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Longitudinal stability of the effect of depression on social decision-making

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Abstract

Depression affects everyday decision-making, yet it remains unclear if such effects depend on the decision context or fluctuate over time. In this repeated-measures study, online participants completed a social exchange task (ultimatum game) and a non-social reversal learning task at baseline (n=236) and 1-month later (n=131). Mood symptoms were assessed using the Beck Depression Inventory and the Positive Valence System Scale. Psychiatric symptoms were stable over time, and dropout was unrelated to symptom severity. Mixed-effects regression revealed consistent behavioral effects of depressive symptoms—while controlling for anhedonia—across time points. Specifically, greater depressive severity predicted slower reaction times and reduced acceptance of unfair offers in the ultimatum game. An interaction between depressive and anhedonic symptoms on mood ratings emerged at baseline but did not replicate at follow-up. There were no consistent significant effects of depression on the non-social reversal learning task across time points. These findings highlight the longitudinal stability of depressive symptoms on social decision-making.

Keywords: depression; anhedonia; social decision-making

Introduction

Depression is a multifaceted experience that alters how individuals make decisions, particularly in emotionally and socially charged contexts. Yet, identifying how mood symptoms shape decision-making in different contexts over time remains a major challenge. There has been a growing body of work uses computational modeling to study reward learning in depression, but relatively few have examined social decision-making processes—a domain that is often more ecologically valid and may be more sensitive to depressive features like social withdrawal and rejection sensitivity (Rhoads et al., 2024). Moreover, despite the rapid expansion of online behavioral research, concerns remain about the reproducibility and temporal stability of task-based measures collected outside laboratory settings. Many studies rely on one-time assessments, leaving it unclear whether observed effects reflect robust, symptom-linked cognitive patterns or transient noise.

Depression has been linked to slowed psychomotor speed and increased sensitivity to social feedback (Christensen et al., 2020; Paolo Fusar-Poli et al., 2023), whereas anhedonia disrupts motivation and reward valuation (Cooper et al., 2018). Studies that collapse across these symptoms or focus solely on diagnostic categories limit our insight into what aspect of mood symptoms drive prolonged influence on cognition and behavior.

Psychomotor alteration—manifesting as either slowness or agitation in movements, speech, and mental activity—is a key feature of depression that significantly impairs psychosocial functioning (Bennabi et al., 2013). Numerous studies have linked depression to slowed psychomotor speed, though the cognitive mechanisms underlying this relationship remain unclear (Northoff et al., 2021; Wüthrich et al., 2022). For instance, reward-based decision-making studies using computational models suggest that slower response times in depressed individuals may stem from reduced evidence accumulation rates (Lawlor et al., 2019; Pitliya et al., 2022). Meanwhile, anhedonia, initially defined as the inability to experience pleasure (Ribot, 1897), is now understood to reflect disruptions across various stages of reward processing, including anticipation, motivation, and feedback integration (Kring & Barch, 2014; Rizvi et al., 2016). Evidence suggests that depression is associated with reduced learning rates and attenuated sensitivity to reward value

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during probabilistic reward tasks (Cooper et al., 2018; Mukherjee et al., 2023). While mood symptoms tend to exert broad psychological effects in decision-making, whether those effects are context specific or stable over time remains unclear.

This study addresses these gaps by taking a dimensional, symptom-focused approach to examine how depression shapes decision-making across context and over time. Using two complementary behavioral tasks—a social exchange task (the Ultimatum Game) and a non-social reversal learning task—we assess an online sample of participants at baseline and one-month follow-up. Crucially, we evaluate the stability of psychiatric symptoms and behavioral effects to determine whether our tasks yield reproducible findings across time points. We also examine the main effects of depression while controlling for anhedonia, allowing us to isolate the specific influence of depressive symptoms on behavior.

We hypothesized that psychomotor slowness, as evidenced by longer reaction times, would emerge as a core feature of depressive symptoms across contexts. Additionally, we hypothesized that mood symptoms would exert prolonged effects in social functioning. By combining repeated-measures design with symptom-level modeling, we aim (1) to validate task-based measures of decision-making in an online, general population sample; and (2) to identify stable, symptom-specific behavioral features of depression that extend beyond traditional diagnostic categories.

Method

Participants

250 U.S.-based participants were recruited via Prolific, meeting inclusion criteria (aged 30–100, fluent in English, approval rate ≥95%). After exclusions for failed attention checks and below chance task performance, 236 participants were analyzed for the ultimatum game (UG) and 220 for the reversal learning task (RL) from the baseline session (1 month follow-up: UG n = 131, RL n = 135). Demographics of participants by symptom levels from baseline session are provided in Table 1.

Table 1: Baseline sample characteristics by symptoms level

	Low depression		High depression	
	Low anhedonia (n = 91)	High anhedonia (n = 45)	Low anhedonia (n = 29)	High anhedonia (n = 71)
Demographics (mean ± SD / %)				
Age, year	42.65 ± 10.62	42.58 ± 11.73	42.28 ± 9.54	39.79 ± 7.91
Female	48 (52.75%)	19 (42.22%)	21 (72.41%)	34 (47.89%)
Woman	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
Ladder, median	5	4	4	4
Psychiatric Assessment (mean ± SD / %)				
Prior mood-related diagnosis**	0.46 ± 0.98	0.24 ± 0.71	1.24 ± 1.50	1.54 ± 1.46
BDI-II**	3.74 ± 4.22	5.67 ± 4.27	24.93 ± 9.64	24.90 ± 8.39
PVSS-21**	7.62 ± 0.63	5.78 ± 0.63	7.36 ± 0.48	5.26 ± 0.98
Race and ethnicity (mean ± SD / %)				
White	67 (73.63%)	30 (66.67%)	16 (55.17%)	48 (67.61%)
Multiracial	8 (8.79%)	5 (11.11%)	2 (6.90%)	13 (18.31%)
Asian	7 (7.69%)	3 (6.67%)	3 (10.34%)	3 (4.23%)
Black or African American	5 (5.49%)	3 (6.67%)	4 (13.79%)	4 (5.63%)
Latino or Hispanic	1 (1.10%)	4 (8.89%)	4 (13.79%)	3 (4.23%)
American Indian or Alaska Native	1 (1.10%)			
Other	2 (2.20%)			

Table 1: 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. 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.

Study design and procedure

Data were collected across three time points (baseline, 1-week, 1-month). Participants completed the UG and RL tasks (all sessions) and psychiatric surveys (baseline and 1-month sessions). Subjective social status was assessed using the MacArthur Scale of Subjective Social Status (Adler et al., 2000). Participants earned $7.5 for 30 minutes at baseline, $4.0 for 20 minutes at 1 week, and $7.5 for 30 minutes at 1 month, with performance-based bonuses of $0–$6 per session.

The UG involved 30 trials of unfair monetary splits of $20, with participants deciding whether to accept or reject offers. Mood ratings were collected on ~30% of trials (Figure 1g).

In the RL task, participants chose between two slots under three conditions (negative, mixed, positive) across 35 trials with two reversals per condition. Rewards/punishments were based on predefined probabilities, and participants aimed to maximize earnings (Figure 1h).



Figure 1: Study design. a) Pearson correlation between depression score at baseline and 1-month follow-up. b) Pearson correlation between anhedonia score at baseline and 1-month follow-up. c) Baseline depression score by retention status. d) Baseline anhedonia score by retention status. e) Count plot on symptom severity using the cutoff criteria (depression > 13; anhedonia ≤ 6.67), resulting in four groups with either low(-)/high(+) depression(Dep) with low(-)/high(+) anhedonia(Anh) at baseline. f) Count plot on subdivided groups at 1-month follow-up. g) 30 trials ultimatum game with mood rating (33% trials). Participants played as responders to either accept or reject an unfair offer split of $20 made by a virtual partner. h) 105 trials reversal learning with 3 conditions (35 trial/condition). Participants needed to pick the best winning machine in negative (-$10 or $0), mixed (-$10 or $10), and positive ($0 or $10) conditions. Outcome from the slot machine was probabilistic (80% vs. 20%), and there were 2 reversals in each condition.

Statistical analysis and modeling

Depression (BDI-II > 13) and anhedonia (PVSS-21 ≤ 6.76) were labeled as low (0) or high (1) and mean-centered for regression. Trials with reaction times <0.1s or >10s were excluded (Baseline-UG: 0.45%, RL: 11.06%; 1 month-UG: 0.55%, RL: 12.54%). Reaction times were log-transformed for analysis. Demographics were recoded using the minority stress framework (e.g., female, person of color, gender queer), and objective SES was calculated as a z-score of education and income (Frost & Meyer, 2023; Meyer, 2003; Alegría et al., 2018; Call et al., 2022)

Behavioral results were analyzed using mixed-effect regression in R (lme4 package, Bates et al., 2022), with depression and anhedonia as fixed effects, participant as a random effect, and demographics as covariates. Error bars represent the standard error of the mean (±1 SEM). Statistical analyses and modeling methods were preregistered con OSF[1]. Data curation, visualization, and modeling were conducted in Python and R (Waskom, 2021; RStudio Team, 2020).

Results

Sample description

This online study included 236 U.S. participants (52% female; mean age (yrs) = 41.73, SD = 10.00, range: 27–77). Participants were divided into four groups based on depressive (-/+) and anhedonic (-/+) symptoms (Figure 1e, Table 1). Non-parametric tests showed no significant group differences in education, income, or subjective SES. However, one-way ANOVA revealed significant group differences in prior mood-related diagnoses ($F(3, 232) = 16.33$, $p < 0.01$), BDI-II ($F(3, 232) = 190$, $p < 0.01$), and PVSS-21 ($F(3, 232) = 162.8$, $p < 0.01$). Multivariate regression identified significant predictors of prior mood-related diagnoses: female sex ($\beta = 0.68$, $p < 0.01$), person of color ($\beta = -0.43$, $p = 0.01$), and gender queer ($\beta = 1.41$, $p < 0.01$). Subjective SES (BDI: $\beta = -1.97$, PVSS: $\beta = 4.94$, $p < 0.01$) and prior mood-related diagnoses (BDI: $\beta = 4.40$, PVSS: $\beta = -3.20$, $p < 0.05$) also significantly influenced baseline psychiatric scores.

Longitudinal stability of psychiatric symptoms

To assess the stability of psychiatric symptoms over time, we computed Pearson correlation coefficients between baseline and 1-month follow-up scores for depressive (BDI-II) and anhedonic (PVSS-21) symptoms. Depressive symptoms showed strong longitudinal stability, baseline M = 11.52, SD = 11.73; 1 month M = 11.90, SD = 12.38; $r(127) = .90$, $p < .001$ (Figure 1a). Anhedonic symptoms also demonstrated high stability, baseline M = 6.55, SD = 1.34; follow-up M = 6.56, SD = 1.35; $r(127) = .83$, $p < .001$ (Figure 1b). To examine whether retention was related to baseline symptom severity, we compared participants who completed both sessions ("retained") and those who dropped out after baseline ("dropped out") using independent samples t-tests. No significant differences were observed in baseline depressive symptoms, $t(251) = -0.88$, $p = .38$ (Figure 1c), or anhedonia scores, $t(251) = 0.25$, $p = .80$ (Figure 1d).

Longitudinal stability of social behavior

We assessed the longitudinal stability of UG behavioral metrics using subject-level correlations between baseline and 1-month follow-up. Reaction times demonstrated moderate stability, $r(127) = .60$, $p < .01$ (Figure 2a). Acceptance rates were highly stable, $r(127) = .77$, $p < .01$ (Figure 2b), as were mood ratings, $r(127) = .73$, $p < .01$ (Figure 2c). Behavioral responses across offer sizes were visualized separately for reaction times (Figure 2d), acceptance rates (Figure 2e), and mood ratings (Figure 2f). Paired *t*-tests revealed significant

[1] Statistical methods and modeling details are available from https://osf.io/pxg6f .

changes across time points in reaction times, $t(128) = 5.52$, $p < .01$; acceptance rates, $t(128) = -6.16$, $p < .01$; and mood ratings, $t(128) = -3.11$, $p < .01$.

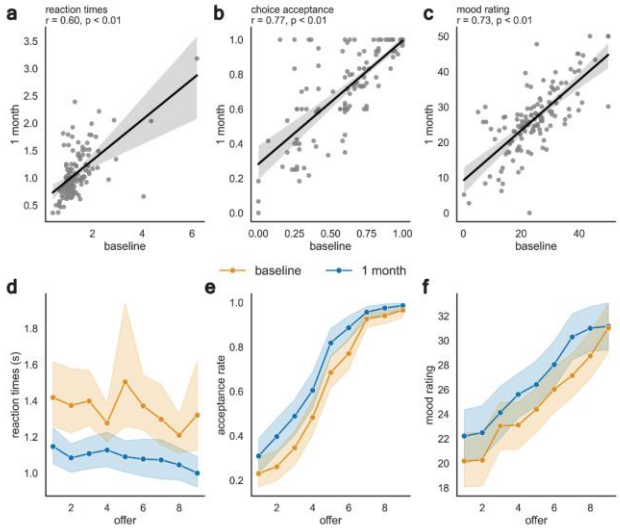


Figure 2: longitudinal stability of social behavior. a) Subject level baseline and 1-month correlation for reaction times. b) Subject level baseline and 1-month correlation for choice acceptance rate. a) Subject level baseline and 1-month correlation for mood rating. d) Reaction times as a function of offer size. e) Acceptance rate as a function of offer size. f) Mood rating as a function of offer size. Shaded areas indicated a 95% confidence interval.

Effects of depressive symptoms on social decision-making across time

At baseline, higher depressive symptoms were associated with slower reaction times in the UG ($\beta = 0.11$, $p = 0.02$; Figure 3a). Participants also responded slower to higher offers ($\beta = 0.05$, $p < 0.01$) and when accepting offers ($\beta = 0.26$, $p < 0.01$), with a significant interaction indicating a faster response when accepting higher offers ($\beta = -0.08$, $p < 0.01$). At the 1-month follow-up, the effect of depression on reaction times remained significant and stronger ($\beta = 0.25$, $p < 0.01$; Figure 3c). Reaction times were again slower for higher offers ($\beta = 0.04$, $p < 0.01$) and for accepted offers ($\beta = 0.12$, $p < 0.01$), with a similar significant offer × acceptance interaction ($\beta = -0.06$, $p < 0.01$). Socioeconomic status ($\beta = 0.05$, $p < 0.01$) and age ($\beta = 0.007$, $p < 0.01$) also contributed to longer response times at follow-up.

Higher depressive symptoms predicted lower acceptance rates at baseline ($\beta = -4.11$, $p = 0.02$; Figure 3b). At the 1-month follow-up, this negative effect of depression on choice behavior was even stronger ($\beta = -13.80$, $p = 0.01$; Figure 3d). Significant depression × offer interactions were observed at baseline ($\beta = 0.76$, $p < 0.01$) and 1-month follow-up ($\beta = 2.05$, $p = 0.03$), suggesting that individuals with higher depressive symptoms were more sensitive to offer fairness. Offer size strongly predicted acceptance at both baseline ($\beta = 2.60$, $p < 0.01$) and 1-month follow-up ($\beta = 4.20$, $p < 0.01$). Additionally, a significant three-way interaction between depression, anhedonia, and offer size was observed only at the 1-month follow-up ($\beta = -3.66$, $p = 0.049$), potentially indicating that co-occurring anhedonia further blunted acceptance responses to fair offers.

At baseline, offer acceptance was associated with lower mood ratings ($\beta = -3.48$, $p < 0.01$), and there was a significant depression × anhedonia interaction ($\beta = -6.02$, $p = 0.03$), suggesting that co-occurring symptoms may linked to blunted affective responses. A significant offer × acceptance interaction ($\beta = 1.27$, $p < 0.01$) indicated that accepted high offers were rated more positively than other outcomes. At the 1-month follow-up, the offer × acceptance interaction remained significant ($\beta = 1.09$, $p < 0.01$), replicating the effect of decision choice on mood ratings, though no symptom-related effects were observed.

In contrast to the UG findings, we only observed a significant effect of depression on slower reaction times in the positive block and a depression × anhedonia interaction on optimal choices in the negative block of the RL task. However, none of these effects replicated at the 1-month follow-up, suggesting that the observed effects may be task-specific and that social decision-making measures may be more sensitive to psychiatric symptoms over time.

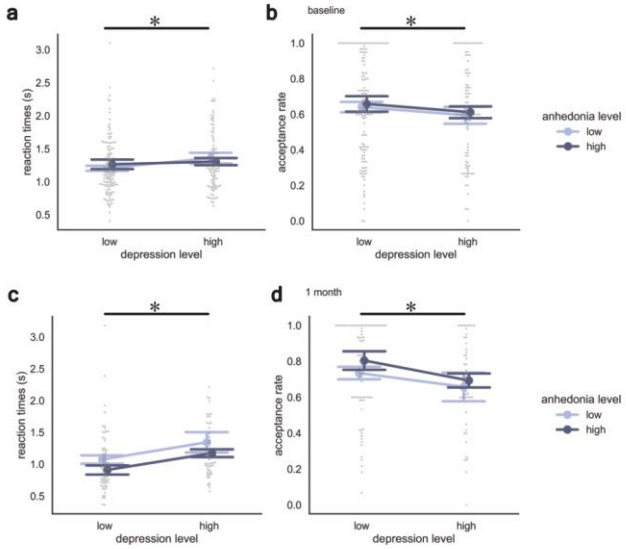


Figure 3: model-agnostic behavior in UG (baseline n = 246; 1-month n = 131). a) Main effect of depressive symptoms on reaction times at baseline. b) Main effect of depressive symptoms on choice acceptance at baseline. c) Main effect of depressive symptoms on reaction times at 1-month follow-up. d) Main effect of depressive symptoms on choice acceptance at 1-month follow-up.

Discussion

This study aimed to examine the effects of depression on decision-making across social and non-social contexts using a longitudinal design. Our findings provide three key contributions to the literature. First, we demonstrate strong longitudinal stability of self-reported depressive and anhedonic symptoms over a one-month period. Second, we identify consistent behavioral effects of depression—particularly slower reaction times and reduced acceptance of unfair offers—in a social decision-making task. And third, we highlight the reproducibility of task-level behavioral patterns across time points in an online general population sample.

Consistent with prior work, we found that depressive symptoms were associated with psychomotor slowing, reflected in significantly longer reaction times during the Ultimatum Game. This effect was robust across both baseline and follow-up sessions, suggesting that slowed decision-making may be a stable cognitive marker of depressive symptom severity, even outside clinical settings. Psychomotor slowing is a well-established feature of major depressive disorder and may reflect broader impairments in evidence accumulation or reduced motivational drive during value-based decisions (Lawlor et al., 2019). Notably, this effect emerged in a social context, suggesting an altered information processing during interpersonal exchanges in depression.

Our findings also revealed that depressive symptoms significantly influenced fairness-related decision-making (Güth et al., 1982; Kirchsteiger, 1994). Participants with higher depressive symptoms were less likely to accept unfair offers but showed greater acceptance rates as offer sizes increased. These results align with previous studies demonstrating altered fairness perceptions in individuals with depression (Gradin et al., 2014; Jin et al., 2022). The consistency of this effect across timepoints further supports the idea that depression-related changes in social decision-making are not transient fluctuations but reflect stable behavioral tendencies. These findings extend previous cross-sectional work on fairness sensitivity in depression and underscore the value of repeated-measures designs in assessing psychiatric-behavioral associations. Future work should explore the broader relationship between income inequality, socioeconomic behavior, and depressive symptoms (Patel et al., 2018).

While mood ratings and other behavioral metrics (e.g., in reversal learning) showed some group-level patterns at baseline (Mukherjee et al., 2020), they did not reliably vary with symptom dimensions longitudinally in this sample. In particular, we found no replicable relationship between psychiatric symptoms and mood ratings in the social exchange task, nor did we observe strong symptom-linked effects on decision-making in the reversal learning task. These null results, while preliminary, raise important questions about the sensitivity of affective ratings and non-social learning paradigms in capturing symptom-specific effects—especially when measured in non-clinical, online samples. Given these limitations, we opted to focus our primary results on the more robust associations observed in the social task and present exploratory findings from reversal learning as supplementary material.

Importantly, our findings support the feasibility and utility of online platforms for repeated psychiatric and behavioral measurement. We observed moderate retention rates and equivalent symptom distributions across timepoints, suggesting minimal attrition bias. The high within-subject stability of depression and anhedonia scores adds further support for the reliability of self-report metrics collected online. This is encouraging for future longitudinal studies of mental health, where remote data collection may offer scalable alternatives to in-lab testing.

One major next step is to incorporate computational modeling to probe latent mechanisms underlying observed behavioral effects. While this study focused on descriptive metrics and linear associations, computational models — such as reinforcement learning — may clarify whether depressive symptoms influence parameters like learning rates or sensitivity to social norms (Gu et al., 2015; Pike & Robinson, 2022). Applying these models longitudinally would allow us to test whether cognitive mechanisms linked to psychiatric symptoms remain stable over time or change with symptom fluctuation. This would help bridge the gap between static symptom reports and dynamic, mechanistic accounts of behavior.

Our results should be interpreted with several limitations in mind. First, while our sample size was adequate for detecting moderate effects, larger and more diverse cohorts will be needed to assess generalizability to clinical populations and across demographic subgroups. Second, while we focused on depression and anhedonia, other transdiagnostic symptoms such as anxiety may also shape decision-making and were not modeled here. Third, the lack of computational modeling limits our current ability to draw inferences about underlying cognitive processes, though planned analyses will address this in future work.

Conclusion

Taken together, these findings contribute to a growing literature on the cognitive and social mechanisms of depression by demonstrating symptom-specific and temporally stable effects on decision-making in a social context. Depression, more so than anhedonia, was associated with consistent slowing of responses and greater rejection of unfair offers in the UG across two time points, suggesting that these behavioral markers may reflect sustained effects of depressive symptoms on cognitive patterns. By incorporating

repeated behavioral and psychiatric assessments in an online sample, this study also provides methodological support for scalable, longitudinal research in computational psychiatry.

Future work should extend this approach using computational models to identify stable cognitive parameters that track symptom profiles and explore whether changes in these parameters predict clinical outcomes. Understanding how different facets of depression shape behavior over time—especially in social contexts—may offer a path toward more nuanced, mechanism-informed interventions that move beyond categorical diagnoses.

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References

Adler, N. E., Epel, E. S., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy, White women. Health Psychology, 19(6), 586–592. https://doi.org/10.1037//0278-6133.19.6.586

Alegría, M., NeMoyer, A., Falgàs Bagué, I., Wang, Y., & Alvarez, K. (2018). Social Determinants of Mental Health: Where We Are and Where We Need to Go. Current Psychiatry Reports, 20(11). https://doi.org/10.1007/s11920-018-0969-9

Bates, D., Maechler, M., Bolker [aut, B., cre, Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., Grothendieck, G., Green, P., Fox, J., Bauer, A., & simulate.formula), P. N. K. (shared copyright on. (2022, July 8). lme4: Linear Mixed-Effects Models using "Eigen" and S4. R-Packages. https://cran.r-project.org/web/packages/lme4/index.html

Beck, A. T., Steer, R. A., & Brown, G. (1996). Beck Depression Inventory–II. PsycTESTS Dataset. https://doi.org/10.1037/t00742-000

Bennabi, D., Vandel, P., Papaxanthis, C., Pozzo, T., & Haffen, E. (2013). Psychomotor Retardation in Depression: A Systematic Review of Diagnostic, Pathophysiologic, and Therapeutic Implications. BioMed Research International, 2013, 1–18. https://doi.org/10.1155/2013/158746

Call, C. C., Eckstrand, K. L., Kasparek, S. W., Boness, C. L., Blatt, L., Jamal-Orozco, N., Novacek, D. M., & Foti, D. (2022). An Ethics and Social-Justice Approach to Collecting and Using Demographic Data for Psychological Researchers. Perspectives on Psychological Science, 18(5), 174569162211373. https://doi.org/10.1177/17456916221137350

Christensen, M. C., Wong, C. M. J., & Baune, B. T. (2020). Symptoms of Major Depressive Disorder and Their Impact on Psychosocial Functioning in the Different Phases of the Disease: Do the Perspectives of Patients and Healthcare Providers Differ? Frontiers in Psychiatry, 11(1), 280. https://doi.org/10.3389/fpsyt.2020.00280

Cooper, J. A., Arulpragasam, A. R., & Treadway, M. T. (2018). Anhedonia in depression: biological mechanisms and computational models. Current Opinion in Behavioral Sciences, 22, 128–135. https://doi.org/10.1016/j.cobeha.2018.01.024

Frost, D. M., & Meyer, I. H. (2023). Minority Stress Theory: Application, Critique, and Continued Relevance. Current Opinion in Psychology, 51, 101579. https://doi.org/10.1016/j.copsyc.2023.101579

Gradin, V. B., Pérez, A., MacFarlane, J. A., Cavin, I., Waiter, G., Engelmann, J., Dritschel, B., Pomi, A., Matthews, K., & Steele, J. D. (2014). Abnormal brain responses to social fairness in depression: an fMRI study using the Ultimatum Game. Psychological Medicine, 45(6), 1241–1251. https://doi.org/10.1017/s0033291714002347

Gu, X., Wang, X., Hula, A., Wang, S., Xu, S., Lohrenz, T. M., Knight, R. T., Gao, Z., Dayan, P., & Montague, P. R. (2015). Necessary, Yet Dissociable Contributions of the Insular and Ventromedial Prefrontal Cortices to Norm Adaptation: Computational and Lesion Evidence in Humans. The Journal of Neuroscience, 35(2), 467–473. https://doi.org/10.1523/jneurosci.2906-14.2015

Güth, W., Schmittberger, R., & Schwarze, B. (1982). An experimental analysis of ultimatum bargaining. Journal of Economic Behavior & Organization, 3(4), 367–388. https://doi.org/10.1016/0167-2681(82)90011-7

Jin, Y., Gao, Q., Wang, Y., Xiao, L., Michael Shengtao Wu, & Zhou, Y. (2022). The perception-behavior dissociation in the ultimatum game in unmedicated patients with major depressive disorders. Journal of Psychopathology and Clinical Science, 131(3), 253–264. https://doi.org/10.1037/abn0000747

Khazanov, G. K., Ruscio, A. M., & Forbes, C. N. (2019). The Positive Valence Systems Scale: Development and Validation. Assessment, 27(5), 1045–1069. https://doi.org/10.1177/1073191119869836

Kirchsteiger, G. (1994). The role of envy in ultimatum games. Journal of Economic Behavior & Organization,

25(3), 373–389. https://doi.org/10.1016/0167-2681(94)90106-6

Kring, A. M., & Barch, D. M. (2014). The motivation and pleasure dimension of negative symptoms: Neural substrates and behavioral outputs. European Neuropsychopharmacology, 24(5), 725–736. https://doi.org/10.1016/j.euroneuro.2013.06.007

Lawlor, V. M., Webb, C. A., Wiecki, T. V., Frank, M. J., Trivedi, M., Pizzagalli, D. A., & Dillon, D. G. (2019). Dissecting the impact of depression on decision-making. Psychological Medicine, 50(10), 1613–1622. https://doi.org/10.1017/s0033291719001570

Meyer, I. H. (2003). Prejudice, Social Stress, and Mental Health in Lesbian, Gay, and Bisexual Populations: Conceptual Issues and Research Evidence. Psychological Bulletin, 129(5), 674–697. https://doi.org/10.1037/0033-2909.129.5.674

Mukherjee, D., Camilla van Geen, & Kable, J. (2023). Leveraging Decision Science to Characterize Depression. Current Directions in Psychological Science, 32(6), 462–470. https://doi.org/10.1177/09637214231194962

Mukherjee, D., Filipowicz, A. L. S., Vo, K., Satterthwaite, T. D., & Kable, J. W. (2020). Reward and punishment reversal-learning in major depressive disorder. Journal of Abnormal Psychology. https://doi.org/10.1037/abn0000641

Northoff, G., Hirjak, D., Wolf, R. C., Magioncalda, P., & Martino, M. (2021). All roads lead to the motor cortex: psychomotor mechanisms and their biochemical modulation in psychiatric disorders. Molecular Psychiatry, 26(1), 92–102. https://doi.org/10.1038/s41380-020-0814-5

Paolo Fusar-Poli, Andrés Estradé, Stanghellini, G., Cecilia Maria Esposito, René Rosfort, Mancini, M., Norman, P., Cullen, J. M., Miracle Ayomikun Adesina, Gema Benavides Jimenez, Caroline, Drah, E. A., Julien, M.-H., Lamba, M., Mutura, E. M., Prawira, B., Agus Sugianto, Jaleta Teressa, White, L. A., & Damiani, S. (2023). The lived experience of depression: a bottom-up review co-written by experts by experience and academics. World Psychiatry, 22(3), 352–365. https://doi.org/10.1002/wps.21111

Patel, V., Burns, J. K., Dhingra, M., Tarver, L., Kohrt, B. A., & Lund, C. (2018). Income inequality and depression: A systematic review and meta-analysis of the association and a scoping review of mechanisms. World Psychiatry, 17(1), 76–89. https://doi.org/10.1002/wps.20492

Pike, A. C., & Robinson, O. J. (2022). Reinforcement Learning in Patients With Mood and Anxiety Disorders vs Control Individuals. JAMA Psychiatry, 79(4). https://doi.org/10.1001/jamapsychiatry.2022.0051

Pitliya, R. J., Nelson, B. D., Hajcak, G., & Jin, J. (2022). Drift-Diffusion Model Reveals Impaired Reward-Based Perceptual Decision-Making Processes Associated with Depression in Late Childhood and Early Adolescent Girls. Research on Child and Adolescent Psychopathology, 50(11), 1515–1528. https://doi.org/10.1007/s10802-022-00936-y

Rhoads, S. A., Gu, X., & Barnby, J. M. (2024). Advancing computational psychiatry through a social lens. Nature Mental Health. https://doi.org/10.1038/s44220-024-00343-w

Ribot, T. A. (1897). The Psychology of the Emotions (pp. 53–54). Paris, F. Alcan. https://www.gutenberg.org/files/67585/67585-h/67585-h.htm

Rizvi, S. J., Pizzagalli, D. A., Sproule, B. A., & Kennedy, S. H. (2016). Assessing anhedonia in depression: Potentials and pitfalls. Neuroscience & Biobehavioral Reviews, 65, 21–35. https://doi.org/10.1016/j.neubiorev.2016.03.004

RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA. http://www.rstudio.com/.

Waskom, M. (2021). Seaborn: Statistical Data Visualization. Journal of Open Source Software, 6(60), 3021. https://doi.org/10.21105/joss.03021

Wüthrich, F., Nabb, C. B., Mittal, V. A., Shankman, S. A., & Walther, S. (2022). Actigraphically measured psychomotor slowing in depression: systematic review and meta-analysis. Psychological Medicine, 52(7), 1208–1221. https://doi.org/10.1017/s0033291722000903