**Supplementary Materials**

**Note 1: Psychometric properties of the bifactor model of anxiety and depression in the Chinese population**.

We tested the validation of the tripartite model of anxiety and depression in the Chinese population (n = 901). All participants were asked to complete a set of anxiety- and depression-related questionnaires (see Methods), as previous literature on the tripartite model1,2. To examine the underlying factor structure, the entire sample was equally divided into two datasets according to the participants’ number for exploratory and confirmatory factor analysis (EFA dataset, the first part, 1-450; CFA dataset, the second part, 451-901), respectively. For the EFA dataset, we determined the number of factors based on theoretical considerations (i.e., the tripartite model of anxiety and depression3–5) and scree plot. Results showed that our data was best explained by three factors (40.24%). We then used the three-factor bifactor model to decompose the item-level covariance matrix into a general factor and two specific factors. The ‘Psych’ package in R was used to perform Schmid-Leiman (SL) orthogonalization procedure to obtain factor loadings for each item. Specifically, the SL procedure used oblique factor analysis and higher order factor analysis based on the lower order factor correlations to extract the shared higher order factor (the common factor). Factor scores for each participant were calculated using the Anderson-Rubin method, which is a weighted-least squares solution that maintains the orthogonality of the common score and each specific factor score. Results of factor loadings indicated that the common factor had high loadings (>0.4) for multiple anxiety-related and depression-related items and moderately high loadings (>0.2) across almost all items (Figure 1D). One specific factor had high loadings (>0.4) on items related to anhedonia while another specific factor had high loadings (>0.4) on items related to worry and anxious arousal (Figure 1D).

In the CFA dataset, all items were allowed to load onto the common factor. Each item was also allowed to load onto either the anxiety-specific factor or the depression-specific factor. The assignment for each item was depended on whether the loading on each specific factor was greater than 0.2 in the EFA dataset. After item assignments, factor loadings were re-estimated with diagonally weighted least squares estimation (DWLS). This method only allowed each item to load on the loaded factor in the EFA dataset (>0.2), because it is more appropriate for ordinal data and less sensitive to deviations from normality, as compared with maximum likelihood estimation6. We implemented this procedure with the specification of an orthogonal solution using the ‘Lavaan’ package in R. The quality of the fit was evaluated by the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root-mean-square residual (SRMR). Results showed excellent goodness-of-fit indices (CFI = 0.989, TLI = 0.989, RMSEA = 0.046, SRMR = 0.061). We additionally performed the same analysis for the CFA dataset as in the EFA dataset to access the similarity between different datasets. That is, we conducted an unconstrained (i.e., exploratory, but not confirmatory) bifactor analysis in the CFA dataset. The resulting factor loadings were highly congruent with the factor loadings in the EFA dataset (cosine-similarity was 0.99 for the common factor loadings, 0.99 for the depression-specific factor loadings, and 0.98 for the anxiety-specific factor loadings). As predicted by the factor structure, the common factor scores are orthogonal to each specific factor scores (Figure 1C&E).

To verify the factor structure underlying anxiety and depression, our model space also included a three-factor high-order model and a simple three-factor model. Comparison of model fit revealed that the bifactor model outperformed than other models (Table S1), confirming the bifactor structure underlying anxiety and depression. In addition, the common factor showed high correlations with all questionnaires (rs > 0.69; Figure 1F), except the anxious arousal subscale of the Mood and Anxiety Symptoms Questionnaire (MASQaa; r = 0.16). The anxiety-specific factor was mainly contributed by the anxiety subscale of the State-Trait Anxiety Inventory (TAIanx, r = 0.60), the neuroticism of the Big Five Inventory-2 (BFIn, r = 0.41), the Penn State Worry Questionnaire (PSWQ, r = 0.41), MASQaa (r = 0.86), the Beck Depression Inventory (BDI; r = 0.52), and the Center for Epidemiologic Studies Depression Scale (CESD; r = 0.54), while the depression-specific factor was mainly contributed by the depression subscale of the State-Trait Anxiety Inventory (TAIdep, r = 0.52) and the anhedonia depression subscale of the Mood and Anxiety Symptoms Questionnaire (MASQad; r = 0.58). Correlations between factors and questionnaires showed the same pattern in different datasets (Figure S1). These results indicated good construct validity of this bifactor model of anxiety and depression. Together, these results validated the bifactor model of anxiety and depression in the Chinese population and supported the classic tripartite model. Regarding the application, the bifactor model was initially derived and validated using the larger psychometric dataset (n = 901). For subsequent analyses for each dataset, we applied this validated bifactor solution by computing factor scores using the loadings obtained from the original psychometric sample. Thus, each dataset remained independent, and factor scores for anxiety- and depression-specific traits were consistently defined across all experiments. This operation was consistent with recent literature of computational psychiatry7.

**Note 2: Computational model of momentary mood**

To quantify how different events impacted participants’ momentary moods during the gambling task, we used the classic model assuming that momentary mood depends on the recency-weighted average of the chosen certain reward (CR), expected value of the chosen gamble (EV), and reward prediction error (RPE; M1; Equation 1). RPE was defined as the difference between the obtained and expected value. We also incorporated a drift parameter to account for the gradual change in happiness over time8,9.

(1)

Here, *t* and *j* are trial numbers, is a baseline mood parameter, other weights capture the influence of different event types. [0,1] is a decay parameter explicitly modeling the influence of previous trials on current happiness ratings, assigning greater weight to recent events and progressively diminishing influence to earlier trials. CR*j* is the CR if the certain option was chosen on trial *j*; otherwise, CR*j* is 0. EV*j* is the EV and RPEj is the RPE on trial *j* if the gamble was chosen. If the certain option was chosen, then EV*j* = 0and RPE*j* =0.

Although M1 has been shown to accurately track mood data, we also fit other candidate mood models. Specifically, to verify the notion that momentary moods depend on RPE in addition to reward expectation, we fit an alternative model in which moods are contributed by the recency-weighted average of CR and the gamble reward (GR; M2; Equation 2).

(2)

To verify that mood ratings are best explained by a shared forgetting factor (i.e., the recency-weighted history of different event types), we compared a model with a single decay parameter to an alternative model including forgetting factors for each event type, e.g., different decay parameters for CR, EV, and RPE (M3; Equation 3).

(3)

It has been shown that moods are influenced by automatically comparing alternative outcomes. We thus considered a component of the outcome difference (OD) between the chosen option and unchosen option (M4; Equation 4) and a regret (R) component (upward comparison; M5; Equation 5) based on M1.

(4)

where OD is the outcome difference between the chosen option and the unchosen option.

(5)

where R represents how much better the outcome could have been if the other option had been chosen. Mathematically, R is the difference between the obtained outcome and the potential better outcome if exists; otherwise, R = 0. We also considered subjective values, rather than objective values in M1, to model mood, as to calibrate the rating scale that participants may use. Approach-avoidance perspective theory model has been consistently shown to explain choice data better than the traditional perspective theory model. There were six parameters in this approach-avoidance model, including risk aversion in the gain domain (: 0.3-1.3), risk aversion in the loss domain (: 0.3-1.3), loss aversion (: 0.5-5), approach ( : 0-1), avoidance (: 0-1), and inverse temperature (: 0-10). Ranges for these parameters were the same as previous research10,11. We therefore fit subjective value-driven mood model (fit the approach-avoidance perspective theory model first and subjective feeling model second; M6; Equations 6-13).

(6)

(7)

(8)

where V*gain* and V*loss* are the objective gain and loss from a gamble, separately. V*certain* is the objective value for the certain option. U*gamble* and U*certain* are subjective utilities of the gamble and the certain option, respectively. Choice probability for gamble (P*gamble*) is jointly determined by the softmax rule and Pavlovian approach/avoidance parameters. For gain trials,

(9)

(10)

For loss trials,

(11)

(12)

Similar to M1, these subjective values were fit to trial-by-trial mood.

(13)

**Note 3: Calibration of rating scales**

There was an important issue that individual differences in risk preference may affect the subjective calibration of mood rating scales. Specifically, individuals with nonlinear utility functions (e.g., risk-seeking participants) could display disproportionately high mood responses for large relative to small wins, potentially affecting model interpretation. To systematically address this issue, we conducted several complementary analyses:

**First**, we examined whether objective or subjective utility models better explained happiness ratings. To enhance statistical power and simplify interpretation, we combined our laboratory and two online datasets into a single healthy dataset. Model comparisons consistently favored the objective happiness model (M1) over the subjective model (M6), as indicated by lower Bayesian Information Criterion (BIC) values and significantly higher exceedance probabilities (EP > 0.95, Table S3), suggesting the objective model better captured happiness ratings at both individual and group levels.

**Second**, within the winning model (objective one), we replicated opposed roles of RPE in mood dynamics of depression and anxiety after controlling for risk attitudes (*ps* < 0.009).

**Third**, we explicitly assessed whether risk preferences moderated the relationship between wins and mood ratings. Linear mixed-effects analyses on z-scored happiness with subject as a random factor and with different wins and risk preference for gain showed no significant interaction effects between risk preference and win size on happiness ratings for either certain or gamble trials (all *p*-values > 0.05, Table S6).

**Fourth**, we validated these findings externally by examining two open datasets using similar risk-based decision-making tasks with repeated happiness ratings: Vanhasbroeck et al.12 (2021; n = 49) and Rutledge's smartphone App dataset (n = 46,204). Consistent with our own data, model comparisons again favored the objective happiness model (Table S3), and interaction analyses revealed no meaningful moderation by risk preferences (Table S6).

**Finall**y, we fitted a simple happiness model with unit wins and losses (Equations 17; mean R2 = 0.65 for healthy dataset and 0.43 for clinical dataset). Mood sensitivity parameters were not significantly correlated with individual differences in risk preferences, either in our healthy (wins: r = 0.017, p = 0.588; losses: r = 0.009, p = 0.765) or clinical datasets (wins: r = 0.072, p = 0.441; losses: r = 0.014, p = 0.882).

(17)

Collectively, these comprehensive analyses suggest that individual differences in risk preference did not significantly affect the calibration of mood ratings or alter our primary findings regarding distinct mood dynamics in anxiety versus depression. Instead, these results possibly suggest dissociable processes for decision-making (i.e., value perception) and mood dynamics.

**Note 4: Orthogonality of happiness weights on CR, EV and RPE**

One potential concern was the orthogonality of happiness weights on CR, EV and RPE. Indeed, we found significant correlation between them (healthy dataset: 0.348 < rs < 0.625, ps < 0.001; clinical dataset: 0.260 < rs < 0.679, ps < 0.005). Parameter recovery analysis showed high correlations between the matched simulated and real parameters (healthy dataset: 0.818 < rs < 0.943, *ps* < 0.001; clinical dataset: 0.815 < rs < 0. 955, ps < 0.001) and low correlations between the mismatched simulated and real parameters (healthy dataset: 0.269 < rs < 0.572, *ps* < 0.001; clinical dataset: 0.172 < rs < 0. 635, ps < 0.065; Figure S5), confirming the identification of these parameters. To examine whether risk preferences influence their orthogonality, correlation analyzes did not show significant correlation between risk preferences and model fit (e.g., R2; healthy dataset: abs(r) < 0.042, ps > 0.182; clinical dataset: abs(r) < 0.105, ps > 0.261). When controlling for risk attitudes and model fit, our findings of opposed roles of RPE in mood dynamics of depression and anxiety can be replicable (healthy dataset: *ps* < 0.002; clinical dataset: for depression: p=0.016). In addition, we fitted a simple happiness model with unit wins and losses (Equations 17; mean R2 = 0.65 for healthy dataset and 0.43 for clinical dataset). Mood sensitivity parameters were not significantly correlated with individual differences in risk preferences, either in our healthy (wins: r = 0.017, p = 0.588; losses: r = 0.009, p = 0.765) or clinical datasets (wins: r = 0.072, p = 0.441; losses: r = 0.014, p = 0.882). These results suggest that the current parameters can be identified and individual differences in risk attitudes do not influence parameter recovery.

**Note 5: Time effect on happiness**

Although we incorporated a drift parameter to account for the gradual change in happiness over time (βt : t = -5.84, p < 0.001), time may also interact with event parameters, affecting mood sensitivity dynamically. Therefore, we tested three additional models explicitly incorporating interactions between time-on-task and different event parameters (Models M7–M9; see Equations 14–16), enabling us to systematically evaluate how mood responses to events might change with time.

(14)

(15)

(16)

Model comparisons consistently favored the simpler intercept-only drift model (M1) over these interaction models (M7–M9), as indicated by lower Bayesian Information Criterion (BIC) values (Table S4). Furthermore, we validated these results externally using two publicly available datasets with similar paradigms (Vanhasbroeck et al.12, 2021; n = 49; and Rutledge's smartphone app dataset, n = 46,204). These external validations also strongly favored the simpler drift model without time-event interactions (see Table S4). Taken together, these analyses suggest that while overall mood indeed exhibits gradual drift over time, there is minimal evidence to support time-on-task by event interactions substantially affecting mood sensitivity to event parameters in our task, supporting the robustness and generalizability of our primary findings.

**Note 6: Contributions to model fit**

To elaborate on which components (CR, EV or RPE) contributed most to model fit, we tested three additional models. Specifically, based on the winning model (M1), we kicked out each event component separately (M10-12, see Equations 17–19).

(17)

(18)

(19)

The results showed that removing RPE led to the most substantial drop in model fit: ΔR² = 0.26 in the healthy dataset and ΔR² = 0.18 in the clinical dataset (Table S5). This indicates that RPE was the most important contributor to explaining mood dynamics. In contrast, excluding either CR or EV resulted in only modest reductions in model fit (ΔR² < 0.09 in the healthy dataset and ΔR² < 0.07 in the clinical dataset). We replicated this pattern in two independent, publicly available datasets (Vanhasbroeck et al., 2021, n = 49; and Rutledge’s smartphone app dataset, n = 46,204), further supporting the robustness and generalizability of the central role of RPE in momentary mood computations (Table S5). These analyses confirm that reward prediction error is the dominant predictor of trial-by-trial mood changes.

**Reference**

1. Gagne, C., Zika, O., Dayan, P. & Bishop, S. J. Impaired adaptation of learning to contingency volatility in internalizing psychopathology. *Elife* **9**, (2020).

2. Gagne, C., Agai, S., Ramiro, C., Dayan, P. & Bishop, S. Biased belief priors versus biased belief updating: Differential correlates of depression and anxiety. *PLoS Comput Biol* **18**, e1010176 (2022).

3. Clark, L. A. & Watson, D. Tripartite Model of Anxiety and Depression: Psychometric Evidence and Taxonomic Implications. *J Abnorm Psychol* **100**, 316–336 (1991).

4. Brodbeck, J., Abbott, R. A., Goodyer, I. M. & Croudace, T. J. General and specific components of depression and anxiety in an adolescent population. *BMC Psychiatry* **11**, 191 (2011).

5. Simms, L. J., Grös, D. F., Watson, D. & O’Hara, M. W. Parsing the general and specific components of depression and anxiety with bifactor modeling. *Depress Anxiety* **25**, E34–E46 (2008).

6. Li, C.-H. The performance of ML, DWLS, and ULS estimation with robust corrections in structural equation models with ordinal variables. *Psychological Methods* **21**, 369–387 (2016).

7. Lee, J. K., Rouault, M. & Wyart, V. Compulsivity is linked to suboptimal choice variability but unaltered reinforcement learning under uncertainty. *Nature Mental Health* **3**, 229–241 (2025).

8. Jangraw, D. C. *et al.* A highly replicable decline in mood during rest and simple tasks. *Nat Hum Behav* **7**, 596–610 (2023).

9. Vinckier, F., Rigoux, L., Oudiette, D. & Pessiglione, M. Neuro-computational account of how mood fluctuations arise and affect decision making. *Nat Commun* **9**, 1708 (2018).

10. Rutledge, R. B. *et al.* Risk Taking for Potential Reward Decreases across the Lifespan. *Current Biology* **26**, 1634–1639 (2016).

11. Rutledge, R. B., Skandali, N., Dayan, P. & Dolan, R. J. Dopaminergic Modulation of Decision Making and Subjective Well-Being. *Journal of Neuroscience* **35**, 9811–9822 (2015).

12. Vanhasbroeck, N. *et al.* Testing a computational model of subjective well-being: a preregistered replication of Rutledge et al. (2014). *Cogn Emot* **35**, 822–835 (2021).

13. Coplan, J. D. Treating comorbid anxiety and depression: Psychosocial and pharmacological approaches. *World J Psychiatry* **5**, 366 (2015).

**Supplementary Figures**

**Figure S1**. Correlations of factor scores from the winning model (the bifactor model) with questionnaire scores for each dataset.



**Figure S2.** Gambling rate in each dataset. All datasets showed the same gambling rate pattern, as well as in line with literature.



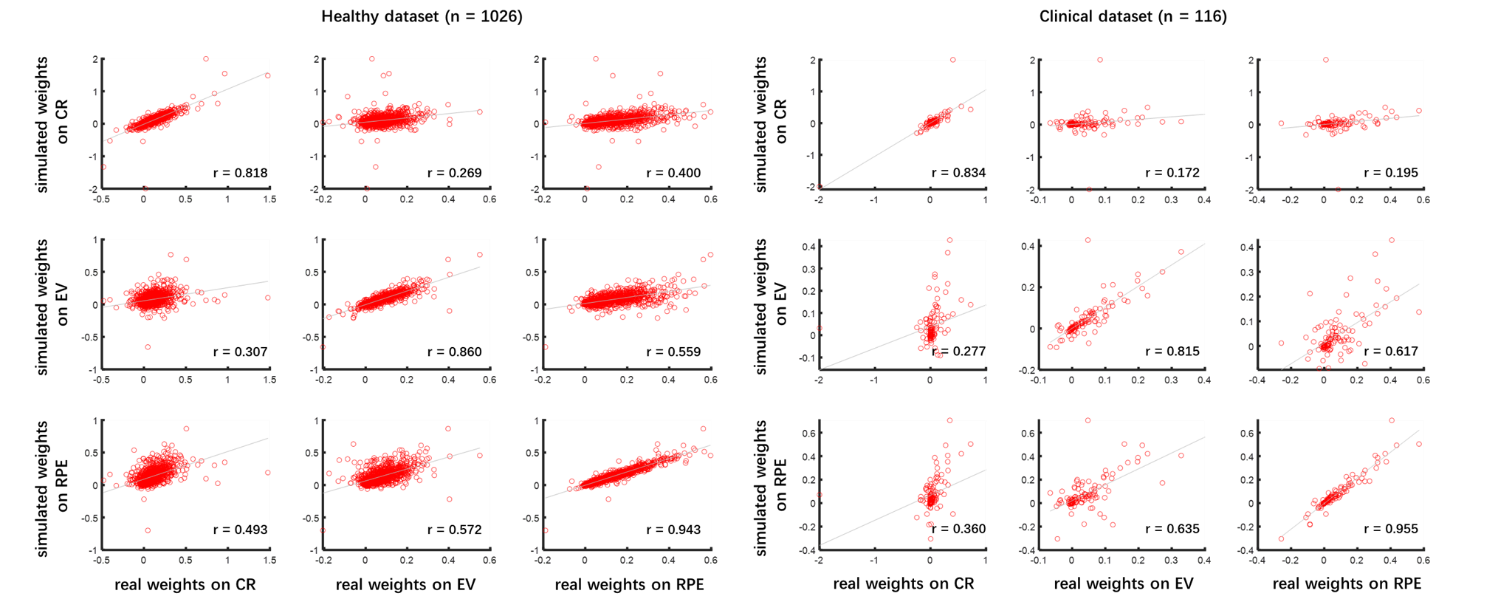
**Figure S3.** Model-agnostic mood results for all datasets. All datasets showed the same initial mood overall before the task, mean mood and mood variation across the task.



**Figure S4.** Replication of the classic mood effects. A) Happier after winning than losing. B) Mood drift across the task.



**Figure S5**. Parameter recovery for the winning model (M1) for the healthy and clinical datasets. Parameter recovery analysis showed high correlations between the matched simulated and real parameters and low correlations between the mismatched simulated and real parameters.



**Figure S6.** Replication of Rutledge et.al., (2017)’s findings using BDI (N =1026). Depression symptom measured by BDI was negatively correlated with the baseline mood parameter. Data was combined from laboratory dataset, online dataset 1, and online dataset 2.



**Table S1**. Psychometric model comparisons

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | CFI | TLI | RMSEA | SRMR |
| Bifactor model | 0.989 | 0.989 | 0.046 | 0.061 |
| Three-factor model | 0.794 | 0.789 | 0.200 | 0.205 |
| High-order model | 0.981 | 0.981 | 0.060 | 0.072 |

**Table S2**. Mood model comparisons

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model Number | # of parameters | Δ BIC | | | |
| Laboratory dataset  N = 44 | Online  dataset 1  N = 747 | Online  dataset 2  N = 235 | Clinical dataset  N=116 |
| Model #1 | 6 | 0 | 0 | 0 | 0 |
| Model #2 | 5 | 43.99 | 918.62 | 228.00 | 41.57 |
| Model #3 | 8 | 122.13 | 1815.15 | 586.31 | 549.73 |
| Model #4 | 7 | 155.22 | 2662.46 | 814.28 | 424.10 |
| Model #5 | 7 | 82.24 | 709.23 | 204.32 | 151.56 |
| Model #6 | 6 | 47.76 | 2514.71 | 743.17 | 601.16 |

Abbreviations: Δ BIC, Bayesian information criterion relative to the winning model (Model #1).

**Table S3.** Objective vs. subjective happiness models

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | # of parameters | Δ BIC | | | |
| Healthy dataset  N = 1026 | Clinical dataset  N = 116 | Vanhasbroeck et.al., dataset  N = 49 | Rutledge’s dataset  N=46204 |
| Model #1 | 6 | 0 | 0 | 0 | 0 |
| Model #6 | 5 | 3305.64 | 601.16 | 118.00 | 4997.29 |
| Model #1 vs. 6 EP | - | 1.00 | 1.00 | 1.00 | 1.00 |

Abbreviations: Δ BIC, Bayesian information criterion relative to the winning model (Model #1); EP, exceedance probability; EP greater than 0.95 was considered significant.

**Table S4.** Time effect on happiness

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model Number | # of parameters | Δ BIC | | | |
| Healthy datasest  N = 1026 | Clinical dataset  N = 116 | Vanhasbroeck et.al., dataset  N = 49 | Rutledge’s dataset  N=46204 |
| Model #1 | 6 | 0 | 0 | 0 | 0 |
| Model #7 | 6 | 1883.39 | 84.88 | 98.15 | 4152.61 |
| Model #8 | 6 | 1487.79 | 66.37 | 61.73 | 2295.40 |
| Model #9 | 6 | 1064.22 | 59.53 | 74.40 | 1458.34 |

Abbreviations: Δ BIC, Bayesian information criterion relative to the winning model (Model #1).

**Table S5.** Contributions to model fit

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model Number | # of parameters | Mean R2 | | | |
| Healthy datasest  N = 1026 | Clinical dataset  N = 116 | Vanhasbroeck et.al., dataset  N = 49 | Rutledge’s dataset  N=46204 |
| M1:CR+EV+RPE | 6 | 0.68 | 0.47 | 0.58 | 0.69 |
| M10: No CR | 5 | 0.62 | 0.42 | 0.52 | 0.60 |
| M11: No EV | 5 | 0.59 | 0.40 | 0.54 | 0.60 |
| M12: No RPE | 5 | 0.42 | 0.29 | 0.34 | 0.50 |

**Table S6.** Interaction between different wins and risk preference for gain on z-scored happiness

|  |  |  |
| --- | --- | --- |
| Datasets | Trial types | |
| Certain trials | Gamble Trials  (better outcomes; nonzero) |
| Healthy dataset  N = 1026 | beta = -0.00; t = -0.07; p = 0.943  95%CI = [-0.01, 0.01] | beta = -0.00; t = -0.24; p = 0.807  95%CI = [-0.00, 0.00] |
| Clinical dataset  N = 116 | beta = -0.01; t = -0.64; p = 0.524  95%CI = [-0.04, 0.02] | beta = -0.00; t = -2.13; p = 0.034  95%CI = [-0.01, -0.00] |
| Vanhasbroeck et.al., dataset  N = 49 | beta = 1.41; t = 0.51; p = 0.609  95%CI = [-4.00, 6.82] | beta = 0.38; t = 0.55; p = 0.581  95%CI = [-0.96, 1.71] |
| Rutledge’s dataset  N=46204 | beta = 0.10; t = 0.84; p = 0.402  95%CI = [-0.14, 0.34] | beta = 0.03; t = 0.82; p = 0.412  95%CI = [-0.04, 0.10] |

**Table S7**. Correlations of the depression-specific factor with mood variation and βRPE.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Laboratory  dataset | Online  dataset 1 | Online  dataset 2 | Clinical  dataset |
| Mood variation | r = -0.309  *p* = 0.041 | r = -0.191  *p* < 0.001 | r = -0.135  *p* = 0.039 | r = -0.239  *p* = 0.009 |
| βRPE | r = -0.352  *p* = 0.019 | r = -0.142  *p* < 0.001 | r = -0.189  *p* = 0.004 | r = -0.216  *p* = 0.020 |
| Mediation | a×b = -0.306  95%CI: [-0.547, -0.065]  *p* = 0.015 | a×b = -0.096  95%CI: [-0.145, -0.047]  *p* < 0.001 | a×b = -0.126  95%CI: [-0.212, -0.040]  *p* = 0.004 | a×b = -0.141  95%CI: [-0.261, -0.038]  *p* = 0.021 |

**Table S8.** Clinical characteristics of patients with affective disorders

|  |  |
| --- | --- |
| Clinical variables | N = 116 |
| Diagnosis (MDD /AD /BD) | 83/54/6 |
| Illness duration (months) | 19.57±19.22 |
| Medications (yes) |  |
| SSRI | 96 |
| Antipsychotics | 57 |
| BZDs | 38 |
| Mood stabilizer | 14 |

Note that mood stabilizer refers to Lithium in this dataset.