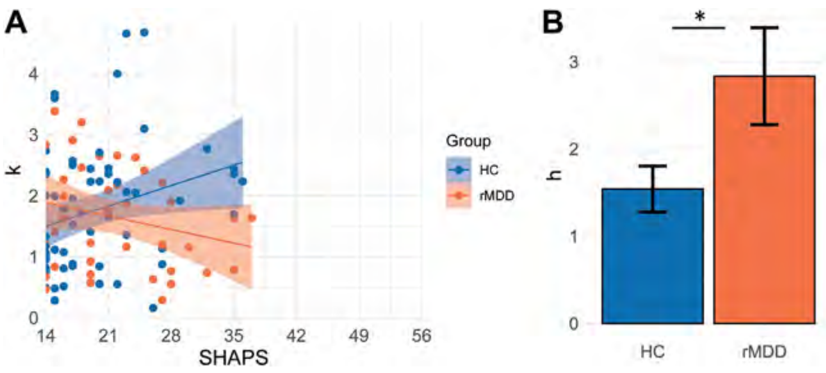


**Figure 4.** Relationship between Snaith-Hamilton Pleasure Scale (SHAPS) scores and model parameter *k* as well as group differences in model parameter *h* for healthy control (HC) and remitted major depressive disorder (rMDD) groups. **(A)** Scatter plot with regression lines showing the relationship between SHAPS scores and the parameter *k* ($n$ = 98). A significant positive association between *k* and SHAPS emerged for the HC group ($B$ = 0.047, SE = 0.021, $t_{58}$ = 2.20, $p$ < .032), while there was no significant association for rMDD ($B$ = −0.034, SE = 0.022, $t_{36}$ = −1.55, $p$ = .129). Shaded areas represent 95% CIs for the regression lines. **(B)** Bar graph comparing the parameter *h* ($n$ = 98) between HC and rMDD groups, demonstrating that the weight on reward probability information is significantly higher in the rMDD group than the HC group ($t_{96}$ = 2.291, $p$ = .024). Error bars represent SE. *$p$ < .05.

it must be considered in light of reduced drift intercept in participants with rMDD indicating that participants with rMDD have a tendency to accumulate evidence away from the high effort option unless the reward benefits are substantial enough. In contrast, HC participants required less incentive to overcome effort costs. In other words, participants with rMDD showed blunted sensitivity to lower levels of reward, but intact sensitivity when reward is high enough, reinforcing the idea that individuals with rMDD require higher incentives to engage in effortful tasks, consistent with an effort-avoidant decision-making strategy.

Finally, SVM analysis revealed that most participants, regardless of group, employed a strategy that integrated both reward magnitude and probability when making decisions about effort expenditure, indicating an absence of cognitive deficits in rMDD for the use of such information. However, participants with rMDD demonstrated a higher weight on probability information than HC participants, in line with the ANOVA and DDM findings, which identified a higher probability sensitivity for effort expenditure decisions. This again suggests that participants with rMDD may place greater emphasis on the likelihood of receiving a reward when deciding whether to exert effort and a heightened sensitivity to certainty, where the prospect of a guaranteed outcome may serve as a stronger motivator compared with HC participants.

Notably, only HC participants exhibited higher perceived costs of effort in relation to SHAPS scores, indicating that anhedonia shapes effort-based decisions. The absence of a significant SHAPS effect on probability sensitivity in rMDD suggests that while they show altered effort-cost computations, their ability to factor in probability remains relatively intact. Further, this observation is intriguing because no associations with SHAPS and parameters from the DDM emerged, which suggests that these models may in fact capture distinct processes, with anhedonia potentially exerting differential effects on the specific aspects of decision making assessed by each approach.

Our findings have important implications for understanding the lingering motivational deficits in individuals with rMDD. The reduced willingness to expend effort for moderate rewards suggests that motivational impairments may persist even when other symptoms of depression, such as mood and cognitive functioning, have improved. Future research should further explore the underlying mechanisms, particularly the role of neurobiological systems implicated in reward processing. Additionally, longitudinal studies should determine whether these motivational deficits persist over time or fluctuate with depressive symptoms. This study further highlights that computational modeling approaches are valuable tools. Specifically, findings that drift rate negatively predicted effort discounting and reward probability sensitivity were related to the weight an individual placed on reward probability in the HC group (but not rMDD group) point to residual impairments in reward processing, cognitive flexibility, and neural circuitry in rMDD.

Some limitations should be noted. First, the exclusion of medicated individuals limits generalizability. It is possible that our sample reflects a healthier subpopulation of individuals with rMDD who do not require maintenance treatment to remain in remission. Second, the observed behavioral pattern might reflect a self-selection bias, with individuals exhibiting a more favorable motivational profile (which contributed to their participation). Third, the EEfRT task does not capture all phases of motivation (e.g., anticipation vs. consumption). Future studies could include paradigms parsing these components to gain a more comprehensive understanding of motivational impairments. Fourth, the truncated range of SHAPS scores may have limited our ability to detect relationships between anhedonia and effort-based decision making. Finally, while our findings suggest an association between motivational deficits and altered reward-cost computations, we were unable to test their direct impact on functional impairment or clinical course due to data limitations.

Taken together, our results have potential implications for treatment approaches, as current interventions may need to be supplemented with strategies specifically targeting motivational deficits, such as behavioral activation or reward-based interventions (41) to fully restore functional capacity. Moreover, the heightened sensitivity to reward magnitude and probability in participants with rMDD highlights the potential for leveraging high-value incentives in therapeutic contexts. Interventions that emphasize clear and substantial rewards may be more effective in motivating individuals with a history of depression to engage in effortful activities, potentially aiding in relapse prevention.

## ACKNOWLEDGMENTS AND DISCLOSURES

This work was partially supported by the National Institute of Mental Health (Grant Nos. P50MH119467 and R01 4R37MH068376-17 [to DAP]. The funders had no role in study design, data collection, or analysis.

These data were presented as a poster at the Anxiety and Depression Association of America 2024 Annual Conference, April 11–14, 2024, Boston, Massachusetts, and as an oral presentation at the 49th Annual Conference "Psychology and Brain," May 29 to June 1, 2024, Hamburg, Germany.

Over the past 3 years, DAP has received consulting fees from Boehringer Ingelheim, Compass Pathways, Engrail Therapeutics, Neumora Therapeutics (formerly BlackThorn Therapeutics), Neurocrine Biosciences, Neuroscience Software, Sage Therapeutics, Sama Therapeutics, and Takeda; he has received honoraria from the American Psychological Association, Psychonomic Society, and Springer (for editorial work) and from Alkermes; he has received research funding from the Israel-United States Binational Industrial Research and Development Foundation, Brain and Behavior Research Foundation, Dana Foundation, Defense Advanced Research Projects Agency, Millennium Pharmaceuticals, National Institute of Mental Health, and Wellcome Leap MCPsych; he has received stock options from Compass Pathways, Engrail Therapeutics, Neumora Therapeutics, and Neuroscience Software. MJF has received consulting fees from Boehringer Ingelheim, Gilgamesh Pharmaceuticals, and F. Hoffmann-La Roche. No funding from these entities was used to support the current work, and all views expressed are solely those of the authors. All other authors report no biomedical financial interests or potential conflicts of interest.

## ARTICLE INFORMATION

From the Center for Depression, Anxiety, and Stress Research, McLean Hospital, Belmont, Massachusetts (MK, EHP, JMB, DCS, YL, GN, DAP); Department of Psychiatry, Harvard Medical School, Cambridge, Massachusetts (MK, GP, DAP); Carney Institute for Brain Science, Department of Cognitive and Psychological Sciences, Brown University, Providence, Rhode Island (GP, MJF); Department of Psychology, Emory University, Atlanta, Georgia (JAC); and Department of Psychiatry and Behavioral Sciences, Emory University School of Medicine, Atlanta, Georgia (MTT).

Address correspondence to Diego A. Pizzagalli, Ph.D., at dap@mclean.harvard.edu.

Received Sep 16, 2024; revised Feb 12, 2025; accepted Feb 15, 2025.

Supplementary material cited in this article is available online at https://doi.org/10.1016/j.bpsc.2025.02.006.

## REFERENCES

1. Pizzagalli DA (2014): Depression, stress, and anhedonia: Toward a synthesis and integrated model. Annu Rev Clin Psychol 10:393–423.
2. Halahakoon DC, Kieslich K, O'Driscoll C, Nair A, Lewis G, Roiser JP (2020): Reward-processing behavior in depressed participants relative to healthy volunteers: A systematic review and meta-analysis. JAMA Psychiatry 77:1286.
3. Pechtel P, Dutra SJ, Goetz EL, Pizzagalli DA (2013): Blunted reward responsiveness in remitted depression. J Psychiatr Res 47:1864–1869.
4. Whitton AE, Kakani P, Foti D, Van't Veer A, Haile A, Crowley DJ, Pizzagalli DA (2016): Blunted neural responses to reward in remitted major depression: A high-density event-related potential study. Biol Psychiatry Cogn Neurosci Neuroimaging 1:87–95.
5. Treadway MT, Zald DH (2011): Reconsidering anhedonia in depression: Lessons from translational neuroscience. Neurosci Biobehav Rev 35:537–555.
6. Treadway MT, Bossaller NA, Shelton RC, Zald DH (2012): Effort-based decision-making in major depressive disorder: A translational model of motivational anhedonia. J Abnorm Psychol 121:553–558.
7. Treadway MT, Buckholtz JW, Schwartzman AN, Lambert WE, Zald DH (2009): Worth the 'EEfRT'? The effort expenditure for rewards task as an objective measure of motivation and anhedonia. PLoS One 4: e6598.
8. Yang X, Huang J, Zhu C, Wang Y, Cheung EFC, Chan RCK, Xie G (2014): Motivational deficits in effort-based decision making in individuals with subsyndromal depression, first-episode and remitted depression patients. Psychiatry Res 220:874–882.
9. Zou YM, Ni K, Wang YY, Yu EQ, Lui SSY, Zhou FC, *et al.* (2020): Effort-cost computation in a transdiagnostic psychiatric sample: Differences among patients with schizophrenia, bipolar disorder, and major depressive disorder. Psych J 9:210–222.
10. Bustamante LA, Barch DM, Solis J, Oshinowo T, Grahek I, Konova AB, *et al.* (2024): Major depression symptom severity associations with willingness to exert effort and patch foraging strategy. Psychol Med 54:4396–4407.
11. Tran T, Hagen AEF, Hollenstein T, Bowie CR (2021): Physical- and cognitive-effort-based decision-making in depression: Relationships to symptoms and functioning. Clin Psychol Sci 9:53–67.
12. Slaney C, Perkins AM, Davis R, Penton-Voak I, Munafò MR, Houghton CJ, Robinson ESJ (2023): Objective measures of reward sensitivity and motivation in people with high v. low anhedonia. Psychol Med 53:4324–4332.
13. Culbreth AJ, Moran EK, Mahaphanit W, Erickson MA, Boudewyn MA, Frank MJ, *et al.* (2024): A transdiagnostic study of effort-cost decision-making in psychotic and mood disorders. Schizophr Bull 50:339–348.
14. Treadway MT, Salamone JD (2022): Vigor, effort-related aspects of motivation and anhedonia. In: Pizzagalli DA, editors, Anhedonia: Preclinical, Translational, and Clinical Integration, vol. 58. Cham: Springer International Publishing, 325–353.
15. Barch DM, Culbreth AJ, Ben Zeev D, Campbell A, Nepal S, Moran EK (2023): Dissociation of cognitive effort–based decision making and its associations with symptoms, cognition, and everyday life function across schizophrenia, bipolar disorder, and depression. Biol Psychiatry 94:501–510.
16. Yang X, Huang J, Harrision P, Roser ME, Tian K, Wang D, Liu G (2021): Motivational differences in unipolar and bipolar depression, manic bipolar, acute and stable phase schizophrenia. J Affect Disord 283:254–261.
17. Berwian IM, Wenzel JG, Collins AGE, Seifritz E, Stephan KE, Walter H, Huys QJM (2020): Computational mechanisms of effort and reward decisions in patients with depression and their association with relapse after antidepressant discontinuation. JAMA Psychiatry 77:513.
18. McCabe C, Mishor Z, Cowen PJ, Harmer CJ (2010): Diminished neural processing of aversive and rewarding stimuli during selective serotonin reuptake inhibitor treatment. Biol Psychiatry 67:439–445.
19. Eaton WW, Shao H, Nestadt G, Lee BH, Bienvenu OJ, Zandi P (2008): Population-based study of first onset and chronicity in major depressive disorder. Arch Gen Psychiatry 65:513–520.
20. Ging-Jehli NR, Kuhn M, Blank JM, Chanthrakumar P, Steinberger DC, Yu Z, *et al.* (2024): Cognitive signatures of depressive and anhedonic symptoms, and affective states, using computational modeling and neurocognitive testing. Biol Psychiatry Cogn Neurosci Neuroimaging 9:726–736.
21. Wiecki TV, Sofer I, Frank MJ (2013): HDDM: hierarchical Bayesian estimation of the drift-diffusion model in Python. Front Neuroinform 7:14.
22. Pedersen ML, Ironside M, Amemori K, McGrath CL, Kang MS, Graybiel AM, *et al.* (2021): Computational phenotyping of brain-behavior dynamics underlying approach-avoidance conflict in major depressive disorder. PLoS Comput Biol 17:e1008955.
23. Milosavljevic M, Malmaud J, Huth A, Koch C, Rangel A (2010): The drift diffusion model can account for the accuracy and reaction time of value-based choices under high and low time pressure. Judgm Decis Mak 5:437–449.
24. Soutschek A, Nadporozhskaia L, Christian P (2022): Brain stimulation over dorsomedial prefrontal cortex modulates effort-based decision making. Cogn Affect Behav Neurosci 22:1264–1274.

25. Saleh Y, Le Heron C, Petitet P, Veldsman M, Drew D, Plant O, *et al.* (2021): Apathy in small vessel cerebrovascular disease is associated with deficits in effort-based decision making. Brain 144:1247–1262.
26. Pagnier GJ, Asaad WF, Frank MJ (2024): Double dissociation of dopamine and subthalamic nucleus stimulation on effortful cost/benefit decision making. Curr Biol 34:655–660.e3.
27. Cooper JA, Barch DM, Reddy LF, Horan WP, Green MF, Treadway MT (2019): Effortful goal-directed behavior in schizophrenia: Computational subtypes and associations with cognition. J Abnorm Psychol 128:710–722.
28. van Buuren S, Groothuis-Oudshoorn K (2011): mice: Multivariate Imputation by Chained Equations in R. J Stat Softw 45:1–67.
29. Trøstheim M, Eikemo M, Meir R, Hansen I, Paul E, Kroll SL, *et al.* (2020): Assessment of anhedonia in adults with and without mental illness: A systematic review and meta-analysis. JAMA Netw Open 3: e2013233.
30. Renz KE, Schlier B, Lincoln TM (2023): Are effort-based decision-making tasks worth the effort?—A study on the associations between effort-based decision-making tasks and self-report measures. Int J Methods Psychiatr Res 32:e1943.
31. R Development Core Team (2024): R: A language and environment for statistical computing. Available at: https://www.r-project.org/. Accessed December 9, 2022.
32. Singmann H, Bolker B, Westfall J, Aust F, Ben-Shachar MS (2024): afex: Analysis of factorial experiments. Available at: https://CRAN.R-project.org/package=afex. Accessed April 23, 2023.
33. Lenth RV (2024): emmeans: Estimated marginal means, aka least-squares means Available at: https://CRAN.R-project.org/package=emmeans. Accessed July 1, 2024.
34. Bates D, Mächler M, Bolker B, Walker S (2015): Fitting linear mixed-effects models using lme4. J Stat Softw 67:1–48.
35. Wiecki TV, Poland J, Frank MJ (2015): Model-based cognitive neuroscience approaches to computational psychiatry: clustering and classification. Clin Psychol Sci 3:378–399.
36. Wiecki TV, Antoniades CA, Stevenson A, Kennard C, Borowsky B, Owen G, *et al.* (2016): A computational cognitive biomarker for early-stage Huntington's disease. PLoS One 11:e0148409.
37. Fengler A, Govindarajan LN, Chen T, Frank MJ (2021): Likelihood approximation networks (LANs) for fast inference of simulation models in cognitive neuroscience. eLife 10:e65074.
38. Fengler A, Bera K, Pedersen ML, Frank MJ (2022): Beyond drift diffusion models: fitting a broad class of decision and reinforcement learning models with HDDM. J Cogn Neurosci 34:1780–1805.
39. Kruschke JK (2015): Doing Bayesian Data Analysis: A Tutorial with R, JAGS, and Stan, Second Edition Waltham, MA: Academic Press.
40. Pizzagalli DA, Iosifescu D, Hallett LA, Ratner KG, Fava M (2008): Reduced hedonic capacity in major depressive disorder: evidence from a probabilistic reward task. J Psychiatr Res 43:76–87.
41. Richards DA, Ekers D, McMillan D, Taylor RS, Byford S, Warren FC, *et al.* (2016): Cost and Outcome of Behavioural Activation versus Cognitive Behavioural Therapy for Depression (COBRA): a randomised, controlled, non-inferiority trial. Lancet 388:871–880.

# SUPPLEMENTARY INFORMATION

# Computational Phenotyping of Effort-Based Decision Making in Unmedicated Adults With Remitted Depression

Kuhn *et al.*

# Supplementary Methods

## Inclusion and exclusion criteria for participants

Participants were screened by a masters or PhD-level clinician using the Structured Clinical Interview for DSM-5 Research Version (SCID-5-RV; (1)). Based on criteria from our prior work (e.g., 2–4), participants met criteria for rMDD if they had experienced at least one major depressive episode in the past five years and if their depression was in remission for at least two months prior to the screening session. In addition, clinical scores had to be below the following thresholds: Beck Depression Inventory–II (BDI-II; (5)) ≤ 9; Quick Inventory of Depression Symptomatology (QIDS; (6)) ≤ 5; Hamilton Rating Scale for Depression (HRSD-17; (20)) ≤ 7 as well as no more than two symptoms of depression reported to more than a mild degree [SCID-5-RV rating of 2] in the eight weeks prior to testing. Accordingly, depressed mood and anhedonia symptoms had to be rated 1 on the SCID, excluding even subthreshold level of depressed mood and anhedonia for rMDD. All participants were unmedicated. Among the rMDD participants with usable task data (see below), 50% (N=20) had never received any antidepressant medication. The other half were off medication for at least two weeks before the screening session (six weeks for fluoxetine) and, on average, this sample was off medication for 29.3 months (range: 2 weeks to 113 months) before testing. Participants were classified as HCs if they had no current or past psychiatric illness. Exclusion criteria for the full sample were current or past serious medical illness, current comorbid psychiatric disorders, first-degree relatives with a history of a psychotic disorder or psychotic symptoms outside of the context of a mood disorder, current use of psychoactive drugs, and more than 15 alcohol-induced blackouts.

## Effort Expenditure for Rewards Task (EEfRT)

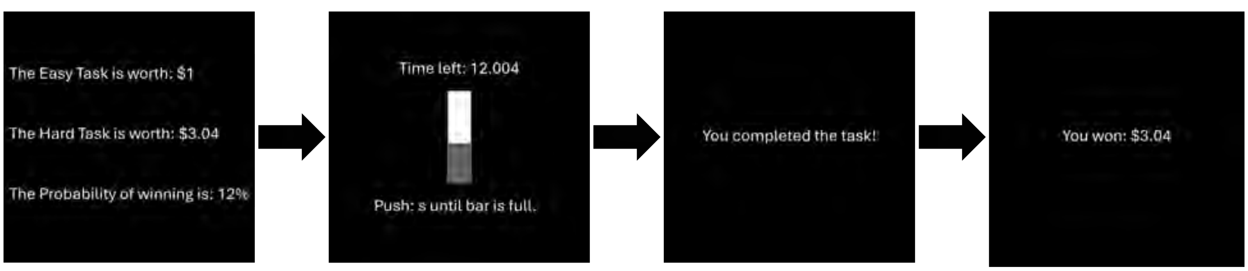


**Figure S1. Schematic Overview of the Effort Expenditure for Rewards Task (EEfRT) Trial Structure.** Illustrated is the structure of a single example trial. Initially, reward and probability information are displayed, indicating for this example the values for the easy task ($1) and the hard task ($3.04) with a 12% probability of winning. Participants have 4 seconds to select a task, after which a task is randomly assigned if no selection is made. The task involves repeatedly pressing a button to fill a progress bar within a specified time limit (7 seconds for the easy task, 21 seconds for the hard task). Upon task completion, participants receive feedback on their performance and whether they earned the reward.

## Generalized linear mixed-effects model

To analyze the interaction effects of Group, Reward Probability, and the continuous measures of Reward Magnitude on the binary outcome variable Choice (to select the hard trial), we employed a generalized linear mixed-effects model using the glmer function from the lme4 package in R. The model was specified with a binomial family to account for the dichotomous dependent variable. The formula for the model was:

Choice ~ Group × Reward Probability × Reward Magnitude + (1|ID)

Fixed effects: The interaction between Group, Reward Probability, and Reward was tested to assess their combined influence on the outcome variable.

Random effects: A random intercept for ID was included to account for within-subject variability, recognizing that observations from the same individual are not independent.

We utilized the anova function from the car package to conduct a Type III Wald chi-square test. This method evaluates the significance of each fixed effect (main effects, two-way interactions, and the three-way interaction) while controlling for all other effects in the model.

**Hierarchical Bayesian Drift Diffusion Modeling**

Two separate Weibull models were fit for data of each group, respectively. The following HDDM equation was used:

$[v \sim 1 \ + \ hardRewardAmountZScore + RewardProbZScore', 'a{\sim}1', 'z{\sim}1', 't{\sim}1', 'alpha{\sim}1', 'beta{\sim}1']$.

Alpha and beta correspond to the Weibull-specific parameters that dictate the time at which the boundary starts to collapse (alpha) and the degree of collapse (beta). Because the effort level does not change on a trial-by-trial basis, effort is not included as a trial-by-trial regressor but is considered in the intercept. Other parameters varying by 1 allow to assess group-level distributions of these parameters.

*Supplementary DDM for binned reward magnitude*

While the above DDM (**Figure 3** in main text) is the best performing model for describing participants' empirical behavior, an additional DDM binning reward magnitude and reward probability was fit separately to the HC and rMDD groups to visually see how reward magnitude and reward probability interact with the drift rate intercept. This DDM allowed drift rate (v) to vary by three parameters: a group intercept, three levels of reward magnitude (categorized as low: $1.24-$2.00, medium: $2.01-$3.00, high: $3.01-$4.12) and three levels of reward probability. 4 chains each of length 1000 were run for each group and convergence was assessed via visually inspecting parameter traces and confirming the Gelman-Rubin statistic was 1.1 or below for all parameters.

**Subjective Value Modeling**

Following the approach of Cooper et al. (7), the following models were included:

*Model 1: Full SV Model*

A full SV model is best suited for participants who consistently consider both trial-wise reward and probability information when deciding how much effort to exert. In this model, the subjective value (SV) of a given trial is determined by taking the objective reward, R (ranging from $1 to $4.30), and probability information, P, and reducing it by the required effort (easy, hard), E. The individual difference in how much reward should be discounted by effort is captured by the free parameter weights in the SVF equation:

$$Full\ Subjective\ Value\ model\ (SVF)\!: SV = R\ \times P^h - kE.$$

Effort which is perceived as highly costly is leads to a higher value of $k$, while the weighting of probability is represented by the value of $h$. SVs are then transformed into probabilities of selecting each option using the Softmax decision rule (8), where $t$ is an inverse temperature parameter that indicates a tendency to prefer options with higher SVs:

$$p(hard) = \frac{e^{SVhard \cdot t}}{e^{SVhard \cdot t} + e^{SVeasy \cdot t}}$$

Taken together, the full SV model fit to the data includes three free parameters: $k$, $h$, and $t$. As such, the $k$ parameter reduces subjective value based on the effort required, the $h$ parameter adjusts subjective value according to the probability of receiving the reward, and the $t$ parameter influences choices towards options with higher SV.

Additionally, following the approach of Cooper et al. (7) some participants might be better described by a SVF model that does not distort probability (i.e., the free parameter $h$ held constant at 1). These participants may be overpenalized for the additional free parameter $h$ and accordingly, an alternative variant of the SVF model with $h$ constrained to 1 was fit to avoid overpenalization. Participants best fit by either the SVF model with a flexible $h$ parameter or the SVF model with $h$ fixed at 1 are included in the SVF model group, because this fit indicates that they integrate all information of reward, effort, and probability in their decision-making.

*Model 2: Reward-Only SV Model*

A simpler model was for participants who base their effort solely on the available rewards. This model does not include a parameter for scaling probability information. The reward-only SV model is similar to the SVF model but assumes that $h$ is zero, removing the probability information from the equation:

$$Reward - Only\ SV\ model: SV = R - kE.$$

The reward-only SV model and the SVF model both describe behavior for participants who do not significantly modulate their responses based on probability but still systematically guide their effort allocation based on reward magnitude. Note that while this model and the SVF model with $h$ set to 1 both have $h$ fixed and therefore the same number of free parameters, their interpretations differ significantly. Setting $h$ to 0 indicates choice behavior that does not consider the probability of receiving the reward, whereas setting h to 1 reflects probability information to influence subjective value.

*Model 3: Probability-Only SV Model*

We also included a model that based valuation only on probability of reward receipt. For this model, the value of the low effort option was held constant at 0.5, while the value of the high effort option was dependent on the probability value of the current trial:

$$Probability - Only\ SV\ model: SV = P \times h.$$

The value of the high and low effort option was transformed into probabilities of taking each option using the Softmax equation. This model does not include trial-wise reward information and is thus able to capture behavior of participants who are relatively insensitive to reward information but show differences in willingness to exert effort based on the probability of reward receipt.

*Model 4: Bias Model*

The bias model provides a better fit than the SV models for participants who consistently favor one option, respond randomly, or make choices that do not align with the assumptions of the SV models (e.g., favoring effort allocation for low reward). This model includes one free parameter, b, which represents a bias towards the low-effort option. The probability of selecting the high-effort option is therefore:

$$\text{Bias model: } p(hard) = 1 - \text{c.}$$

The bias model assumes that participants disregard the information of probability or reward leading to a consistent probability of choosing the low-effort option across trials.

*Model fitting procedure and group comparison*

All three models were fit to individuals' data in MATLAB (MATLAB R2020a with statistics toolbox). A maximum likelihood estimation was performed using fminsearch as the optimization function. Model parameters were fit to optimize the behavioral data for each participant. Following Cooper et al. (7), two variants of the full subjective model were fit with k, capturing perceived effort, being estimated freely in both variants and h, capturing probability, to either be estimated freely or set to 1. k and h parameters were constrained to values between 0 and 10 for the subjective value models and t was constrained between 0 and 100. All models were fit with 200 random parameter initializations. The Bayesian information criterion (BIC) (9) was used for model comparisons. By incorporating the goodness of fit, number of free parameters (which differ between models), and the number of observations, the BIC accounts for differences in model and model complexity, penalizing complex models when log-likelihood is similar. After model fitting, BIC values were compared across models and participants were assigned the model with the lowest BIC.

After individual model fitting, to analyze whether there was an association between group (i.e., rMDD/HC) and choice strategy, a Fisher's exact test using the Freeman-Halton (10) extension was conducted. This test was chosen because observed counts in four out of the six categories failed to meet the minimum number of observations (i.e., at least 5) required for conducting a chi-squared test.

## Supplementary Results

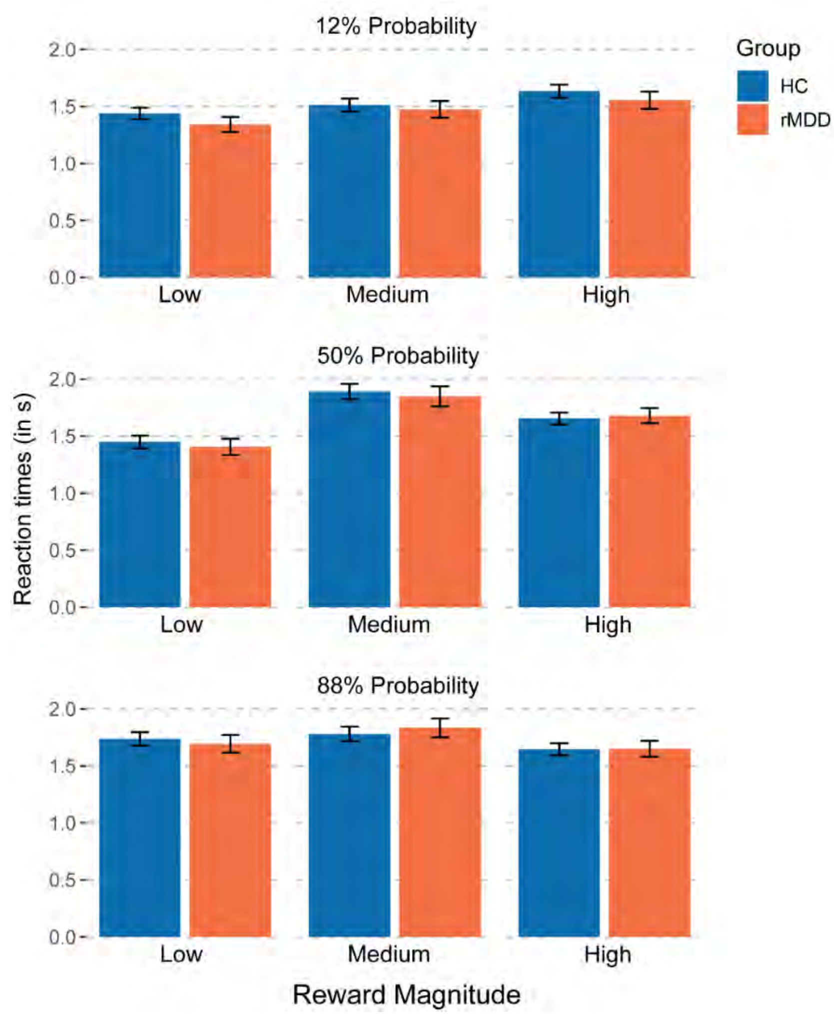


**Figure S2. Estimated Marginal Means of Reaction Times for Different Reward Magnitudes and Probabilities.** Reaction times (in seconds) are displayed for healthy controls (HC) and individuals with remitted Major Depressive Disorder (rMDD) across three levels of reward magnitude (low, medium, high) and three levels of reward probability (12%, 50%, 88%). Error bars represent standard errors of the mean. No significant pair-wise differences between the HC and rMDD groups were observed across any of the conditions.

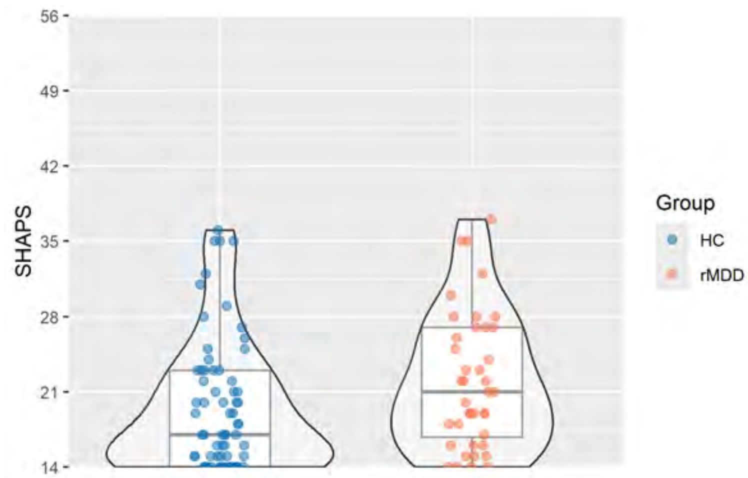


**Figure S3. Distribution Snaith-Hamilton Pleasure Scale (SHAPS) Scores.** Distribution of SHAPS (N=108) scores, displayed at the full ranges of possible scores (14-56).

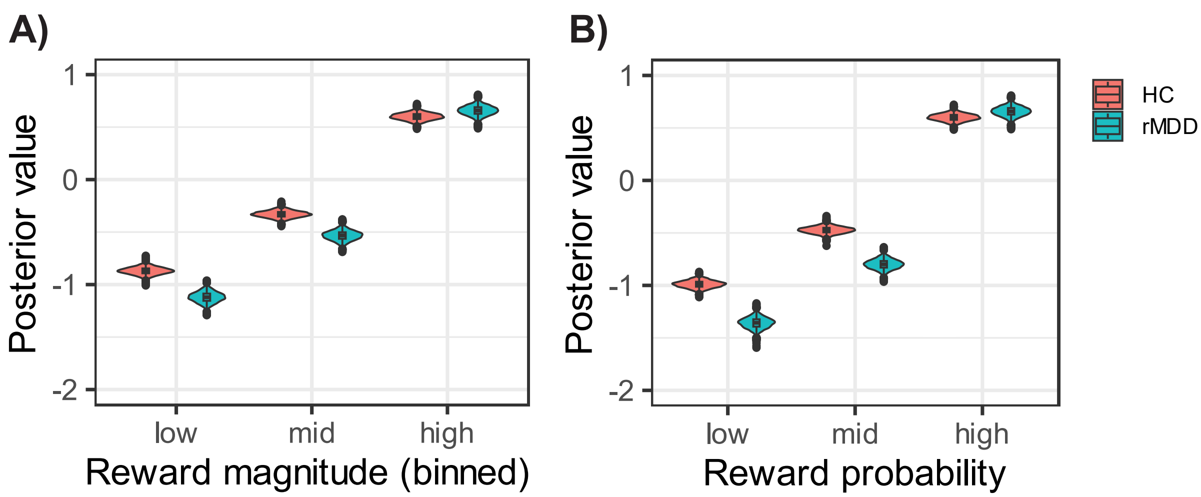


**Figure S4. Drift rate posteriors as a function of reward magnitude and probability.** Drift rate posterior values for binned reward magnitude A) and reward probability B). Violin plots represent the entire estimated Bayesian posterior for each of the respective parameters. The intercept was estimated in the high magnitude/high probability condition with additional parameters estimating the effect of low and mid magnitude/probability bins on the drift rate. HC and rMDD groups were fit with separate models.

## Control analyses accounting for anhedonic symptoms

Because anhedonia plays a central role in MDD and SHAPS scores were significantly different between rMDD and HC, a control analysis was performed for the omnibus repeated measures ANOVA including self-reported SHAPS as covariate. Results revealed a similar pattern to the results without SHAPS as covariate. However, the Group main effect was reduced to a trend ($p=0.057$, **Table S5**). Notably, there was no effect of SHAPS on the significant three-way interaction. Compared to the model not correcting for SHAPS, follow-up pairwise ANOVAs showed an equivalent pattern when including SHAPS as covariate into the model, with the only change for the significant low-reward/medium-probability group difference being reduced to a trend ($p=0.053$, **Table S6**).

## Exploration of convergence between modeling approaches

Explorative analyses probed the targeted hypotheses that a) drift rate is negatively predicted by the discounting of effort, k, as higher perceived cost would diminish evidence accumulation towards the hard task and b) an increased reward probability sensitivity would be predicted by an increased weight of reward probability information in the SVM. To test these hypotheses, multiple linear regression models were performed (for subjects with SVF as the winning model, N=98) including *Group* as factor because both drift rate and reward probability sensitivity differed between groups in separate DDM analyses. Results showed in fact that a mean drift rate was significantly negatively predicted by k ($p<0.001$, **Table S8**), demonstrating a higher perception of effort cost leading to a reduced evidence accumulation towards the hard task. In addition, and as observed in the separate DDM approach, *Group* predicted differences in drift rate ($p<0.001$) while a trend for an interaction of *Group* and k ($p<0.060$) was observed. Similarly, h, significantly predicted the reward probability sensitivity effect on drift rate ($p<0.001$, **Table S9**), indicating that the higher the probability information is weighted in the SVM approach, the more impact the probability information has on evidence accumulation towards the hard task. Again, as observed in the separate DDM analyses, *Group* predicted differences in the effect of reward probability sensitivity on drift rate ($p=0.036$). Notably, a significant *Group* by h interaction ($p=0.007$) was observed indicating that this relationship might be different in both groups with simple slopes analyses indicating a significant relationship in HC ($p=0.004$) while not being significant in rMDD ($p=0.967$).

## Supplementary Tables

**Table S1.** *Full ANOVA: ratio of hard easy task choices.*

| Predictor | $df_{Num}$ | $df_{Den}$ | $F$ | $p$ | $\eta_p^2$ |
|---|---|---|---|---|---|
| Group | 1.00 | 106.00 | 4.04 | .047* | 0.037 |
| Probability | 1.65 | 174.73 | 242.18 | <.001*** | 0.696 |
| Reward Magnitude | 1.95 | 207.02 | 291.96 | <.001*** | 0.102 |
| Group x Probability | 1.65 | 174.73 | 2.43 | .102 | 0.734 |
| Group x Reward Magnitude | 1.95 | 207.02 | 2.64 | .075 | 0.024 |
| Probability x Reward Magnitude | 3.28 | 347.50 | 66.12 | <.001*** | 0.384 |
| Group x Probability x Reward Magnitude | 3.28 | 347.50 | 3.79 | .009** | 0.035 |

*Note.* $df_{Num}$ indicates degrees of freedom numerator. $df_{Den}$ indicates degrees of freedom denominator. Greenhouse-Geisser correction applied where necessary. *<.05, **<.01, ***<.001

**Table S2.** *ANOVAs split by Reward Probability: ratio of hard easy task choices.*

| Predictor | $df_{Num}$ | $df_{Den}$ | $F$ | $p$ | $\eta_p^2$ |
|---|---|---|---|---|---|
| *Low Probability* | | | | | |
| Group | 1.00 | 106.00 | 3.49 | .065 | 0.032 |
| Reward Magnitude | 1.85 | 196.48 | 16.34 | <.001*** | 0.134 |
| Group x Reward Magnitude | 1.85 | 196.48 | 1.46 | .234 | 0.014 |
| *Medium Probability* | | | | | |
| Group | 1.00 | 106.00 | 7.19 | .009** | 0.063 |
| Reward Magnitude | 1.83 | 193.65 | 113.98 | <.001*** | 0.518 |
| Group x Reward Magnitude | 1.83 | 193.65 | 1.63 | .201 | 0.015 |
| *High Probability* | | | | | |
| Group | 1.00 | 106.00 | 0.27 | .607 | 0.003 |
| Reward Magnitude | 1.98 | 209.88 | 243.26 | <.001*** | 0.696 |
| Group x Reward Magnitude | 1.98 | 209.88 | 5.39 | .005** | 0.048 |

*Note.* $df_{Num}$ indicates degrees of freedom numerator. $df_{Den}$ indicates degrees of freedom denominator. Greenhouse-Geisser correction applied where necessary. *<.05, **<.01, ***<.001 All significant effects remain after Bonferroni correction for multiple comparisons (i.e., p=0.0167).

**Table S3**: Results of the binomial generalized linear mixed-effects model assessing the main and interaction effects of Group, Reward Probability, and the continuous measures of Reward Magnitude on the binary outcome variable Choice (to select the hard trial).

| Effect | $\chi^2$ | *df* | *p* |
|---|---|---|---|
| (Intercept) | 131.41 | 1 | <0.001*** |
| Group | 2.12 | 1 | 0.145 |
| Reward Probability | 1.65 | 2 | 0.439 |
| Reward Magnitude | 38.96 | 1 | <0.001*** |
| Group x Reward Probability | 1.71 | 2 | 0.426 |
| Group x Reward Magnitude | 0.25 | 1 | 0.614 |
| Reward Probability x Reward Magnitude | 44.60 | 2 | <0.001*** |
| Group x Reward Probability x Reward Magnitude | 9.10 | 2 | 0.011* |

**Table S4.** Full ANOVA: hard easy task choice reaction times.

| Predictor | $df_{Num}$ | $df_{Den}$ | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|---|
| Group | 1.00 | 106.00 | 0.14 | .704 | 0.001 |
| Probability | 1.85 | 196.38 | 39.03 | <.001*** | 0.269 |
| Reward Magnitude | 1.96 | 208.02 | 35.39 | <.001*** | 0.250 |
| Group x Probability | 1.85 | 196.38 | 1.04 | .351 | 0.010 |
| Group x Reward Magnitude | 1.96 | 208.02 | 0.61 | .541 | 0.006 |
| Probability x Reward Magnitude | 3.49 | 369.82 | 21.23 | <.001*** | 0.167 |
| Group x Probability x Reward Magnitude | 3.49 | 369.82 | 0.40 | .780 | 0.004 |

*Note.* $df_{Num}$ indicates degrees of freedom numerator. $df_{Den}$ indicates degrees of freedom denominator. Greenhouse-Geisser correction applied where necessary. *<.05, **<.01, ***<.001

**Table S5.** *Full ANOVA including SHAPS as covariate: ratio of hard easy task choices.*

| Predictor | $df_{Num}$ | $df_{Den}$ | $F$ | $p$ | $\eta_p^2$ |
|---|---|---|---|---|---|
| Group | 1.00 | 103.00 | 3.89 | 0.057 | 0.034 |
| SHAPS | 1.00 | 103.00 | 0.02 | 0.892 | <0.001 |
| Probability | 1.63 | 167.79 | 23.97 | <.001*** | 0.182 |
| Reward Magnitude | 2.00 | 206.00 | 20.33 | <.001*** | 0.166 |
| Group x Probability | 1.63 | 167.79 | 2.62 | 0.116 | 0.021 |
| SHAPS x Probability | 1.63 | 167.79 | 0.21 | 0.810 | 0.002 |
| Group x Reward Magnitude | 2.00 | 206.00 | 2.32 | 0.086 | 0.023 |
| SHAPS x Reward Magnitude | 2.00 | 206.00 | 0.20 | 0.837 | 0.002 |
| Probability x Reward Magnitude | 3.26 | 335.41 | 6.26 | <.001*** | 0.053 |
| Group x Probability x Reward Magnitude | 3.26 | 335.41 | 3.57 | 0.017* | 0.031 |
| SHAPS x Probability x Reward Magnitude | 3.26 | 335.41 | 0.61 | 0.663 | 0.005 |

*Note.* $df_{Num}$ indicates degrees of freedom numerator. $df_{Den}$ indicates degrees of freedom denominator. Greenhouse-Geisser correction applied where necessary. *<.05, **<.01, ***<.001.

**Table S6.** Pairwise comparisons (HC – rMDD) based on estimated marginal means, corrected for SHAPS scores.

| Reward Magnitude | Probability | Mean Difference | Std. Error | Sig.[a] | 95% Confidence Interval for Difference[a] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| low | low | 0.011 | 0.023 | 0.640 | -0.035 | 0.056 |
| | medium | 0.054 | 0.027 | 0.053 | -0.001 | 0.108 |
| | high | 0.051 | 0.051 | 0.325 | -0.051 | 0.12 |
| Medium | low | 0.081 | 0.037 | 0.031* | 0.008 | 0.154 |
| | medium | 0.135 | 0.057 | 0.019* | 0.022 | 0.247 |
| | high | 0.096 | 0.076 | 0.210 | -0.055 | 0.246 |
| High | low | 0.075 | 0.049 | 0.129 | -0.022 | 0.172 |
| | medium | 0.133 | 0.065 | 0.042* | 0.005 | 0.262 |
| | high | -0.085 | 0.041 | 0.042* | -0.167 | -0.003 |

*Note:* Based on estimated marginal means. *<.05, **<.01, ***<.001.

**Table S7.** *Multiple regression predicting k of the Full SV model by Group and SHAPS.*

| Predictor | *Estimate* | 95% CI | *p* |
|---|---|---|---|
| Intercept | 0.83 | 0.02 – 1.66 | 0.08* |
| Group [rMDD] | 1.56 | 0.16 – 2.95 | 0.029* |
| SHAPS | 0.05 | 0.01 – 0.09 | 0.021* |
| Group [rMDD] * SHAPS | -0.08 | -0.14 – -0.02 | 0.012* |

*Note.* Observations 98; $R^2$ = 0.077; $R^2$ adjusted = 0.047; *<.05, **<.01, ***<.001

**Table S8.** *Multiple regression predicting DDM drift rate by SVM k and Group.*

| Predictor | *Estimate* | 95% CI | *p* |
|---|---|---|---|
| Intercept | 0.21 | 0.08 – 0.34 | 0.002* |
| *k* | -0.23 | -0.29 – -0.16 | <0.001*** |
| Group | -0.42 | -0.65 – -0.20 | <0.001*** |
| *k* * Group [rMDD] | 0.11 | 0.01 – 0.023 | 0.060 |

*Note.* Observations 98; $R^2$ = 0.425; $R^2$ adjusted = 0.407; *<.05, **<.01, ***<.001

**Table S9.** *Multiple regression predicting DDM probability sensitivity effect on drift rate by SVM h and Group.*

| Predictor | *Estimate* | 95% CI | *p* |
|---|---|---|---|
| Intercept | 0.69 | 0.63 – 0.75 | <0.001*** |
| *h* | 0.04 | 0.02 – 0.07 | <0.001*** |
| Group | 0.11 | 0.01 – 0.21 | 0.036* |
| *h* * Group [rMDD] | -0.04 | -0.07 – -0.01 | 0.007** |

*Note.* Observations 99; $R^2$ = 0.121; $R^2$ adjusted = 0.093; *<.05, **<.01, ***<.001

**Supplemental References**


1. First MB, Williams JBW, Karg RS, Spitzer RL (2015): *Structured Clinical Interview for DSM-5—Research Version (SCID-5 for DSM-5, Research Version; SCID-5-RV)*. Arlington, VA: American Psychiatric Association.

2. Kuhn M, Steinberger DC, Bendezú JJ, Ironside M, Kang MS, Null KE, *et al.* (2025): Psychobiological Stress Response Profiles in Current and Remitted Depression: A Person-Centered, Multisystem Approach. *Biological Psychiatry Global Open Science* 5: 100400.

3. Duda JM, Moser AD, Ironside M, Null KE, Holsen LM, Zuo CS, *et al.* (2024): Effects of GABA, Sex, and Stress on Reward Learning in Current and Remitted Major Depression. *Biol Psychiatry Cogn Neurosci Neuroimaging* 9: 606–615.

4. Whitton AE, Van't Veer A, Kakani P, Dillon DG, Ironside ML, Haile A, *et al.* (2017): Acute stress impairs frontocingulate activation during error monitoring in remitted depression. *Psychoneuroendocrinology* 75: 164–172.

5. Beck AT, Steer RA, Brown G (1996): Beck Depression Inventory–II. American Psychological Association. https://doi.org/10.1037/t00742-000

6. Rush AJ, Trivedi MH, Ibrahim HM, Carmody TJ, Arnow B, Klein DN, *et al.* (2003): The 16-Item quick inventory of depressive symptomatology (QIDS), clinician rating (QIDS-C), and self-report (QIDS-SR): a psychometric evaluation in patients with chronic major depression. *Biological Psychiatry* 54: 573–583.

7. Cooper JA, Barch DM, Reddy LF, Horan WP, Green MF, Treadway MT (2019): Effortful goal-directed behavior in schizophrenia: Computational subtypes and associations with cognition. *Journal of Abnormal Psychology* 128: 710–722.

8. Sutton RS, Barto AG (1998): *Reinforcement Learning: An Introduction*. Cambridge, MA: MIT Press.

9. Schwarz G (1978): Estimating the Dimension of a Model. *The Annals of Statistics* 6: 461–464.

10. Freeman GH, Halton JH (1951): Note on an exact treatment of contingency, goodness of fit and other problems of significance. *Biometrika* 38: 141–149.