Scientific Reports

https://doi.org/10.1038/s41598-026-63736-0

Article in Press

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Received: 11 November 2025

Accepted: 21 July 2026

Published online: 31 July 2026

Cite this article as: Fu Q.X., Shevlin B.R.K., Davis A.N. *et al.* Context-sensitivity and longitudinal stability of the effects of depressive symptoms on social and reward decision-making. *Sci Rep* (2026). https://doi.org/10.1038/s41598-026-63736-0

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Context-sensitivity and longitudinal stability of the effects of depressive symptoms on social and reward decision-making

Qi Xiu Fu[1,2], Blair R. K. Shevlin[1,3], Arianna Neal Davis[1,2,3], Matthew Heflin[4,5,6], Kaustubh R. Kulkarni[2], Ignacio Saez[2,7,8], Shawn A. Rhoads[1,2,3], Helen S. Mayberg[7,8], Xiaosi Gu[1,4,5,6]

Corresponding Authors: Qi Xiu Fu, PhD (qixiu_fu@yahoo.com); Xiaosi Gu, PhD (xiaosi.gu@yale.edu)

Keywords: depression; anhedonia; social decision-making; reinforcement learning

[1]Center for Computational Psychiatry, Icahn School of Medicine at Mount Sinai, New York, NY, USA
[2]Department of Neuroscience, Icahn School of Medicine at Mount Sinai, New York, NY, USA
[3]Department of Psychiatry, Icahn School of Medicine at Mount Sinai, New York, NY, USA
[4]Department of Psychiatry, Yale School of Medicine, New Haven, CT, USA
[5]Department of Biomedical Informatics and Data Science, Yale School of Medicine, New Haven, CT, USA
[6]Center for Brain & Mind Health, Yale School of Medicine, New Haven, CT, USA
[7]Department of Neurosurgery, Icahn School of Medicine at Mount Sinai, New York, NY, USA
[8]Center for Advanced Circuit Therapeutics, Icahn School of Medicine at Mount Sinai, New York, NY, USA

Abstract

Depressive symptoms could affect decision-making in multiple ways, yet it remains unclear whether these effects are context-sensitive and stable over time. In this longitudinal study, 236 online participants (129 at 1-month follow-up) completed a social exchange task (Ultimatum Game) and a reward learning task (Reversal Learning). Mixed-effects regression analyses revealed consistent effects of depressive, but not anhedonic, symptoms on social decision-making. Specifically, participants with elevated depressive symptoms (BDI-II > 13) exhibited slower response times and lower acceptance of unfair offers in the Ultimatum Game across both time points relative to participants below the clinical threshold. In contrast, symptom-related effects in the Reversal Learning task were less consistent across behavioral and longitudinal analyses. Analyses using continuous symptom measures yielded weaker and less stable effects than the primary categorical models, suggesting that symptom–behavior relationships may be non-linear. Overall, these findings indicate that the effects of depressive symptoms on decision-making are context-sensitive and robustly expressed during social exchange. This work highlights the importance of considering both

symptom severity and decision context when identifying behavioral phenotypes relevant to depression.

Main

Depression is a multifaceted condition that impacts cognition and decision-making across domains[1-3]. One hallmark feature is psychomotor slowing[4], which has been consistently observed in both clinical and subclinical populations and contributes to impaired daily functioning[5-6]. Computational accounts suggest this slowing reflects impaired information processing during decision-making[7-8]. A recent review found that depressed participants make fewer optimal decisions in learning tasks, expressing more pessimistic predictions, and showing reduced persistence when waiting was optimal compared to healthy controls[9]. Other studies report reduced learning rates and attenuated sensitivity to reward value[9-10], while a recent meta-analysis found elevated punishment learning rates in depression and anxiety compared with controls[11]. Findings from reinforcement learning studies have advanced understanding of how depression affects reward-based learning, but the results remain inconsistent[12-13].

Anhedonia represents a distinct, though often co-occurring, set of symptoms within depression[14-15]. Classically defined as an inability to experience pleasure[16], anhedonia involves broader disruptions in motivation, reward anticipation and processing, representing key stages of the reward learning system[17-18]. Emerging evidence suggests that anhedonia may shape reinforcement learning patterns, with anhedonic subgroups of depressed patients showing distinct responses compared to non-anhedonic patients and healthy controls[15]. However, most prior studies do not explicitly account for anhedonia severity when assessing depression, making it difficult to determine whether observed effects reflect core depressive features, anhedonic processes, or differences in sample composition. This lack of symptom specificity may contribute to inconsistencies across studies. Together, these findings highlight the importance of anhedonia assessment when investigating reward learning as a marker of mood symptoms.

Depression has also been linked to altered responses in social contexts, particularly in sensitivity to fairness and social feedback[19]. Individuals with depressive symptoms are more likely to reject unfair offers and to interpret social norms differently during socio-economic exchanges. For example, studies using the ultimatum game suggest that patients with major depressive disorder show higher rejection rates of unfair offers and difficulties adjusting acceptance behavior based on fairness perceptions, potentially reflecting altered sensitivity to social reward and norm violations[20-21]. These findings align with broader evidence of reduced social engagement and heightened negative emotional responses to interpersonal interactions in depression[21-22]. However, few studies have directly examined whether the effects of depression on decision-making

are context specific (e.g., social vs. reward learning) or whether such relationships are stable over time.

To address these gaps, the present study used a longitudinal, symptom-focused approach to examine how depression, while controlling for anhedonia, influences decision-making across time and context. Participants completed both a social decision-making task (ultimatum game) and a reward-learning task (reversal learning) at baseline and one-month follow-up. In this study, we tested (1) whether symptom-linked effects on decision behavior are stable over time, and (2) whether decision-making contexts differentially capture these effects. This approach provides a test of how mood symptoms influence behavior within and across contexts, and whether behavioral modeling can yield reproducible insights into these mechanisms.

Results

Sample overview and symptom characterization

236 U.S.-based online participants completed the baseline session (52% female; mean age = 41.73 years, SD = 10.00; range = 27–77), and 129 participants completed the one-month follow-up (51% female; mean age = 43.27 years, SD = 10.85, range = 27–77) (see **Fig. 1a** for task-specific sample details; see **Methods** for inclusion criteria). Given evidence that anhedonia represents a distinct modulatory feature of depression[14-15], we assessed depressive and anhedonic symptoms separately and modeled them as binarized two-level factors in statistical inference (high vs. low depression, and high vs. low anhedonia). Depressive symptoms were classified using the clinical cutoff on the Beck Depression Inventory, the BDI-II[23] (>13), and anhedonic symptoms were classified using the sample median on the Positive Valence Systems Scale, the PVSS-21[24] (<6.67), based on baseline self-report measures. Raw scores on the BDI-II and PVSS-21 showed a moderate negative correlation at baseline (BDI-II: M = 13.17, SD = 12.16, range = 0–53; PVSS-22: M = 6.51, SD = 1.31, range = 2–9; $r(242) = -.44$, $p = 6.27 \times 10^{-13}$) and at one-month follow-up (BDI-II: M = 11.03, SD = 11.92, range = 0–52; PVSS-21: M = 6.58, SD = 1.33, range = 2.33–9; $r(141) = -.60$, $p = 3.73 \times 10^{-15}$).

To assess whether longitudinal drop-out was associated with baseline symptom severity, we compared participants who completed both sessions (“retained”) and those who did not (“not retained”). No significant group differences were found for baseline depression scores, $t(242) = -0.88$, $p = 0.38$ (**Fig. 1b**), with a Bayesian independent samples t-test indicated moderate evidence for the null hypothesis ($BF_{01} = 4.93$), or anhedonia scores, $t(251) = 0.25$, $p = 0.80$, $BF_{01} = 7.05$ (**Fig. 1c**).

We also evaluated the temporal consistency of self-report psychiatric score using intra-class correlations (ICCs) between baseline and one-month scores. Depression scores demonstrated high stability (baseline: M = 11.52, SD = 11.73; follow-up: M = 11.90, SD

= 12.38), ICC(3,1) = 0.90, r(120) = 0.90, p = 3.40 × 10^{-46} (**Fig. 1d**). Anhedonia scores also showed strong stability (baseline: M = 6.55, SD = 1.34; follow-up: M = 6.56, SD = 1.35), ICC(3,1) = 0.83, r(120) = 0.83, p = 5.90 × 10^{-32} (**Fig. 1e**). Symptom-stratified demographic characteristics are presented in **Table 1**, and exploratory analyses on demographic predictors of symptom severity are reported in **Supplementary Table 1**.

Longitudinal stability of task behaviors

Participants completed both a social exchange task (ultimatum game) and a reward-learning task (reversal learning) at baseline and one-month follow-up. Within-subject changes in symptom measures and task performance across time points are summarized in **Table 3**. In the UG, participants decided whether to accept or reject unfair monetary offers ($20 splits) from a virtual partner and reported their momentary mood rating on approximately one-third of trials (30 trials, 2 blocks; **Fig. 1f**). Key behavioral variables included response times, acceptance rates, and mood ratings. To assess the test–retest reliability of these behavioral metrics, we computed participant-level averages and calculated ICCs. Response times showed moderate reliability (ICC(3,1) = 0.58, r(127) = 0.59, p = 2.62 × 10^{-13}; **Fig. 2a**), while acceptance rates (ICC(3,1) = 0.76, r(127) = 0.77, p = 4.79 × 10^{-26}; **Fig. 2b**) and mood ratings (ICC(3,1) = 0.73, r(127) = 0.73, p = 1.07 × 10^{-22}; **Fig. 2c**) demonstrated high test-retest reliability.

In the reversal learning task, participants selected between two slot machines across three blocks (punishment, mixed, and reward) with two reversals per block (35 trials/block; **Fig. 1g**). Key behavioral variables included response times and optimal choices. Response times demonstrated low reliability across blocks (punishment: ICC(3,1) = 0.33, r(117) = 0.35, p = 1.19 × 10^{-4}; **Fig. 2d**; mixed: ICC(3,1) = 0.48, r(117) = 0.48, p = 2.30 × 10^{-8}; **Fig. 2e**; reward: ICC(3,1) = 0.37, r(117) = 0.38, p = 2.08 × 10^{-5}; **Fig. 2f**). In addition, optimal choice rates showed poor reliability (punishment: ICC(3,1) = 0.29, r(117) = 0.29, p = 1.14 × 10^{-3}; **Fig. 2g**; mixed: ICC(3,1) = 0.07, r(117) = 0.07, p = 0.44; **Fig. 2h**; reward: ICC(3,1) = 0.21, r(117) = 0.21, p = 2.06 × 10^{-2}; **Fig. 2i**).

Taken together, these results suggest that behavioral measures in the social exchange task had better test–retest reliability than those in the probabilistic reward-learning task.

The effects of depressive symptoms on social behavior and psychomotor effects were stable over time

To examine the relationship between mood symptoms and decision-making behavior, we applied mixed-effects regression to trial-level data at each timepoint separately (see **Methods**). Full model specifications and results are provided in **Supplementary Tables 2-5**.

Participants above the depressive symptom cutoff showed consistently slower response times and altered social decision-making in the ultimatum game. At baseline, the high-depression groups had slower responses (β = 0.10, p = 0.026; **Fig. 3a**). This association was also observed at follow-up (β = 0.25, p = 4.14×10^{-4}; **Fig. 4a**), suggesting that psychomotor slowing in social contexts in the high depression groups was stable over time.

For rejection behavior, we found that at baseline, the high-depression groups were less likely to accept offers (β = -4.11, p = 0.023; **Fig. 3b**), and this association was again present at follow-up (β = -13.80, p = 0.010; **Fig. 4b**). Significant depression × offer size interactions were observed at both timepoints (baseline: β = 0.76, p = 0.007; follow-up: β = 2.05, p = 0.030), indicating that the high depression groups were also more sensitive to offer fairness.

Next, we examined how participants' choices influenced their mood ratings. At both timepoints, accepting unfair offers was associated with lower mood ratings, with a significant offer × acceptance interaction at baseline (β = 1.27, $p < 2 \times 10^{-16}$) and follow-up (β = 1.09, p = 4.82×10^{-7}), indicating that mood ratings improved more when participants accepted better offers. Symptom-related effects on mood ratings were only observed at baseline: a depression × anhedonia interaction (β = -6.02, p = 0.028; **Fig. 3c**) showed that the high-depression and high-anhedonia group reported more negative mood ratings following social decisions. Additionally, offer acceptance was associated with lower mood ratings overall (β = -3.48, p = 6.12×10^{-5}). No choice- or symptom-related effects on mood ratings were observed at follow-up (**Fig. 4c**).

In contrast to these robust and replicable effects of depression on the social task, findings from the reversal learning task were less stable. At baseline, the high-depression groups were associated with slower response times in the reward block (β = 0.15, p = 0.041; **Fig. 3f**), and a depression × anhedonia interaction predicted improved optimal choice rates in the punishment block (β = 0.37, p = 0.025; **Fig. 3g**). However, neither effect persisted during follow-up, suggesting weaker and less reliable associations between mood symptoms and choice behavior under probabilistic learning contexts (**Fig. 4d-i**).

We conducted supplementary analyses using continuous symptom modeling, in which raw BDI and PVSS scores (reverse-coded to maintain consistent directionality) were entered as continuous predictors along with their interaction. These analyses did not consistently reproduce the symptom-related effects observed in the primary categorical models across either task (**Supplementary Tables 6-9**). Model comparison using BIC generally indicated comparable or better fit for the categorical specification based on clinically relevant symptom thresholds (**Supplementary Tables 10-11**). Additional exploratory analyses examining block × symptom interactions in the reversal learning task suggested valence-dependent effects of depressive symptoms on baseline

response time, although these effects showed limited stability at the 1-month follow-up (**Supplementary Tables 12–13**).

Task-specific computational parameter stability and associations with symptoms

To further examine whether cognitive processes underlying behavior varied with symptom severity, we applied computational modeling to trial-level choice data from ultimatum game and reversal learning at both timepoints (see **Methods**). For each task, we estimated a series of models, using an iterative Hierarchical Expectation Maximization algorithm with maximum a posterior (MAP) estimation, and computed integrated BIC to determine the model fit for model comparison[25-27].

Consistent with our previous work, the best-fitting model for the ultimatum game at both baseline and follow-up was a norm adaptation model with a variable, participant-specific initial norm. This model estimated three free parameters: initial norm (subjective fairness expectation), sensitivity to norm violations (how sensitive to fairness prediction error), and norm adaptation rate (the extent of updating subjective fairness expectation). Parameter-level stability was weak across timepoints, with low internal consistency and test–retest correlations (initial norm: $\alpha = 0.15$, $r(82) = 0.09$, $p = 0.378$; sensitivity to norm violations: $\alpha = 0.21$, $r(82) = 0.12$, $p = 0.243$; norm adaptation rate: $\alpha = 0.14$, $r(82) = 0.08$, $p = 0.455$). We also found no significant associations between depressive symptoms and ultimatum game parameters at baseline (**Table 2**). At follow-up, a depression × anhedonia interaction emerged for sensitivity to norm violations ($\beta = -2.14$, $p = 0.021$; **Supplementary Table 14**), suggesting that co-occurring symptoms may reduce responsiveness to deviations from expected fairness norms. However, given the lack of consistency with baseline, this relationship should be interpreted with caution.

In the reversal learning task, at baseline, the best-fitting model was a valence model that estimated separate learning rates for positive and negative prediction errors, along with an inverse temperature governing choice stochasticity (for full model comparison see **Supplementary Table 16**). At baseline, high depression was associated with a lower negative learning rate ($\beta = -0.03$, $p = 0.004$) and slightly increased choice stochasticity (inverse temperature; $\beta = -8.71 \times 10^{-8}$, $p = 0.013$), although the magnitude of this effect was negligible. In contrast, high anhedonia was associated with reduced choice stochasticity ($\beta = 6.96 \times 10^{-8}$, $p = 0.044$). However, the reversal learning results were difficult to interpret longitudinally, as the best-fitting model changed at follow-up (context model, estimating separate learning rates based on block type), with no significant symptom associations observed at the one-month follow-up (**Supplementary Table 15**).

Discussion

This study examined how depressive and anhedonic symptoms influence decision-making across social and reward learning contexts using a longitudinal design. We contributed two key findings. First, greater depressive severity was consistently associated with psychomotor slowing and reduced acceptance of unfair offers during social decision-making. Second, the social task captured more stable and reproducible behavioral phenotypes associated with depression compared to the reward learning task, where symptom-behavior association was not consistent over time. Together, these findings emphasized the context-sensitive and temporally stable effects of mood symptoms on decision-making, specifically in socially relevant environments.

Consistent with prior work[4-6], depressive symptoms were associated with psychomotor slowing, reflected in longer response times during the social task across both timepoints. This finding aligns with evidence that depression is linked to slowed processing speed in value-based decision-making[7-8]. Our results suggest that delayed responses may represent a stable cognitive signature of depressive symptoms, even in a non-clinically diagnosed population. Participant-level response times were moderately correlated across timepoints, and the effect of depression on psychomotor slowing was stable at follow-up, beyond task-related variance in response times. In contrast, we did not observe consistent symptom-related effects on response time in the non-social task, underscoring the context dependence of this behavioral marker, supporting theories that the interpersonal context may heighten or amplify the effects of depression on decision-making [28].

The ultimatum game is a widely used paradigm for studying fairness, cooperation, and social punishment. Although the economically rational choice is to accept any non-zero offer, a meta-analysis showed that participants reject approximately 16% of offers on average[29]. This behavior demonstrates how the perceived value of fairness can outweigh immediate financial gain. Prior work has shown that individuals with depression exhibit heightened sensitivity to fairness violations and alterations in social norm processing. For example, depressed patients have been found to over-sanction unfair proposals[22], and reject unfair offers at higher rates[20,30]. A neuroimaging study further linked these behavioral differences to altered activity in reward- and social-processing regions, including the nucleus accumbens and dorsal caudate, which may underlie differences in processing fairness and social rewards in depression[21]. Neural encoding of social reward is also context dependent, and sensitive to fairness considerations[31-32]. Together, this literature suggested that depression is associated with both behavioral and neural alterations in social exchange.

Our findings extended this work by demonstrating that participants above the depressive symptom cutoff (BDI-II >13) were consistently less likely to accept unfair offers, while still adjusting their choices in response to increasing offer size. The effect was stable across baseline and follow-up, suggesting that reduced acceptance of unfair offers may represent a reproducible, symptom-linked behavioral marker of depression. While choice–related effects on mood during ultimatum game were replicated across time points, the depression and anhedonia interaction on mood was observed only at baseline. This attenuation at follow-up may reflect the context-sensitive and state-dependent nature of momentary mood ratings, which are susceptible to affective drift and learning-related dynamics over time[33-34]. We also observed that continuous symptom models did not consistently reproduce the behavioral effects observed using the primary categorical specification. One possible explanation is that symptom–behavior relationships are not uniformly linear across the full range of symptom severity [35-36]. Instead, behavioral differences may emerge primarily beyond clinically meaningful thresholds[36-37]. Despite these behavioral effects, our computational modeling did not identify significant associations between depressive symptoms and model-derived parameters. Future work should investigate whether additional cognitive mechanisms, such as integrating choice behavior with psychomotor dynamics, may better account for stable, symptom-related variation in social decision-making. Advancing modeling frameworks and refining task designs will be critical for translating behavioral phenotypes into clinically meaningful markers in mood disorders and for determining whether these patterns reflect stable traits or state-dependent processes in patient populations.

Our findings also underscored the importance of task context in capturing stable, symptom-linked effects on decision-making. Across levels of analyses, the social task consistently yielded stable associations between depressive symptoms and key performance metrics, including response times and choice behavior. In contrast, the reward learning task provided limited and less consistent insights, with some associations with mood symptoms emerging at baseline only. While psychometric reliability remains a key consideration in computational psychiatry research, the absence of detectable associations between reversal learning measures and symptom severity in the present study likely reflects more than measurement limitations alone. Converging evidence from large-scale and naturalistic samples suggests that previously reported negative learning biases in depression may be less robust or less generalizable than initially proposed[38]. In this context, the present findings contribute to ongoing efforts to delineate the conditions under which reversal learning metrics serve as reliable markers of depressive symptomatology[11, 39-40]. The differing longitudinal stability across tasks may reflect multiple interacting factors beyond a simple social versus non-social distinction. Although the Ultimatum Game does not involve

probabilistic learning, it is intended to engage complex social-cognitive evaluations that may produce relatively stable individual differences, whereas reversal learning requires ongoing updating and cognitive flexibility. Thus, task demands, learning dynamics, and measurement reliability likely jointly contribute to the observed differences in behavioral association with depressive symptoms. Future work should further explore how decision context influences the stability and interpretability of symptom-related effects, particularly when extending computational modeling approaches to real-world social interaction[41].

Several limitations should be addressed. First, although our sample was not clinically evaluated, the observed symptom distribution overlapped with clinically reported ranges. Larger and more diverse cohorts are needed in the future to improve generalizability and more precisely estimate the effects of depression severity on behavior across decision contexts. Second, depressive symptoms were binarized based on self-report clinical cutoffs to enhance interpretability for threshold effects and only assessed from self-enrolled online participants[42]. Third, structural differences between tasks (e.g. the absence of mood ratings in the reversal learning task) limited direct comparisons between decision-making tasks on momentary affective responses. Future studies using more parallel designs with compatible incentives may better isolate context-specific effects. Finally, while we focused on reinforcement learning, alternative computational frameworks may provide insight into mechanisms such as perceived control, learned helplessness, and agency[43-45]. These directions will be important for clarifying how distinct mood symptom dimensions shape cognition and behavior.

In conclusion, this study demonstrated the stability and context sensitivity of depressive symptoms in tuning decision-making. Depressive symptoms showed robust stability over one month and were consistently associated with slower responses and reduced acceptance of unfair offers in a social task, suggesting that altered social decision-making behavior may reflect a durable, symptom-linked cognitive phenotype. In contrast, reversal learning tasks yielded less consistent and less robust relationships between depressive symptom severity and behavioral performance. Together, these findings emphasized the importance of both symptom-specific and context-senstive approaches when examining the effects of depression on decision-making.

Tables

	low depression		high depression	
	low anhedonia (*n* = 91)	high anhedonia (*n* = 45)	low anhedonia (*n* = 29)	high anhedonia (*n* = 71)

Demographics				
Age (yrs), mean ± SD	42.65 ± 10.62	42.58 ± 11.73	42.28 ± 9.54	39.79 ± 7.91
Female, *n* (%)	48 (52.75%)	19 (42.22%)	21 (72.41%)	34 (47.89%)
Woman, *n* (%)	46 (50.55%)	19 (42.22%)	21 (72.41%)	31 (43.66%)
Education level, median	5	5	4	5
Income level, median	6	5	5	6
SES, median	5	4	4	4
Psychiatric Assessment				
Prior mood-related diagnosis. mean ± SD**	0.46 ± 0.98	0.24 ± 0.71	1.24 ± 1.50	1.54 ± 1.46
BDI-II, mean ± SD**	3.74 ± 4.22	5.67 ± 4.27	24.93 ± 9.64	24.90 ± 8.39
PVSS-21, mean ± SD**	7.62 ± 0.63	5.78 ± 0.63	7.36 ± 0.48	5.26 ± 0.98
Race and ethnicity				
White, *n* (%)	67 (73.63%)	30 (66.67%)	16 (55.17%)	48 (67.61%)
Multiracial, *n* (%)	8 (8.79%)	5 (11.11%)	2 (6.90%)	13 (18.31%)
Asian, *n* (%)	7 (7.69%)	3 (6.67%)	3 (10.34%)	3 (4.23%)
Black or African American, *n* (%)	5 (5.49%)	3 (6.67%)	4 (13.79%)	4 (5.63%)
Latino or Hispanic, *n* (%)	1 (1.10%)	4 (8.89%)	4 (13.79%)	3 (4.23%)
American Indian or Alaska Native, *n* (%)	1 (1.10%)			
Other, *n* (%)	2 (2.20%)			

Table 1. Demographics and clinical characteristics of the sample (*n* = 236): prior mood-related diagnosis included any prior physician-told diagnoses of bipolar disorder, major depressive disorder, general anxiety disorder, panic disorder, post-traumatic stress disorder, or seasonal affective disorder; Socioeconomic status (SES) was assessed using the MacArthur Scale of Subjective Social Status[47](adult version). A one-way ANOVA test showed significant differences between groups on prior mood-related diagnosis, BDI-II scores, and PVSS-21 scores (** $p < 0.01$).
Legends: Education level, 4-some college (13-15 yrs.); 5-bachelor's degree in college (16 yrs.). Income level, 5-$40,000 ~ $49,000; 6-$50,000 ~ $59,000.

task (timepoint)	model	parameter(s)	estimate	std. error	p
		initial norm (f_0)	–0.24	0.6	0.688

ultimatum game (baseline)	variable initial norm	sensitivity to norm violation (α)	0.13	0.31	0.677
		norm update rate (ε)	–0.01	0.01	0.353
reversal learning (baseline)	valence	negative learning rate (α^-)	**–0.03**	0.01	**0.004**
		positive learning rate (α^+)	0.03	0.02	0.178
		inverse temperature (β)	**–8.7e–8**	3.5e–8	**0.013**
ultimatum game (one-month)	variable initial norm	initial norm (f_0)	0.04	0.61	0.952
		sensitivity to norm violation (α)	–0.21	0.46	0.655
		norm update rate (ε)	–0.02	0.01	0.102
reversal learning (one-month)	context	punishment block α	–1.87e–6	1.05e–6	0.077
		mixed block α	–3.31e–3	0.012	0.776
		reward block α	–9.31e–7	9.6e–7	0.334
		inverse temperature (β)	–1.94e–8	1.81e–8	0.285

Table 2. Multivariate regression estimates for contribution of depression symptoms on parameters from task-specific winning models. Bolded values indicates $p < 0.05$. Full regression results are presented in Supplementary Tables 14-15.

measure	baseline (mean ± SD)	1-month (mean ± SD)	t(df)	p
BDI-II	13.17 ± 12.16	11.03 ± 11.92	t(121) = 0.38	0.708
PVSS-21	6.51 ± 1.31	6.58 ± 1.33	t(121) = −0.21	0.832
Reaction time (UG, s)	1.25 ± 0.40	1.08 ± 0.44	t(128) = 4.89	**3.01×10^{-6}**
Choice accepts (UG, proportion)	0.63 ± 0.28	0.73 ± 0.26	t(128) = −6.17	**8.51×10^{-9}**
Mood rating (UG)	24.79 ± 9.95	26.75 ± 9.69	t(128) = −3.08	**0.003**
Reaction time (RL, s)	0.79 ± 0.37	0.67 ± 0.39	t(118) = 3.28	**0.001**
Optimal choice (RL, proportion)	0.71 ± 0.09	0.73 ± 0.07	t(118) = −2.70	**0.008**

Table 3. Paired t-tests comparing baseline and 1-month follow-up measurements for symptom measures and task performance among participants who completed both sessions. Values are reported as mean ± SD. UG: Ultimatum Game; RL: reversal learning. Bolded values indicate $p < 0.05$.

Figures

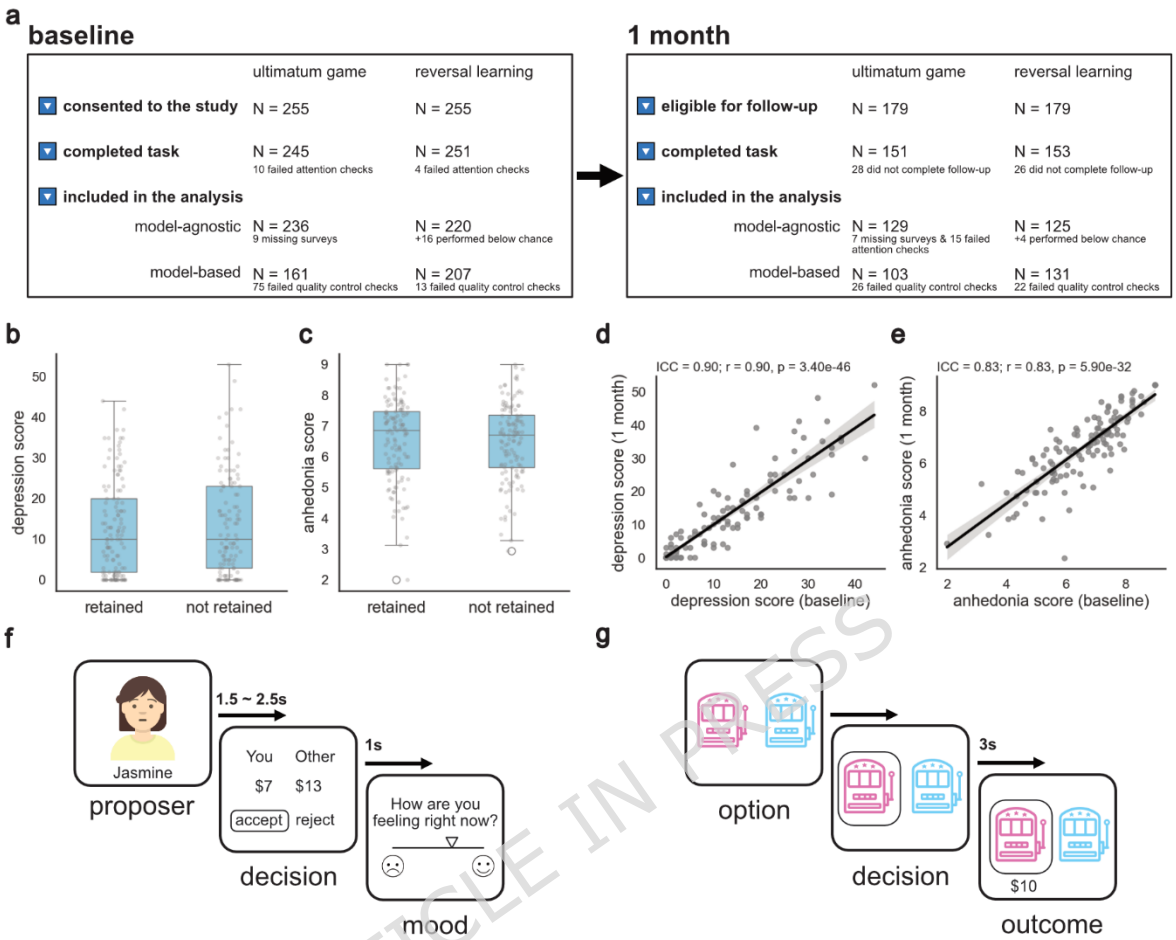

Fig 1. Study design and symptom stability.

a, Overview of participant inclusion. A total of 255 participants were consented based on the following criteria: age 30–100, fluent in English, Prolific approval rate of 95–100%, and 50–10,000 prior submissions. **b–c**, No significant differences in baseline depression (b, t(242) = -0.88, p = 0.38, BF_{01} = 4.93) or anhedonia (c, t(251) = 0.25, p = 0.80, BF_{01} = 7.05) scores were observed between participants who completed both timepoints (retained) and those who did not (not retained). **d–e**, Depression (d) and anhedonia (e) scores showed high test–retest reliability between baseline and one-month follow-up. **f**, Ultimatum game schematic. Participants responded to unfair monetary splits of $20 proposed by a virtual partner across 30 trials in two repeats; mood ratings were collected on approximately one-third of trials. **g**, Reversal learning (RL) schematic. Participants completed 105 trials across three blocks (35 trials/block): punishment (–$10 or $0), mixed (–$10 or $10), and reward ($0 or $10). Outcomes were probabilistic (80% vs. 20%), with two reversals per block.

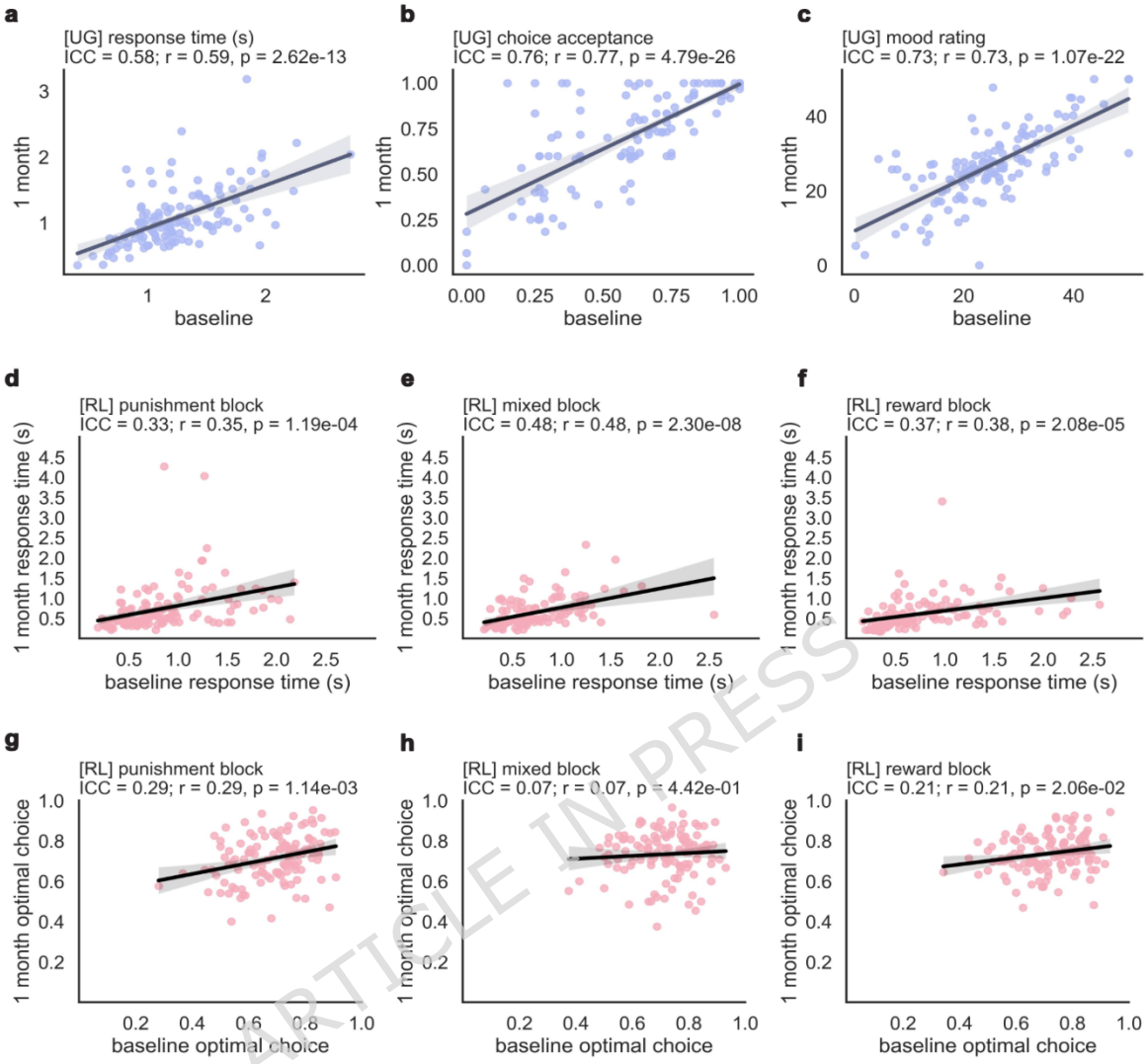

Fig 2. Longitudinal stability of task behavior.

a, Moderate test–retest reliability of mean response times between baseline and one-month follow-up in the ultimatum game. **b**, High test–retest reliability of acceptance rates across timepoints in the ultimatum game. **c**, High test–retest reliability of mean mood ratings across timepoints in the ultimatum game. **d–f**, Low test–retest reliability of mean response times in the reversal learning (RL) task across timepoints for the punishment (d), mixed (e), and reward (f) blocks. **g–i**, Low test–retest reliability of mean optimal choice rates in the reversal learning task across timepoints for the punishment (g), mixed (h), and reward (i) blocks.

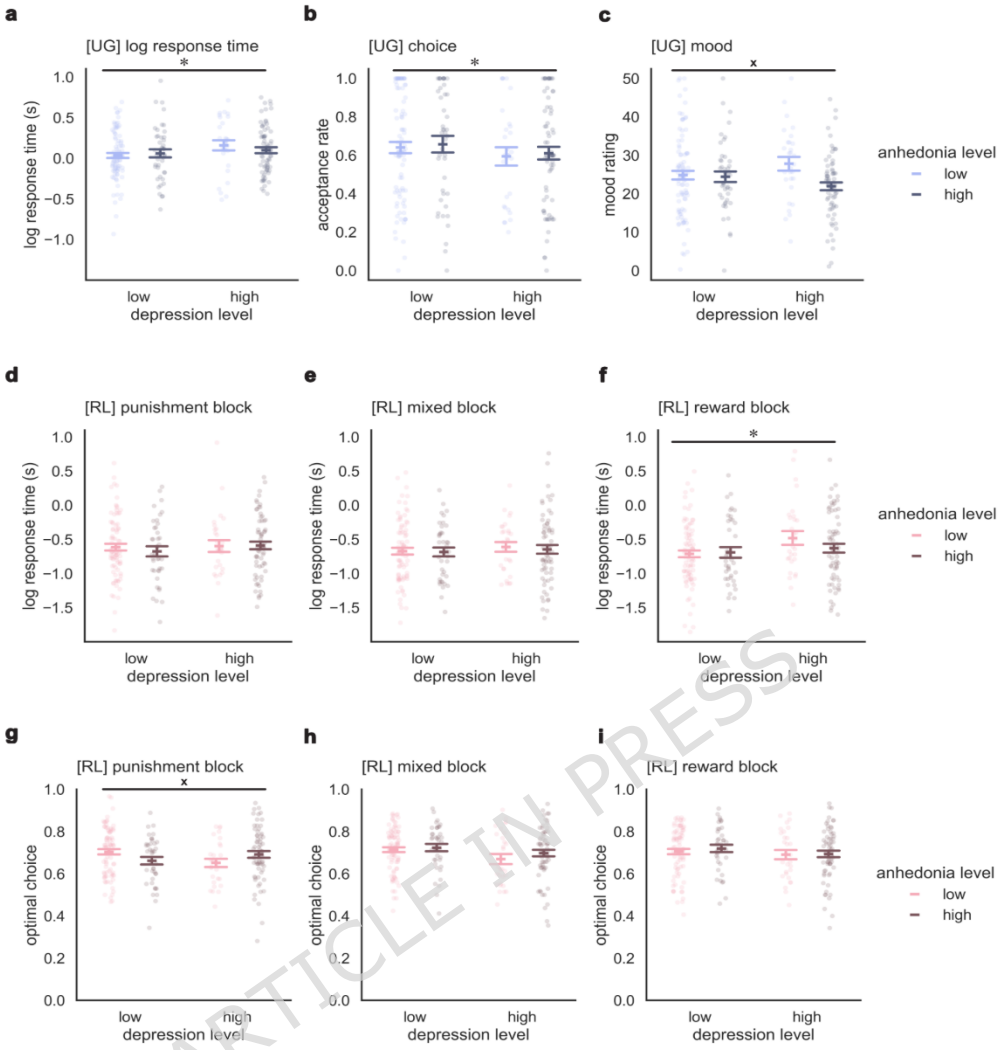

Fig 3. Baseline mood symptom effects on decision behavior in social and reward learning tasks.

Model-agnostic behavioral outcomes are shown at baseline for the ultimatum game (response times, left; offer acceptance rate, middle; mood ratings, right) and reversal learning task (punishment block, left; mixed block, middle, reward block, right). **a**, Main effect of high depression (β = 0.10, p = 0.026) on response times in the ultimatum game. **b**, Main effect of high depression (β = -4.11, p = 0.023) on offer acceptance in the ultimatum game. **c**, Interaction effect of depression and anhedonia (β = -6.02, p = 0.028) on mood ratings in the ultimatum game. **d–f**, Main effect of high depression on response times (β = 0.15, p = 0.041) in the reward block of reversal learning (f). **g–i**, Interaction effect of depression and anhedonia (β = 0.37, p = 0.025) on optimal choice

in the punishment block of reversal learning (g). Error bars represent standard error of the mean (±1 SEM). * Sign labels for significant main effect ($p < 0.05$). X Sign labels for significant interaction ($p < 0.05$).

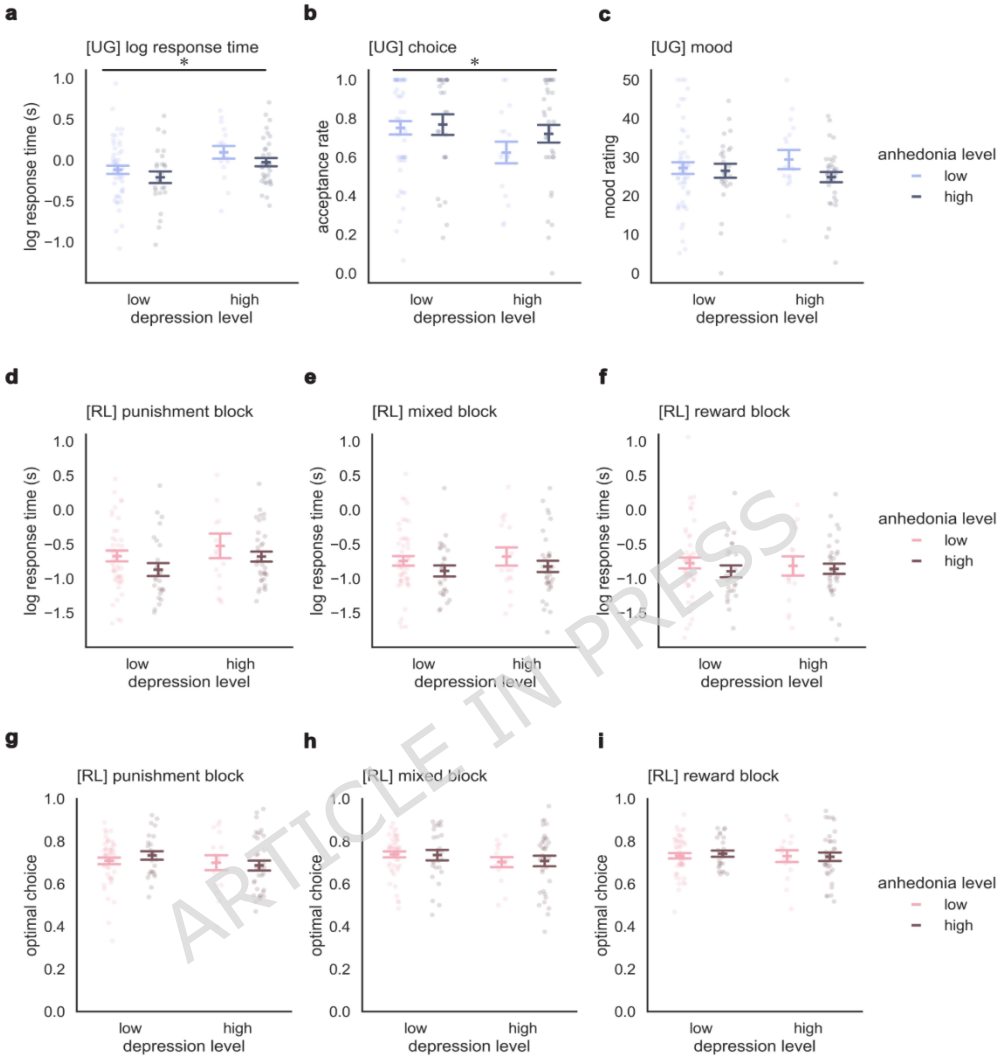

Fig 4. Longitudinal mood symptom effects on decision behavior in social and reward learning tasks.

Model-agnostic behavioral outcomes are shown at the one-month follow-up timepoint for the ultimatum game (response times, left; offer acceptance rate, middle; mood ratings, right) and reversal learning task (punishment block, left; mixed block, middle, reward block, right). **a**, Main effect of high depression ($\beta = 0.25$, $p = 4.14 \times 10^{-4}$) on response times in the ultimatum game. **b**, Main effect of high depression ($\beta = -13.80$, $p = 0.010$) on offer acceptance in the ultimatum game. **c**, No mood symptom association

on mood ratings in the ultimatum game. **d–f**, No mood symptom association on response times in the punishment (d), mixed (e), and reward (f) blocks of reversal learning. **g–i**, No mood symptom association on optimal choice in the punishment (g), mixed (h), and reward (i) blocks of reversal learning. Error bars represent standard error of the mean (±1 SEM). * Sign labels for significant main effect ($p < 0.05$).

Method

Participants

The online study was approved by the Icahn School of Medicine at Mount Sinai Institutional Review Board (IRB Protocol #18-01274). All participants provided informed consent electronically prior to participation. All methods were performed in accordance with the relevant guidelines and regulations. We recruited U.S. based participants through online participant pool Prolific (http://prolific.co). A total of 236 participants were included for analysis with complete behavior and psychiatric data at baseline, and 129 at one-month follow-up (see **Fig. 1a** for task-specific sample size). Sample demographics by symptoms levels on their age, sex, gender, education, income, subjective socioeconomic status (SES), psychiatric assessment, race and ethnicity, were listed in **Table 1**.

Study Procedure

This longitudinal study spanned three timepoints (baseline, one-week, one-month). The current analyses include only the baseline and one-month sessions, which contained both behavioral and psychiatric survey data. At each session, participants completed two decision-making tasks: the ultimatum game and reversal learning. Psychiatric surveys (BDI-II[23], PVSS-21[24], BAI[46], OCI[47], SAS[48], the Ability to Participate in Social Roles and Activities[49]) were administered at baseline and one-month. Subjective socioeconomic status was assessed using the MacArthur Scale of Subjective Social Status[50](adult version). A total of 255 participants were consented based on the following criteria: age 30–100, fluent in English, Prolific approval rate of 95–100%, and 50–10,000 previous submissions (**Fig. 1a**). Participants were paid $7.50 for 30 minutes at baseline and one-month, and $4.00 for 20 minutes at the 1-week session. In the Ultimatum Game, one trial was randomly selected for a bonus payment. If the participant accepted the offer on that trial, they received a bonus equal to 20% of the accepted dollar amount, while rejected offers yielded no bonus. In the reversal learning task, total points earned were converted to a monetary bonus using a fixed exchange rate (200 points = $1 or $0.005 per point). Across both tasks, participants could earn performance-based bonuses ranging from $0 to $6 per session. Completion of each session was required to advance to the next.

Behavioral Paradigms

We used a modified multi-trial one-shot ultimatum game (UG, **Fig. 1f**) to study social decision-making, where a virtual avatar proposes a monetary split of $20 between themselves and the participant. On each trial, participants acted as the responder and interacted with a virtual avatar that varied in gender, race, visual features, and name, deciding whether to accept or reject the proposed monetary split. If the participant accepted, both partners would receive the proposed amount. If the participant rejected it, both partners would receive nothing. There were 30 trials with 2 repeats, and participants were asked to report their current mood on a Likert scale from bad (0, sad face) to good (50, simile face) in about a third of the total trials. The participants were not aware that they would only be offered unfair offers, and their offer ranged from $1 to $9 based on a predefined offer list. Participants always started with a $5 proposal followed by randomized offers, and the task was self-paced.

We used a 3-block, 2-arm reversal learning task (RL, **Fig. 1g**) to study reward decision-making. On a single trial, the participant needed to choose between two slots in which one yields the better outcome 80% of the time while the other yields the better outcome 20% of the time. There were 35 trials in each block and 2 reversals between the slot machines within each block. Reward and punishment were operationalized as monetary gain or loss across three blocks 1) in the reward block, $10 is better than $0; 2) in the mixed block, $10 is better than -$10; 3) in the punishment block, $0 is better than -$10.

Reversal trials were predefined and pseudorandomized; slot stimuli and blocks were randomized. Participants were instructed to earn as much money as possible, and the task was self-paced.

Data coding and statistical analysis

To examine symptom-specific effects, depressive and anhedonic scores were binarized as two-level factors in regression models. Depressive symptoms were categorized using the Beck Depression Inventory–II (BDI-II) with the established clinical cutoff (>13) to distinguish elevated from non-elevated symptom severity. Anhedonic symptoms were categorized using the Positive Valence Systems Scale (PVSS-21). As no validated clinical cutoff exists for PVSS, we applied a sample median split (< 6.67 in item-averaged units) to enable parallel treatment of anhedonia and depression within a 2×2 design. The resulting PVSS group means were comparable to ranges reported in clinically characterized inpatient samples[37], supporting the interpretability of this stratification. This specification was chosen to facilitate interpretation of joint symptom effects and to accommodate potential non-linear or threshold-based symptom–behavior relationships[35]. The symptom profile observed in the present sample is broadly comparable to distributions reported in digital mental health studies relying on crowdsourced online recruitment[51]. For regression analyses, depressive and anhedonic levels were coded as factors (0 = low, 1 = high) and mean-centered. Trials with response times <0.1 s or >10 s were excluded (UG: 0.45% of trials; RL: 11.06%). Response times were log-transformed for mixed-effects regression analysis. All categorical variables were entered as factors in regression models.

Statistical analysis and modeling are registered on the Open Science Framework (https://osf.io/pxg6f). Data curation, visualization, and computational modeling were performed in Python[52-53], and statistical analyses were conducted in R using the lme4 package[54-55]. Kruskal–Wallis tests and one-way ANOVAs were used to assess demographic group differences for ordinal and continuous variables, respectively. Multivariate regression was used for exploratory demographic analyses and model-based outcomes. Bayesian independent samples t-tests were conducted in JASP[56]. We used the default Cauchy prior on effect size (r = 0.707). Bayes factors are reported as BF_{01} when interpreting evidence in favor of the null hypothesis.

Mixed-effects regression models were used for behavioral analyses, with depressive and anhedonic symptoms as fixed effects, participant as a random effect, and task and demographic variables as covariates[57-58]. In UG, task-specific variables, including offer size and choice, were included as predictors, along with their interaction. Both variables were modeled with random slopes at the participant level to account for within-subject variability. In RL, mixed-effects regression models included random intercepts only. A block-wise modeling approach was used to analyze each learning context separately, which reduced model complexity and avoided high-order interactions. Covariate

selection was informed by exploratory multivariate regression examining demographic predictors of symptom severity (**Supplementary Table 1**). Demographic variables were recoded based on the minority stress framework[59-60]: "person of color" included individuals identifying as non-white and not multiracial; "queer" included those identifying as transgender, non-binary, or other. Objective socioeconomic status (SES) was computed as a z-score combining education and income levels. Full model specifications are provided in **Supplementary Tables 2-3**.

Computational Modeling

Choice behavior in the ultimatum game was modeled using the Norm Adaptation Model[61], which combines the Fehr-Schmidt inequity aversion utility computation with a Rescorla-Wagner update rule for social norm update. The utility of accepting instead of rejecting a proposed offer is based on the participant's aversion to unequal offer split, where internal norm *f* at trial *i* is the subjective reference point for assessing fairness, modulated by a sensitivity to norm violation parameter (alpha, $\alpha \in [0,10]$) on the norm prediction error.

$$U(accept_i - reject_i) = offer_i - \alpha \cdot \max\{f_i - offer_i, 0\}$$

(Equation 1)

The participant's choice is computed through a softmax function with an inverse temperature parameter beta fixed at one based on the utility defined above.

$$p(accept_i) = \frac{1}{1 + e^{-\beta U(accept_i - reject_i)}}$$

(Equation 2.1)

$$p(reject_i) = 1 - p(accept_i)$$

(Equation 2.2)

The participant's initial norm is updated based on a Rescorla-Wagner update rule with a norm adaptation rate parameter ($\varepsilon \in [0,1]$). The initial norm (f_0) can be either fixed at 10 or be adaptive ($f_0 \in [0,20]$).

$$f_{i+1} = f_i + \varepsilon(offer_i - f_i)$$

(Equation 3)

Based on previous studies using this modeling approach, two models were implemented based on these computations regarding norm update with fixed or variable initial norm.

Ultimatum game model name	Fixed parameter(s)	Free parameter(s)
Variable initial norm	$\beta = 1$	α, f_0, ε

Fixed initial norm	β = 1, f_0= 10	α, ε

Choice behavior in the reversal learning was modeled based on the Q-learning reinforcement learning model[62-63], which combines different types of learning rate for value update and an inverse temperature for computing choice probabilities. The participant learns the expected value of each slot machine by using a learning rate (α∈[0,1]) to update the value of the chosen slot machine based on different types of update rules. The value of choice *c* on trial *i* (vc,t) is updated as follows defined in the basic rule, with no counterfactual update.

$$v_{c,\,i+1} = v_{c,\,i} + \alpha(outcome_i - v_{c,\,i})$$

(Equation 4)

The participant's choice is modeled through a softmax function with an inverse temperature parameter (β∈[0,10]), where higher inverse temperature corresponds to choosing more deterministically on the higher value option.

$$p_{c,i+1} = \frac{e^{\beta v_{c,i+1}}}{\sum e^{\beta v_{c,i+1}}}$$

(Equation 5)

Based on previous literature on reversal learning, four reinforcement learning models were constructed with different learning rate and update rules.

Reversal learning model name	Free parameter(s)	Update rule
Basic	α, β	Equation 4
Valence	α_{neg}, α_{pos}, β	Based on the prediction error sign
Outcome	α_{pun}, α_{rew}, β	Based on the outcome type
Context	α_{pes}, α_{mix}, α_{opt}, β	Based on the block type

All models were estimated using pyEM, which uses an iterative Hierarchical Expectation Maximization algorithm with maximum a posteriori (MAP) estimation[25-27, 64]. This method provides a better estimation than a single-step maximum likelihood estimation (MLE) alone by being less susceptible to the influence of outliers. It does this via implementing two levels: the lower level of the individual subjects and the higher-level reflecting the full sample. For the MAP procedure, we initialized group-level Gaussians as uninformative priors with means of 0.1 (plus some added noise) and variance of 100. During the expectation step, we estimated the model parameters for each participant using an MLE approach calculating the log-likelihood of the participant's series of choices given the model. We then computed the maximum posterior probability estimate, given the observed choices and given the prior computed from the group-level Gaussian and recomputed the Gaussian distribution over parameters during the maximization step. We repeated expectation and maximization steps iteratively until convergence of the posterior likelihood averaged over the group, or a maximum of 800

steps. Convergence was defined as a change in posterior likelihood <0.001 from one iteration to the next. Note that bounded free parameters were transformed from the Gaussian space into the native model space via appropriate link functions (e.g., a sigmoid function in the case of the learning rate) to ensure accurate parameter estimation near the bounds. Parameter recovery was performed using randomly simulated parameters with 100 simulated agents. All models were fitted to participants' choice data, and integrated BIC was computed for model comparison (**Supplementary Table 16**). The winning model, with the lowest integrated BIC, was selected for follow-up statistical analysis. Model implementations were available at https://github.com/fuqixiu/leap-online-study.

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Acknowledgments
We are grateful to Hannah Hao for her guidance on the analysis of socioeconomic demographic variables. This work is supported by internal funding from the Icahn School of Medicine (XG). The data in this paper were used in a dissertation as partial fulfillment of the requirements for a Ph.D. degree at the Graduate School of Biomedical Sciences at Mount Sinai.

Code availability
The code used for data preprocessing, statistical analyses, computational modeling, and figure generation is publicly available through Zenodo at https://doi.org/10.5281/zenodo.21416865. The corresponding development repository is available at https://github.com/fuqixiu/SciRep-code-public. The computational modeling was adapted from the open-source pyEM toolbox, with modifications for the analyses performed in this study (https://github.com/fuqixiu/pyEM).

Data availability
The preprocessed behavioral data supporting the findings of this study are publicly available at https://doi.org/10.5281/zenodo.21416865. Participant-level demographic data are not publicly available because they contain information collected from human participants but are available from the corresponding author upon reasonable request and subject to institutional ethics approval and data-sharing policies.

Competing interests
HSM received consulting and IP licensing fees from Abbott Neuromodulation. XG is a scientific advisor to Soihtu Dx.

Contributions
QXF and XG led the conceptualization, with support from BRKS. Methodology was led by QXF, with support from BRKS and SAR. Software was developed by QXF, with support from BRKS and SAR. Validation was supported by BRKS. QXF, BRKS, and AND led the investigation, supported by MH and KRK. Resources were coordinated by MH, with support from QXF and BRKS. Data curation was led by QXF, with support from BRKS and AND. Formal analysis was led by QXF, with support from BRKS, SAR, and XG. QXF led the original draft writing, with support from BRKS and XG. Review and editing were led by QXF, with support from BRKS, SAR, IS, HSM, and XG. Visualization was led by QXF. Supervision was provided by HSM and XG, with support from BRKS and SAR. Project administration was led by QXF, with support from BRKS and MH.