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Mood computational mechanisms underlying increased risk behavior in adolescent suicidal patients

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This **important** study combined careful computational modeling, a large patient sample, and replication in an independent general population sample to provide **convincing** evidence in support of a computational account of a difference in risk-taking between people who have attempted suicide and those who have not. It is proposed that this difference reflects a general change in the approach to risky (high-reward) options and a lower emotional response to certain rewards. While the findings advance our understanding of cognitive mechanisms at the group level, the observation that computational phenotype is predictive of suicidal behavior only in the clinical sample and not in the online sample limits its applicability for individual prediction, early detection and prevention of suicidality.

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Abstract

Suicidal thoughts and behaviors (STB) are among the leading causes of death worldwide. Although previous research has consistently documented elevated risk-taking in individuals with STB and identified mood disturbances as central features of suicidality, the precise cognitive and affective computational mechanisms underlying this increased risky behavior remain poorly understood. Here, 83 adolescent inpatients with affective disorders—including 58 patients with STB (S^+) and 25 without STB (S^-)—and 118 age- and sex-matched healthy controls (HC) completed a decision-making task involving choices between certain and gamble options, alongside momentary mood ratings. Behavioral analyses showed that S^+ exhibited greater risk-taking than both S^- and HC. Computational modeling of choice behavior using a prospect-theory framework augmented with value-insensitive approach–avoidance parameters indicated that this increase in risky behavior was specifically driven by an elevated approach parameter in S^+. In addition, mood-model analyses revealed reduced sensitivity to certain rewards in S^+ relative to S^- and HC. Importantly, these computational signatures predicted suicidal symptom severity and showed generalizability in an independent general-population sample (n = 747). In S^+, lower mood sensitivity to certain rewards was associated with greater gambling, providing a computational affective account of increased risk-taking in STB. These findings remained robust after adjusting for demographic,

clinical, and medication-related variables. Overall, our study identifies cognitive and affective computational mechanisms contributing to elevated risk-taking in STB and highlights their potential relevance for the early identification and prevention of suicidality.

Introduction

Every 40 seconds, a life is lost due to suicide(1). Suicidal thoughts and behaviors (STB) are one of leading causes of death worldwide that have devastating impacts on individuals, families, and societies. STB occurs from adolescence(2,3), especially in the context of mood disorders, e.g., major depressive disorder (MDD), anxiety disorder (AD), and bipolar disorder (BD)(4). Despite the progress made during the last 50 years for identifying risk factors (5) and developing preventing strategies(6), death rate from STB has not declined(7). The limited comprehension of cognitive and affective mechanisms creates a substantial gap in pinpointing targets for early prediction, screening, detection, and intervention in cases of suicidal thoughts. Understanding what is impaired in STB patients' decision process would be key to prevent STB, for example through cognitive behavioral therapy (9,10).

Although meta-analyses have shown increased risk behavior in patients with STB across different risk domains (for a short summary, see Table S1) (11–13), the underlying cognitive computational mechanism is still unknown. Specifically, some studies found heightened loss aversion in STB in the context of the balloon analog risk task and the gambling task (14,15), while others observed the opposite pattern using the Iowa gambling task (16). Although all these results aligned with their hypotheses (for a short summary, see Table S1), this contradictory evidence may originate from the use of underspecified models. A growing literature indeed shows that risky behavior can be far better explained after adding value-insensitive approach and avoidance components to prospect theory(17,18), that is by including a decision bias in favor of the highest gain (approach) and another decision bias against the lowest loss (avoidance), above and beyond options value difference. This class of models highlights the important role of value-insensitive motivational components in decision making in addition to risk attitude-driven valuation (e.g., loss/risk aversion)(19). Importantly, STB has been proposed in theoretical work to result from abnormal motivational system(20–23), but no direct evidence support such proposals. Therefore, investigating motivational components may facilitate understanding why STB is associated with increased risk-taking behavior. We therefore hypothesized that heightened approach motivation, or weakened avoidance motivation, would account for increased risk behavior in STB.

While suicide is a decision process per se, atypical mood dynamics have been thought to be at the core of STB(3). Contemporary theories of suicide converge on the idea that STB is initially caused by low mood experience. The interpersonal theory of suicide proposes that suicidal desire arises when people simultaneously feel socially disconnected ("thwarted belongingness") and like a burden on others ("perceived burdensomeness"), experiences that are tightly linked to chronically low mood(24). The motivational– volitional model(25) and the three-step theory (27,28) similarly emphasize that when negative mood and feelings of defeat or entrapment are experienced as inescapable, they can give rise to suicidal ideation, and that the progression from ideation to suicide attempts depends on additional factors such as reduced fear of death, increased pain tolerance, and a tendency to act impulsively under intense affect. Some official organizations, e.g., National Institute of Mental Health, have also listed mood problems as warning signals(8). Interestingly, within the framework of decision making under uncertainty, gambling on lotteries with a revealed outcome has been found to induce high mood variance(28), providing an opportunity to assess the relationship between deficient mood and increased gambling decisions in STB. Specifically, in a gambling task with momentary mood ratings (also referred to happiness or subjective well-being), where participants were asked to make decisions between certain vs. gamble options (2 possible outcomes, 50% probability for each), Rutledge et.al., (2014) found that mood was sensitive to certain rewards (CR), reward expectation (EV), and reward prediction error (RPE; the difference between experienced and expected outcome)(28). Although mood is thought to persist for hours, days, or even weeks(29–32), momentary mood, measured over the timescale in the laboratory setting, represents the accumulation of the impact of multiple events at the scale of

minutes (29,31,33–37). Momentary mood external validity is demonstrated e.g., through its association with depression symptoms (36). Mood is different from emotions, which reflect immediate affective reactivity and is more transient (e.g. from surprise to fear) (30–32,38). Here, we investigated which mood computational components (among CR, EV and RPE) are associated with STB. We expect the mood response to gambling-related quantities (EV and RPE) to be higher in STB compared to the control groups. In contrast, riskier decisions may result from aversion to CR in STB. Therefore, another possibility is that lower mood sensitivity to CR would relate to increased risk behavior in STB.

To summarize, the aim of this study is to examine cognitive and affective computational mechanisms underlying increased risk behavior in adolescent patients with STB, as adolescent period might provide a developmental window for opportunities for early intervention(2). This study aligns with the principles of Computational Psychiatry(39), which assumes that psychiatric symptoms arise from alterations in cognitive and affective computations. The ultimate aim for this field is to uncover "computational phenotypes" — distinct patterns of computational dysfunctions — potentially enabling targeted treatments, improved outcome predictions, and more precise diagnostic frameworks. Specifically, we employed a gambling task with momentary mood ratings to assess risk behavior and track mood fluctuations in response to various events. We applied computational models of risky decision making and momentary mood to dissect cognitive and affective processes contributing to heightened risky behavior in patients with STB. Regarding choices, we hypothesized heightened approach motivation, or weakened avoidance motivation, in STB, which would account for increased risk behavior. Regarding mood dynamics, we hypothesized that greater mood sensitivity to gambling-related variables (i.e., RPE and EV), or reduced mood sensitivity to CR, would explain increased risk behavior in STB.

Methods and materials

Participants

We recruited 95 adolescent patients with mood disorder from the Clinical Hospital of Chengdu Brain Science Institute, University of Electronic Science and Technology of China (The Mental Health Center of Chengdu, Sichuan, China). According to medical records and information from family and friends by the researcher (T.N) and psychiatrists (F.L, Y.Y, X.C, & Z.H), patients with suicidal thoughts and behaviors were categorized as suicidal group (S^+), while patients without suicidal thoughts and behaviors were identified as control group (S^-). The definition for suicidal thoughts in this study was active thoughts of suicide, i.e., wishing to die and having some intention to do so (see Supplementary Note 1 for details). This grouping operation was consistent with previous suicidal-related literature (40–45), reflecting the general tendency for suicidal risks among adolescence. As baseline control, we also recruited 124 sex- and age-matched healthy adolescents (HC). We assert that all procedures contributing to this work comply with the ethical standards of the ethical committee of The Clinical Hospital of Chengdu Brain Science Institute, University of Electronic Science and Technology of China (number: 2022(33)) on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. All procedures involving human subjects/patients were approved by the ethical committee of The Clinical Hospital of Chengdu Brain Science Institute, University of Electronic Science and Technology of China (number: 2022(33)). Informed written consent was obtained. Patients were included if they met the following criteria: 1) both the researcher and psychiatrists agreed on their group classification; 2) they had a current diagnosis of major depressive disorder (MDD; unipolar depression), generalized anxiety disorder (GAD), or bipolar disorder with depressive episodes (BD), confirmed by two experienced psychiatrists using the Structured Clinical Interview for DSM-IV-TR-Patient Edition (SCID-P, 2/2001 revision; see Supplementary Note 1 for details) ; 3) they were between 10 and 19 years of age; 4) they had no organic brain disorders, intellectual disability, or head trauma; 5) they had no history of substance abuse; 6) they had no experience of electroconvulsive therapy. In addition, participants were excluded if they failed more than 1/4 of the catch trials. The final sample consisted of 25 patients for S^-, 58 patients for S^+, and 118 HC participants. See Table 1 and Table S2 for demographic, clinical and psychological

information. The validation dataset was from our previous online study, with 747 general participants completing the same task and numerous anxiety/depression -related questionnaires for different purposes. See (46) for demographic and psychological details.

Self-reported questionnaires

Participants completed a set of Chinese-version suicidal-, emotion regulation-, and depression/anxiety-related questionnaires. These measurements included the Beck Scale for Suicidal Ideation at the current time (BSI-C, 19 items) and at the worst time (BSI-W, 19 items)(47), the Childhood Trauma Questionnaire (CTQ, 28 items)(48), Emotion Regulation Questionnaire-Reappraisal (ERQ-R, 6 items) and Suppression (ERQ-S, 4 items)(49). In addition, as patients were available only for a limited duration, anxiety/depression-related scales from only 50 participants in the S^+ group and only 21 participants in the S^- group were collected. Specifically, patients filled the Trait subscale of the State-Trait Anxiety Inventory (TAI; 20 items)(50), the Penn State Worry Questionnaire (PSWQ; 16 items), the Beck Depression Inventory (BDI; 21 items)(51), and the Center for Epidemiologic Studies Depression Scale (CESD; 20 items)(52).

Experimental Procedure

Participants were asked to make a choice between a certain option and a gamble (50% probability for each outcome) to maximize their points and to rate their momentary moods(17,28). Before performing the task, participants were asked to rate their current happiness that we consider as their initial mood. At the beginning of the task, participants were endowed with 500 points. Each trial started with two options (a gamble option and a certain option) which were presented randomly on each side (Figure 1A). Upon response, the chosen option was highlighted in yellow for 0.5 s. Note that Rutledge et al., (2014) displayed the chosen option for about 6 s(28), a delay we shortened for the sake of time. Then the corresponding outcome at the screen center was presented for 1 s, followed by a fixation cross with a random duration (0.6∼1.4 s). If the gamble was chosen, participants had equal probability to obtain each outcome. The obtained outcome was added to their total score, which was presented at the top-right corner. Every 2∼3 trials, participants rated their mood ("how happy are you at this moment?") from 0 (very unhappy) to 100 (very happy) by moving a slider anchored at midpoint (i.e., 50). Upon identifying their current mood, a fixation cross was presented with a random duration (0.6∼1.4 s). This task consisted of 90 randomly presented trials, including 30 mixed trials, 30 gain trials, and 30 loss trials. The numbers of choice trials and mood ratings were comparable to those in prior computational modeling studies (34,35). In mixed trials, participants made a choice between a certain amount 0 and a gamble with a gain amount {40, 45, or 75} and a loss amount determined by a multiplier {0.2, 0.34, 0.5, 0.64, 0.77, 0.89, 1, 1.1, 1.35, or 2} on the gain amount. For example, with a gain amount of 40 and a multiplier of 2 for the loss (2 times 40 = 80), participants chose between a certain option of 0 and a gambling option, which offered a 50% chance to win 40 and a 50% chance to lose 80. These trials are therefore particularly suited to measuring loss aversion. In gain trials, there was a certain gain amount {35, 45, or 55} and a gamble with 0 and a gain amount determined by a multiplier {1.68, 1.82, 2, 2.22, 2.48, 2.8, 3.16, 3.6, 4.2, or 5} on the certain gain amount. In loss trials, there were a certain loss amount {−35, −45, or −55} and a gamble with 0 and a loss amount determined by a multiplier {1.68, 1.82, 2, 2.22, 2.48, 2.8, 3.16, 3.6, 4.2, or 5} on the certain loss amount. We also added an extra 4 trials in the entire task for attentional checks. For example, participants were asked to make a choice between a certain gain 20 and a gambling 35/55, where the correct response for this trial was the gambling choice (as the worst lottery outcome was higher than the certain reward). All experimental procedures were programmed using Psychopy3 (2021.2.3).

Choice computational models

In line with previous studies(17,18), our choice model space included expected value model (cM1), prospect theory model (cM2)(53), and approach-avoidance prospect theory model (cM3)(17). For cM2 (Equations 1-4), there were 3 parameters, including risk aversion (α, range: [0.3, 1.3]),

	Group			Group contrast		S^+ vs. S^-	
	HC (n=118)	S^- (n=25)	S^+ (n=58)	F/χ^2	p	t/χ^2	*p*
Sex (female/male)	75/43	16/9	41/17	0.912	0.634	0.363	0.547
Age	15.31±2.15	15.68±1.75	14.83±1.80	1.868	0.157	**1.997**	**0.049**
BSI-C	1.29±3.62	2.84±2.66	18.02±7.56	224.230	<0.001	-9.754	<0.001
BSI-W	3.58±6.60	4.04±3.22	27.98±6.02	326.242	<0.001	-18.723	<0.001
CTQ	13.98±11.29	22.64±12.34	33.00±17.03	40.023	<0.001	-2.743	0.008
ERQ-R	14.77±4.38	13.08±6.34	8.48±5.39	31.317	<0.001	3.376	0.001
ERQ-S	6.86±3.64	8.80±3.77	10.79±3.79	22.322	<0.001	-2.200	0.031
Suicidal attempts history (yes)	---	---	29	---	---	---	---
Illness duration (months)	---	31.76±18.80	31.38±18.70	---	---	0.085	0.933
Family history (yes)	---	2	10	---	---	1.206	0.272
Current diagnosis (GAD/MDD/BD)	---	24/55/9	10/17/6	---	---	1.790	0.409
Medication (yes)	---	25	57	---	---	0.436	0.509
SSRI	---	16	39	---	---	0.082	0.775
SNRI	---	0	2	---	---	0.883	0.347
Trazodone	---	6	16	---	---	0.115	0.734
Antipsychotics	---	14	32	---	---	0.005	0.945
BZDs	---	20	45	---	---	0.060	0.807
Other anxiolytics	---	12	13	---	---	**5.434**	**0.020**
Mood stabilizer	---	13	18	---	---	3.282	0.070
TAI	43.49±8.54	50.38±12.19	65.36±7.62	108.863	<0.001	-6.276	<0.001
PSWQ	44.75±10.94	50.67±15.17	68.56±9.58	80.213	<0.001	-5.990	<0.001
BDI	9.45±9.43	18.62±15.11	38.30±9.67	129.516	<0.001	-6.573	<0.001
CESD	32.96±11.09	42.86±15.66	62.52±9.99	118.084	<0.001	-6.347	<0.001

Note: For anxiety/depression-related questionnaires (TAI, PSWQ, BDI, and CESD), due to time limitation, data from 8 participants in the S^+ group and 4 participants in the S^- group was not collected. Abbreviations: HC, healthy control; S^-, patients without suicidal thoughts and behavior; S^+, patients with suicidal thoughts and behavior; BSI-C, Beck Scale for Suicidal Ideation at the current time; BSI-W, Beck Scale for Suicidal Ideation at the worst time; CTQ, Childhood Trauma Questionnaire; ERQ-R, Emotion Regulation Questionnaire-Reappraisal; ERQ-S, Emotion Regulation Questionnaire-Suppression; AD, anxiety disorders; MDD, major depressive disorders; BD, bipolar disorders; SSRI, Selective Serotonin Reuptake Inhibitor; SNRI, serotonin-norepinephrine reuptake inhibitors; BZDs, Benzodiazepines; TAI, Trait Anxiety Inventory; PSWQ, Penn State Worry Questionnaire; BDI, Beck Depression Inventory, CESD, Center for Epidemiologic Studies Depression Scale.

Table 1. Demographics, clinical, psychological characteristics of patients with and without suicidal thoughts and behaviors.

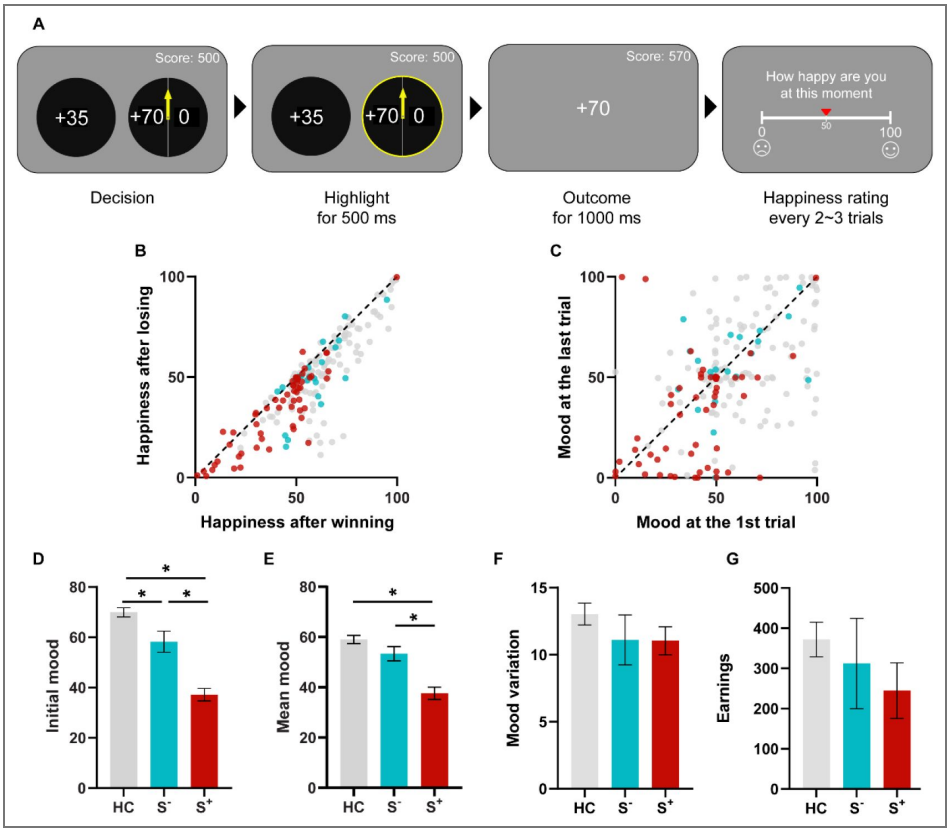


Figure 1. Task design, outcome and time effects on mood, and group differences in mood.

A) Gambling task with mood ratings. On each trial, participants were asked to choose between a certain option and a gambling option (self-paced). Once selected, the chosen option was highlighted in yellow for 500 ms. Then the corresponding outcome was displayed in the center of the screen for 1000 ms. The cumulated score was always shown in the right-upper corner. Every 2 to 3 trials, participants were asked to complete a self-paced rating of their happiness, answering the question "How happy are you at the moment" on a slider from 0 (very unhappy) to 100 (very happy). B) Patients and healthy controls felt happier after winning than losing. C) Mood drifted over time. D) Group difference in mood before the task shows weakened mood in S^+. E) Group difference in average mood displays lower mood experience in S^+. F) Mood variance was similar for all the three groups, as indexed by standard deviation of happiness ratings across the task. G) Each group earned about the same amount of points by the end of the task. Abbreviations: HC, healthy control; S^-, patients without suicidal thoughts and behavior; S^+, patients with suicidal thoughts and behavior; *p<0.05. Error bars correspond to the standard error.

loss aversion (λ: [0.5, 5]), and inverse temperature (μ: [0, 10]).

$$U_{\text{gamble}} = 0.5(V_{\text{gain}})^{\alpha} - 0.5\lambda(-V_{\text{loss}})^{\alpha} \quad (1)$$

$$U_{\text{certain}} = (V_{\text{certain}})^{\alpha} \text{ if } V_{\text{certain}} \geq 0 \quad (2)$$

$$U_{\text{certain}} = -\lambda(-V_{\text{certain}})^{\alpha} \text{ if } V_{\text{certain}} < 0 \quad (3)$$

$$P_{\text{gamble}} = \frac{1}{1 + e^{-\mu(U_{\text{gamble}} - U_{\text{certain}})}} \quad (4)$$

where V_{gain} and V_{loss} are the objective gain and loss from a gamble, respectively. Please note that V_{gain} is 0 in loss trials and V_{loss} is 0 in gain trials. $V_{certain}$ is the objective value for the certain option. U_{gamble} and $U_{certain}$ denote the subjective utilities of the gamble and the certain option, respectively. Choice probability for gamble (P_{gamble}) is determined by the softmax rule. Building on cM2, cM3 decomposes the decision process into risk-attitude-driven valuation (e.g., loss and risk aversion) and value-insensitive motivational components (Equations 1-3 & 5-7). That is, choice probability for P_{gamble} in cM3 is jointly determined by the softmax rule and approach/avoidance parameters (β_{gain}: [-1, 1], β_{loss}: [-1, 1]). Approach/avoidance parameters are not applied in mixed trials. Please note that a higher gambling rate does not imply a change in risk attitude per se: it can arise from an increased value-insensitive approach bias even when risk-attitude parameters are comparable between groups. Risk attitude is indeed conceptualized in economics as the curvature of the utility function (i.e., the subjective value) of the objective outcomes, with concave curves associated with risk aversion, and convex curves associated with risk seeking (54,55). By contrast, the approach or avoidance bias apply to all the value. A possible interpretation of the approach bias is that participant approach the option with the highest possible gain (the lottery) in the gain frame; the avoidance bias would then reflect a tendency to systematically avoid the highest potential losses (the lottery) in the loss frame.

$$P_{\text{gamble}} = \frac{1 - \beta_{\text{val}}}{1 + e^{-\mu(U_{\text{gamble}} - U_{\text{certain}})}} + \beta_{\text{val}} \text{ if } \beta_{\text{val}} \geq 0 \quad (5)$$

$$P_{\text{gamble}} = \frac{1 + \beta_{\text{val}}}{1 + e^{-\mu(U_{\text{gamble}} - U_{\text{certain}})}} \text{ if } \beta_{\text{val}} < 0 \quad (6)$$

$$\beta_{\text{val}} \begin{cases} \beta_{\text{gain}}, & \text{gain trials}, \\ \beta_{\text{loss}}, & \text{loss trials}. \end{cases} \quad (7)$$

Mood computational models

To quantify how different events impacted participants' momentary mood during the gambling task, we conducted a stage-wise model construction procedure(56). That is, we added or removed each component to the model progressively, based on the best model from the previous stage. In Stage 1, we fit 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; mM1; Equation 8). RPE was defined as the difference between the obtained and expected value.

$$\text{Happiness}(t) = \beta_0 + \beta_{CR}\sum_{j=1}^{t}\gamma^{t-j}CR_j + \beta_{EV}\sum_{j=1}^{t}\gamma^{t-j}EV_j + \beta_{RPE}\sum_{j=1}^{t}\gamma^{t-j}RPE_j \quad (8)$$

Here, t and j are trial numbers, β_0 is a baseline mood parameter, other weights β capture the influence of different event types, $\gamma \in [0,1]$ is a decay parameter representing how many previous trials influence happiness. CR_j is the CR if the certain option was chosen on trial j; otherwise, CR_j is 0. EVj is the EV and RPEj is the RPE on trial j if the gamble was chosen. If the certain option was chosen, then $EV_j = 0$ and RPEj =0.

To check 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 (mM2; Equation 9).

$$\text{Happiness}(t) = \beta_0 + \beta_{CR}\sum_{j=1}^{t}\gamma_{CR}^{t-j}CR_j + \beta_{EV}\sum_{j=1}^{t}\gamma_{EV}^{t-j}EV_j + \beta_{RPE}\sum_{j=1}^{t}\gamma_{RPE}^{t-j}RPE_j \quad (9)$$

In Stage 2, to identify whether mood can be better explained by RPE, we fit an alternative model in which mood ratings are explained by the recency-weighted average of the certain reward (CR) and the gamble reward (GR; mM3; Equation 10), a simple model providing a mood sensitivity parameter for certain rewards and gamble rewards. We also fit a model with two forgetting factors, one for CR and one for GR (mM4; Equation 11).

$$\text{Happiness}(t) = \beta_0 + \beta_{CR}\sum_{j=1}^{t}\gamma^{t-j}CR_j + \beta_{GR}\sum_{j=1}^{t}\gamma^{t-j}GR_j \quad (10)$$

$$\text{Happiness}(t) = \beta_0 + \beta_{CR}\sum_{j=1}^{t}\gamma_{CR}^{t-j}CR_j + \beta_{GR}\sum_{j=1}^{t}\gamma_{GR}^{t-j}GR_j \quad (11)$$

In Stage 3, to check whether mood data can be better explained by a single event (CR or GR), we compared a CR-mood model (mM5) and a GR-mood model (mM6).

Model fitting and comparison

We fit model parameters by using the method of maximum likelihood estimation (MLE) with fmincon function of MATLAB (version R2015a) at the individual level. To avoid local minimum, we ran this optimization function with random starting locations 50 times. Bayesian information criteria (BIC) were used to compare model fits.

Replication of suicidal-related results in an independent dataset (n = 747)

We next verified our results in an independent dataset, including the same task and BDI questionnaire in 747 general participants (500 females; age: 20.90±2.41)(46). One item in BDI involves the measurement of STB. In item 9 of BDI, participants chose one option that describes them best: Option 1, “I don’t have any thoughts of killing myself.”; Option 2, “I have thoughts of killing myself, but I would not carry them out.”; Option 3, “I would like to kill myself.”; Option 4, “I would kill myself if I had the chance.”. In line with the current definition of S^+/S^- in the clinical dataset, we identified S^+ group as choosing Option 2, 3, or 4, while participants selecting Option 1

were categorized as S^- group. Therefore, there were 129 participants in S^+ and 618 participants in S^-. We did not find significant group difference in sex and age (*ps* > 0.075). To make it comparable, we fit the winning choice and mood models from the clinical study.

Predictive model of suicidal risks

Internal Validation

To evaluate the out-of-sample predictive utility of computational parameters for STB, we used lasso regression within a repeated nested 5-fold cross-validation framework. In each of 100 iterations, the full sample was randomly divided into five folds. For each outer fold, the model was trained on four folds and tested on the remaining fold. Predictor variables were z-scored within the training data, and the corresponding training-set means and standard deviations were then applied to normalize the test data. Within each training set, the lasso penalty parameter was selected via an inner 5-fold cross-validation procedure using the minimum mean squared error criterion. The resulting coefficients were then used to generate predictions for the held-out fold. After all outer folds had been completed, the cross-validated predictions for all participants were combined, and model performance was quantified as the Spearman correlation between predicted and observed STB scores, given that suicidal symptom scores (BSI-C) were not normally distributed (Kolmogorov–Smirnov test, $p < 0.001$). This entire procedure was repeated 100 times to obtain a stable estimate of predictive performance.

External Validation

To further assess robustness and generalizability beyond the original sample, we conducted an external validation analysis using an independent dataset ($n = 747$). Specifically, regression coefficients and intercepts were averaged across folds and repetitions from the internal validation procedure to derive a stable final model. This model was then applied to the external dataset, using the same predictors (β_{gain} and β_{CR}), to generate predicted scores. External validity was assessed by calculating the Spearman correlation between model-predicted scores and scores on item 9 of BDI.

Statistical analysis

We performed chi-square, independent-sample t-test or repeated measure ANOVA to test group-related differences. Spearman correlations were used to check correlations among suicidal-related questionnaires, choice data, and mood data. Generalized linear model was conducted for control analysis using Matlab R2015a. Mediation analysis was conducted using R (4.1.0) and the R package 'mediation'. All reported tests are two-tailed unless otherwise specified. For the replication of previous findings in the validation dataset, we used one-tailed tests in line with our clinically motivated directional hypothesis. We set the significance level at p = 0.05. Multiple comparisons were corrected using Benjamini-Hochberg false discovery rate (FDR) correction (see Supplementary Note 8 for details).

Results

Demographic and clinical characteristics

Overall, sex and age were comparable among S^+, S^-, and HC groups (*ps* > 0.157), though S^+ was significantly younger than S^- (t = 1.997, $p = 0.049$). As expected, S^+ scored significantly higher than S^- and HC in suicidal-related scales (e.g., BSI-C; *ps* < 0.001), further validating our grouping of participants. There was no significant difference between S^+ and S^- in illness duration, family history, diagnosis, and various medications use (*ps* > 0.07), except other anxiolytics (χ^2=5.434, $p = 0.020$). See Table 1 and Table S2 for details.

Sanity checks

To ensure engagement and task validation, we performed sanity checks. As expected, we found significant group differences in psychological measurements (*ps* < 0.001), including childhood trauma, emotion regulation, and anxiety/depression (Table 1 and Table S2). In addition, we replicated the classic mood-related effects(57,58): 1) subjects were happier after winning than losing (t = 11.001, $p < 0.001$; Figure 1B) and 2) mood drifted over time (t = −3.254, $p = 0.001$; Figure 1C). As grouping checks, we found a hierarchical pattern of mood level both before the task and across the task ($S^+ < S^- <$ HC; for initial mood, F = 53.415, $p < 0.001$; S^+ vs. S^-: t = −4.525, $p < 0.001$; S^+ vs. HC: t = −10.427, $p < 0.001$; S^- vs. HC: t = −2.634, $p = 0.009$; Figure 1D; for mean mood, F = 28.018, $p < 0.001$; S^+ vs. S^-: t = −3.773, $p < 0.001$; S^+ vs. HC: t = −7.292, $p < 0.001$; S^- vs. HC: t = −1.458, $p = 0.147$; Figure 1E). No significant group difference in mood variation was found (F = 1.270, $p = 0.284$; Figure 1F) which suggests that any parameter difference between groups is unlikely to be explained by mood variance. Moreover, there was no group difference in terms of mood drift effect, or earnings (Figure 1G; *ps* > 0.276).

Patients with suicidal thought and behavior approached gambles more than patient controls and healthy controls, while risk attitude was comparable across groups

To replicate previous findings of increased risk behavior in suicidal populations, we conducted a two-way ANOVA on gambling rate with group (S^+/S^-/HC) as a between-subject factor and trial type (mix/gain/loss) as a within-subject factor. We found a significant main effect of group (F = 3.655, $p = 0.028$, partial $\eta^2 = 0.036$; Figure 2A), with more gambling behavior for S^+ than S^- (two-sample t-test, t = 2.145, $p = 0.035$) and HC (t = 2.465, $p = 0.015$) and comparable gambling behavior between S- and HC (t = −0.439, $p = 0.661$) across the task. We also observed the main effect of trial type (F = 51.225, $p < 0.001$, partial $\eta^2 = 0.206$; gain > mix > loss). We did not observe any significant interaction effect between group and trial type (F =0.270, partial $\eta^2 = 0.003$). Within patients, this group effect on gambling rate remained significant after controlling for sex, illness duration, family history, diagnosis, and various medications use (*ps* < 0.05), as well as general symptoms (e.g., depression and anxiety; $p = 0.024$; also see Figure S4 and Table S10). Given high correlations among anxiety and depression questionnaires (rs > 0.753, *ps* < 0.001), we performed Principal Components Analysis (PCA) to extract main components, where each component explained 86.95%, 7.09%, 3.27%, and 2.68% variance, respectively. To further control for anxiety and depression, linear regression using these components as covariates revealed that the group effect on gambling rate remained significant ($p = 0.024$; Table S11). There was also no significant age/other anxiolytics use difference in gambling behavior (*ps* > 0.109; Figure S2).

We next performed a model comparison to select the model that best explains choice data. This analysis revealed that the winning model to formally quantify mechanisms for observed risky behavior is the approach-avoidance prospect theory model (cM3; mean $R^2 = 0.37$; Table 2). Parameter and model recovery analyses showed that each model and parameter can be identified (see Supplementary Note 5; Figure S5 & S6). As predicted, we found a (marginally) significant group effect in approach parameter (F = 2.989, $p = 0.053$; Figure 2C), with a significant stronger approach motivation for S^+ than S^- (t = 2.217, $p = 0.029$) and HC (t = 2.091, $p = 0.038$), and comparable between S- and HC (t = −0.737, $p = 0.463$). No other significant group difference in these parameters was found (*ps* > 0.135). Within patients, this group effect on the approach parameter remained significant after controlling for sex, illness duration, family history, diagnosis, and various medications use (*ps* < 0.05), as well as general symptoms (e.g., depression and anxiety; $p = 0.027$; also see Figure S4, Table S10). Linear regression using PCA components as covariates revealed that the group effect on approach parameter remained significant ($p = 0.027$; Table S11). There was also no significant age/other anxiolytics use difference in gambling behavior (*ps* > 0.223; Figure S2). Given significant correlations between group, approach parameter, and gambling rate for gain trials (*ps* < 0.017), we further conducted a mediation analysis with the assumption of the mediating effect of approach motivation of suicidality on the

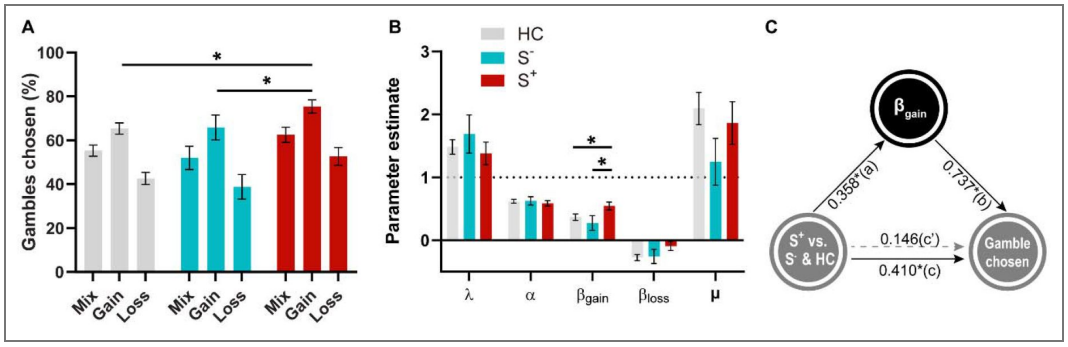


Figure 2. **Choice results.**

A) Group differences in gambling behavior. The grey dots represent the winning model prediction. B) The estimated parameters from the winning choice model differed across groups. S^+ exhibited stronger approach motivation than S^- and HC. C) The mediation model among the group, β_{gain}, and gambling behavior in the gain condition. The approach parameter mediated the effects of STB group on increased gambling behavior in the gain condition. Abbreviations: HC, healthy control; S^-, patients without suicidal thoughts and behavior; S^+, patients with suicidal thoughts and behavior; *p<0.05.

risk behavior. Given that we aimed to test the effect of STB, with S- and HC as controls, and S^- and given that HC did not differ in gambling behavior or in the approach parameter, we merged these two groups for the mediation analysis. Results supported our hypothesis (a×b = 0.321, 95% CI = [0.070, 0.549], p = 0.016; Figure 2C), confirming that suicidal thoughts and behavior increase risk behavior through stronger approach motivation.

Mood sensitivity to certain rewards was reduced in patients with suicidal thought and behavior compared to patient controls and healthy controls

Next, we turned to mood model comparison. We observed inconsistent mood winning models for different groups (Table 3), suggesting an effect of STB on mood dynamics. Given that the focus of the current study was STB effect, especially for the S^+ group, with the baseline control of S^- and HC groups, we specially focused on the winning model from the S^+ group. Parameter and model recovery analyses showed that each model and parameter can be identified (see Supplementary Note 5; Figure S5 & S6 and TableS7). The winning mood model from S^+ assumed that momentary mood fluctuations were explained by the recency-weighted average of certain reward (CR) and the gamble reward (GR; mM3; mean R^2 = 0.42; Table 3). Overall, both CR and GR weights were significantly higher than 0 (CR: t = 8.033, p < 0.001; GR: t = 9.853, p < 0.001). The baseline parameter β_0 was significant correlated with the initial mood (rho = 0.580, p < 0.001), validating this model. We also replicated previous depression-related findings (59): depression symptom measured by Beck Depression Inventory (BDI) was negatively correlated with the baseline mood parameter β_0 (rho = −0.530, p < 0.001; Figure S7). We found significantly lower β_0 in S^+ than S^- (F = 22.861, p <0.001; t = −3.513, p < 0.001) and HC (t = −6.606, p < 0.001), which mirrors the lower initial mood pattern. Importantly, a two-way ANOVA on mood parameters with group (S^+/S^-/HC) as a between-subject factor, event type (CR/GR) as a within-subject factor showed a significant main effect of group (F = 3.835, p = 0.023, partial η^2 = 0.037), with lower mood sensitivity for S^+ than S^- (t = −2.080, p = 0.041) and HC (t = −2.758, p = 0.006) and comparable between S- and HC (t = −0.110, p = 0.913). We also observed a significant interaction effect between group and event type (F = 4.283, p = 0.015, partial η^2 = 0.041; Figure 3B). Simple effect analysis revealed that S^+ group exhibited significant lower mood sensitivity to CR as compared to GR (F = 4.823, p = 0.029, partial η^2 = 0.024), while there was no significant CR-GR difference in S^- (although trendy; F = 2.783, p = 0.097, partial η^2 = 0.014) and HC (F = 0.989, p = 0.321, partial η^2 = 0.005). This interaction was driven by the group difference in CR (F = 6.085, p = 0.003, partial η^2 = 0.058) rather than in GR (F = 0.801, p = 0.450, partial η^2 = 0.008). Specifically, S^+ showed lower mood sensitivity to CR than S^- (t = −2.661, p = 0.009) and HC (t = −3.381, p <0.001), while S^- and HC were comparable (t = 0.450, p = 0.679), suggesting S^+ was specifically more insensitive to certain outcome than gamble outcome. No significant main event type (CR vs. GR) effect was found (F = 0.285, p = 0.594, partial η^2 = 0.001). Within patients, this group effect on β_{CR} remained significant after controlling for gambling rate, earnings, mood-related outcome effect, mood drift effect, sex, illness duration, family history, diagnosis, and various medications use (ps < 0.032), as well as general symptoms (e.g., depression and anxiety; p = 0.001; also see Figure S4 and Table S10). Linear regression using PCA components as covariates revealed that the group effect on this mood parameter remained significant (p = 0.001; Table S11). There was also no significant age/other anxiolytics use difference in gambling behavior (ps > 0.582; Figure S2). These results indicate decreased mood sensitivity for certain rewards in suicidal populations.

In addition to the winning model (mM3) from S^+ group, we also checked results from the classic mood model (mM1). Overall, we replicated previous findings (Figure S8): 1) mood sensitivity to CR, EV, and RPE were all significantly higher than 0 (ps < 0.001); 2) higher weight for RPE than EV (t = 5.760, p < 0.001). Although no significant group difference between S^+ and S^- was found in each parameter (ps > 0.115), we replicated significant correlation between BSI-C and β_{CR} (rho = −0.239, p = 0.030). To explore why the classic mood model (mM1) did not outperform the CR-GR model, we examined expectation effect on mood, as previous literature showed impaired value expectation in patients with STB(60). Our data suggests a lower mood sensitivity to RPE relative to EV in S^+

Table 2. **Choice model comparison.**

Model #	Model specification	# of parameters	Δ BIC	meanR^2	Δ BIC for each group		
					HC	S-	S+
1	μ	1	3873.16	0.08	2272.48	370.19	1230.49
2	λ, α, μ	3	3153.79	0.18	1822.07	263.97	1067.75
3	**λ, α, β_{gain}, β_{loss}, μ**	5	0	0.37	**0**	**0**	**0**

Abbreviations: Δ BIC, Bayesian information criterion relative to the winning model (cM3); HC, healthy control; S^-, patients without suicidal thoughts and behavior; S^+, patients with suicidal thoughts and behavior.

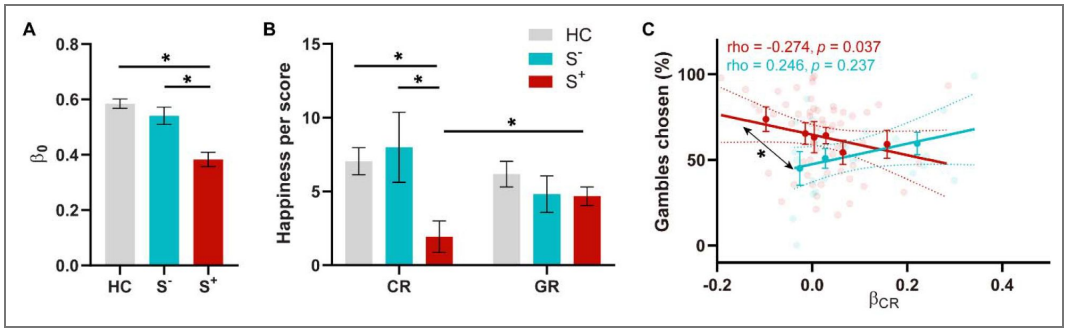
Table 3. **Mood model comparison.**

Model #	Model specification	# of parameters	Δ BIC	meanR^2	Δ BIC for each group		
					HC	S^-	S^+
1	β_0, β_{CR}, β_{EV}, β_{RPE}, γ	5	-106.77	0.48	-182.04	32.54	42.73
2	β_0, β_{CR}, β_{EV}, β_{RPE}, γ_{CR}, γ_{EV}, γ_{RPE}	7	140.00	0.54	-69.40	83.20	126.20
3	**β_0, β_{CR}, β_{GR}, γ**	4	0	0.42	0	0	**0**
4	β_0, β_{CR}, β_{GR}, γ_{CR}, γ_{GR}	5	-146.81	0.48	-272.15	26.37	98.97
5	β_0, β_{CR}, γ	3	2395.62	0.18	1379.96	264.87	749.79
6	β_0, β_{GR}, γ	3	403.46	0.34	228.69	21.24	153.52

Abbreviations: Δ BIC, Bayesian information criterion relative to the winning model in S^+ group (mM3); HC, healthy control; S^-, patients without suicidal thoughts and behavior; S^+, patients with suicidal thoughts and behavior.

Figure 3. **Effect of Suicidal thoughts and behavior on mood dynamics.**

A) Group difference in mood baseline, β_0. B) Group differences in mood sensitivity to certain reward (CR) and gamble reward (GR). C) Correlational difference in S^- and S^+ between mood sensitivity to CR and gambling behavior. The lighter, semi-transparent dots represent individual participants, while the dark dot with an error bar indicates the mean of binned scores (for illustration purposes only). Abbreviations: CR, certain reward; GR, gamble reward; HC, healthy control; S^-, patients without suicidal thoughts and behavior; S^+, patients with suicidal thoughts and behavior; *p<0.05.



than HC (Figure S9; significant interaction between group and EV/RPE: F = 3.422, p = 0.035; with stronger mood sensitivity to RPE than EV in HC (F = 36.658, p < 0.001), while no such significant difference in S^+ (F = 1.161, p = 0.283) and S^- (F = 3.009, p = 0.084)). Equal weights on EV and RPE suggest that expectations cancel out as RPE is the difference between the outcome and EV, resulting in outcome only. Then, we additionally fit a mood model with CR, GR, and EV components (Figure S9). We expect less negative mood sensitivity to EV in S^+ than HC. As expected, in addition to replication of our main results (ps < 0.045; R^2 for this model: 0.487), we observed a less negative mood sensitivity to EV in S^+ than HC (t = 2.302, p = 0.023), which explains why the winning model shifts to mM3. Given that mM7 (splitting GR into better and worse terms) performed better than our winning model (mM3) in the S^- and HC groups, we also checked results from this model (Figure S10 and Table S6). Again, we found that S^+ had significant lower β_{CR} than S^- and HC (for group effect: F = 44.660, p = 0.011; S^+ vs. S^-: t = −2.659, p = 0.009; S^+ vs. HC: t = −2.589, p = 0.010; S^- vs. HC: t = 1.059, p = 0.292) and significant correlation between BSI-C and β_{CR}, (rho = −0.297, p = 0.006) among patients, suggesting the robustness of mood sensitivity to certain reward in suicidal people. The marginally significant group effect in approach parameter (p = 0.053) remain marginally significant after correction (p=0.068). In addition to this, all results of interest, including gambling chosen, approach parameter, and mood sensitivity to CR, remained significant with FDR correction (ps <=0.05; Supplementary Note 8).

Suicidal thought and behavior effect on gambling was mediated by mood sensitivity to certain rewards

To examine the association between risk behavior and atypical mood dynamics in suicidal patients, we then tested the correlation between participants' gambling rate and mood sensitivity to certain reward ($\beta_{CR)}$ in S^+. We found significant negative correlation between gambling rate and β_{CR} in S^+ (rho = −0.274, p = 0.037; Figure 3C), suggesting the lower mood sensitivity to certain reward, the more gambling behavior suicidal patients made. We did not observe such a significant correlation in S^- (rho = 0.246, p = 0.237) and there was significant correlational difference between S^+ and S^- (Z = −2.109, p = 0.017; 42)), suggesting the suicidal-specific association of mood and choice.

Replication of suicidal-related results in an independent dataset (n = 747)

Next, we collected online data on general volunteers to replicate our findings. In this large online dataset, we found lower mood experience in general volunteers who replied non-negatively to the Suicidal item of the BDI (S^+). Regarding the initial mood rating (before the task), S^+ exhibited significantly lower mood than S^- (t = −6.077, p < 0.001; Figure 4D). There was a trend for lower mood experience across time in S^+ than S^- (t = −1.600, p = 0.055; Figure 4E). Critically, we identified a significantly increased gambling behavior in S^+ than S^-, especially in the gain domain (t = 1.668, p = 0.048; Figure 4F). Approach-avoidance prospect theory model (mean pseudoR^2 = 0.479) revealed a significantly heightened approach parameter in in S^+ than S^- (t = 1.762, p = 0.039; Figure 4B), but not any other choice parameters (ps > 0.172). We also replicated the previous mediation result that STB increase risk behavior through stronger approach motivation (a ×b = 0.143, 95% CI = [0.016, 0.288], p = 0.031; Figure 4C). Regarding CR-GR mood model (mean R^2 = 0.588), we observed significantly lower β_0 in S^+ than S^- (t = −2.018, p = 0.022; Figure 4F). Mood sensitivity to CR (t = −2.237, p = 0.013; Figure 4G), but not GR (t = −0. 187, p = 0.473; Figure 4G), was significantly reduced in S^+ than S^-. After controlling for depression severity using our established bifactor model (see ref 60 for details), these results remained significant (ps ≤ 0.050), except a marginally significant effect of group on gambling behavior (p = 0.059). Despite a trend, this effect with covariates of depression-related questionnaires is strong in our clinical cohort (p = 0.024). This suggests that the link between suicidality and risky behavior persists above and These validation results suggest that our computational markers can generalize to general population. However, we did not observe any significant correlation between mood sensitivity to CR and gambling behavior (ps > 0.389), which suggests that the link between mood sensitivity to CR and

gambling behavior may be specifically observable in suicidal patients. Alternatively, this non-replicated result may also reflect sample-specific or unstable effects, which needs to be interpreted with caution.

Computational parameters were predictive of suicidal risks

To examine whether task-derived computational measures carry predictive information related to suicidal ideation (BSI-C) beyond single-parameter associations, we performed an additional multivariate prediction analysis using lasso regression within a cross-validation framework. Across 100 repetitions of 5-fold cross-validation, STB was significantly predicted by the computational parameters (mean r = 0.205, all ps < 0.039; Table 4), including approach motivation and mood sensitivity to certain rewards, across all participants, including both patients and healthy controls. Importantly, this predictive model generalized to the online sample (n = 747), where model-predicted scores were significantly correlated with scores on item 9 of BDI (r = 0.073, p = 0.045). We further confirmed the robustness of this predictive effect using 10-fold cross-validation, which yielded a similar pattern of results (Table 4). In sum, these internal and external validation analyses corroborated the robustness of the predictive model of suicidal risks using computational markers.

Discussion

The current study tested cognitive and affective computational mechanisms for increased risk behavior in adolescent patients with suicidal thoughts and behaviors (STB), with a control group including adolescent patients without STB and sex/age-matched healthy control (HC). Firstly, we observed an increased gambling behavior and a lower overall mood in STB patients (S^+), as compared to non-STB patients (S^-) and HC, replicating previous findings(11–13,63). Secondly, using an approach-avoidance prospect theory model, we found heightened approach motivation in S^+ than S^- and HC, which explained increased gambling choices for STB, suggesting an over-reactivity of the approach system to approach risky options. Thirdly, using a momentary mood model, we showed that lower mood sensitivity to certain outcomes in S^+ compared to S^- and HC, which was driven by lower mood sensitivity to certain outcomes in S^+ than S^- and HC. These computational markers generalized to general population (n = 747). Importantly, mood hyposensitivity to certain reward specifically correlated to more gambling behavior in S^+, offering a mood computational account for increased risk behavior in STB. Beyond these specific findings, this work highlights the broader utility of combining computational modelling with momentary mood measures to better characterize behavioral differences relevant to psychiatric symptoms, and to show how choice and mood data can jointly inform our understanding of psychiatric phenomena.

Our results suggest a unique reason for the twofold observations that STB patients display an increase in both risk taking and impulsivity, defined as a tendency to act quickly without planning while failing to inhibit a behavior that is likely to result in negative consequences(64–68). Indeed, we did not observe a difference in risk attitude (e.g., risk aversion and loss aversion) per se between STB and controls but instead a higher approach behavior towards largest rewards (i.e., the lotteries) in STB patients. This would result from the value-independent term in the model that represents forms of approach in the face of gains(17,69,70). Such approach actions are elicited without regard to their actual contingent benefits and therefore correspond to impulsive behavior. A substantial body of research has shown that impulsivity, as assessed either through questionnaires or clinical observations, is a key predictor for STB (for a review, see Franklin et.al (2016)). Our study employed computational modeling to quantitively elucidate the altered approach-system processing for increased risky behavior in STB, offering enhanced predictive power and generalizability (39). On the other hand, contrary to the proposal of atypical avoidance system(20,23), we did not observe significant group difference in avoidance, which may be attributed to the different involvement of the motivational system in learning and non-leaning contexts(18,71). In our model specification, motivational systems work in a value independent way in the non-learning context. Consistent with the view that suicide is an escape from intolerable affective states(3), risky behavior in suicidal individuals may be rewarding. In clinical practices,

Figure 4. Validation of suicidal-related results in an independent dataset of general populations (n = 747).

A) Group difference in gambling behavior in the gain domain. B) The estimated parameters from the winning choice model (pseudo R^2 = 0.479) differed across groups, with higher approach behavior for S^+. C) The mediation model among the group, β_{gain}, and gambling behavior in the gain condition. The approach parameter mediated the group effect on increased gambling behavior in the gain condition. **D)** Group difference in mood before the task shows weakened mood in S^+. E) Group difference in average mood displays lower mood experience in S^+. FG) The estimated parameters from CR-GR mood model (mean R^2 = 0.588). F) Group difference in mood baseline, β_0. G) Group differences in mood sensitivity to certain reward (CR) and gamble reward (GR). Abbreviations: S^-, general participants without suicidal thoughts and behavior; S^+, general participants with suicidal thoughts and behavior; *p<0.05, $^+$ p<0.1.

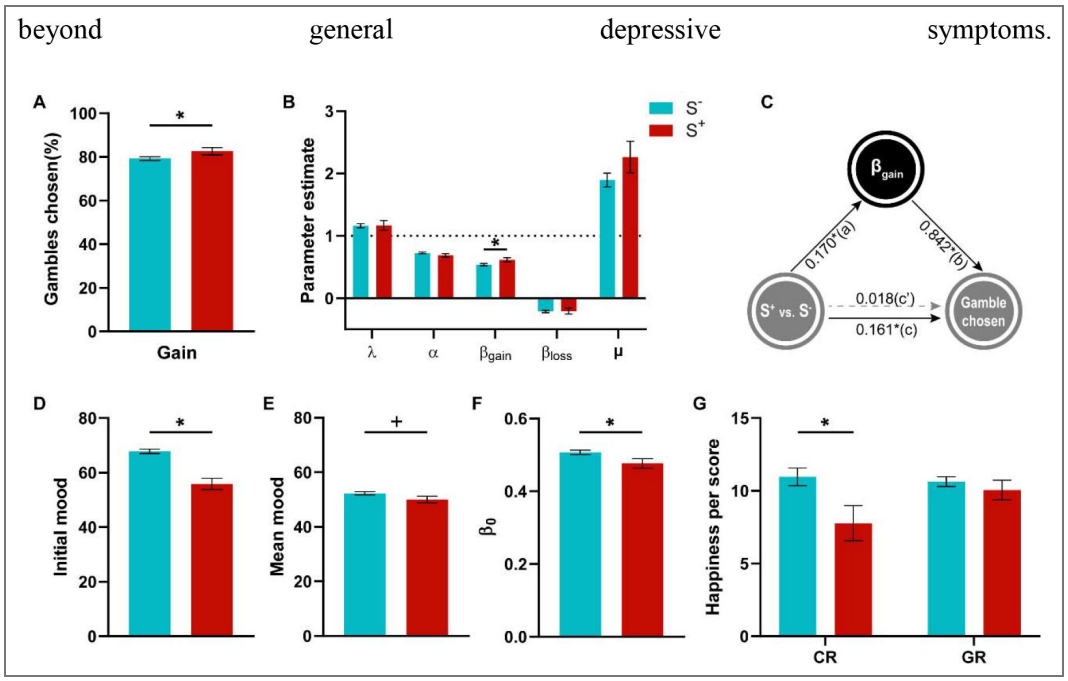


Table 4. Suicidal risk prediction from computational parameters.

Internal validation (n = 201)				External validation (n = 747)	
Cross-validation	Rho (mean±SD)	Rho [min, max]	P values	Rho	P value
5-Fold	0.205±0.016	[0.146, 0.230]	< 0.039	0.073	0.045
10-Fold	0.207±0.011	[0.172, 0.226]	< 0.014	0.073	0.045

understanding the distortion of the approach system in STB may encourage mental health professionals to closely monitor patients who exhibit heightened approach tendencies. Such vigilance may enable early detection of risk-related behaviors, thus facilitating timely intervention strategies tailored to mitigate impulsivity-driven actions that may elevate the likelihood of STB.

Consistent with suicidal-related theories(3,72,73) and as summarized by Millner et.al (2020), we observed lower mood levels in patients with STB, regarding both initial happiness and mood baseline (the latter corresponding to the steady state mood converges to). More importantly, STB patients' mood was less sensitive to certain outcomes than control without STB, which would lead them to take more risk regardless of the gain at stake and therefore to potentially experience more suboptimal outcomes than controls(11). Although no direct causal link was established between STB and happiness ratings in response to wins or losses, recent literature has documented associations between STB and anhedonia symptoms (albeit with mixed evidence; for a review, see (73)), where anhedonia can be assessed through affective reactivity to wins versus losses ((74)). Our findings thus provide support for the presence of anhedonia in STB, particularly in response to certain outcomes. Surprisingly, mood model-based analysis did not support the effect of expectations and prediction errors on mood in healthy people (the "CR-EV-RPE model"(17,28,75)), but suggest instead a dissociation between certain outcomes and lottery outcomes (the "CR-GR model"). These two models differed with respect to the inclusion of reward expectation terms, the former including it unlike the latter. This difference can be explained by the lower expected value signal in patients with STB(60), resulting in insufficient expectation representations of the gamble option to influence mood dynamics. An alternative explanation could be the duration of the chosen option display which was considerably lower in our design than in other mood studies (e.g., 0.5 s in our study versus 6 s in (28)), which would not leave enough time for expectation to be built. It is also possible that the current winning model was specific to adolescents. Given that Rutledge et al., (2017) supported the "CR-EV-RPE model" in adults with depression, our study with adolescent populations may suggest a developmental change for mood sensitivities. Within the winning CR-GR model, we observed that S^+ specifically exhibited lower mood sensitivity to CR than GR, which was driven by mood hyposensitivity to CR in S^+ than S^- and HC. This mood insensitivity was associated with STB severity, which was replicated when using the CR-EV-RPE model. Importantly, we found that mood hyposensitivity to certain reward was specifically correlated to gambling behavior in patients with STB, suggesting the potential mood computational mechanism for increased risk behavior in STB. As for clinical practices, CR-based anhedonia linked to CR (computational reactivity) in STB may prompt mental health professionals to closely monitor patients who exhibit mood insensitivity to certain daily events. This proactive monitoring could aid in identifying and addressing risk-related behaviors early on.

With replication in an independent dataset with large sample size (n = 747), this study provides robust evidence of the affective and cognitive computational mechanisms underlying heightened risky behavior in adolescents with STB. In addition, these results remained significant after controlling for demographics, social and clinical variables, medication factors, and the timing of suicidal events (Supplementary Note 3 & 4). However, this study could not differentiate between suicidal thoughts and suicidal behaviors. Although it has been shown that they represented different decision-making processes with different neural underpinnings (76–78), our data did not reveal significant differences between them (see Supplementary Note 2). Future research would benefit from examining these distinctions at the neural level. Nonetheless, by combining the suicidal ideation and suicidal attempt groups into a single STB group (40–45), our findings highlight why adolescents with suicidality exhibit a preference for risky behavior. These findings carry important clinical implications for early prevention of adolescent suicidality. Notably, this study, like many traditional studies on suicidality (40–42,79,80), does not seek to elucidate the affective and cognitive mechanisms underlying fluctuations in suicidal thoughts. Given the inherently variable nature of suicidal ideation, recent research has increasingly adopted ecological momentary assessments to capture real-time variations in suicidal ideations(45,81,82). While such methods can help predict when suicidal ideation may arise, they fall short of explaining the underlying mechanisms driving these thoughts. In contrast, our approach, consistent with traditional literature (40–44,79), is directed at understanding why individuals with

STB are more inclined toward risky behavior. We acknowledge the interaction between environmental stressor and the occurrence of STB, noting that suicidal severity often diminishes once the stressor is removed (44,83). This is a crucially important issue in current psychiatric research. For instance, patients with MDD sometimes experience depressive episodes, particularly in response to stressful events. However, collecting data during STB is both impractical and ethically challenging. Our grouping approach assumes of trait-driven STB: individuals with a history of STB, despite not during the experiment, represent a cluster of suicidal-related traits (83,84). Sensitivity analyses for STB timeframe support this assumption (see Supplementary Note 3). We also recognize that these affective and cognitive impairments may worsen under stress(44,83). Future studies would benefit from investigating how acute stress influences the propensity for risky behavior in individuals with STB.

Given that STB is a challenging multifactorial phenomenon, the development of a formal theory to quantify suicide seems necessary(20,21,85). Our cognitive and affective computational insights may pave the way for such a formal theory. Although previous literature has shown various cognitive impairments(13), e.g., executive function, in STB(86), our work is the first to quantify mood dynamics impairment and their behavioral consequences, providing insight into potential target to prevent and intervene STB. Our results indeed provide a computational mechanism for the main theories of suicide, linking low mood to suicidal behaviors. Suicide behavior is conceived to result from an intention shaped by various motivational factors (e.g., feeling of entrapment, belongness, burdensomeness(87)). The suicidal intent may then progress to suicidal behavior, which is thought to be moderated by impulsive decisions (e.g., (88)). A possibility is that the approach component becomes excessive as the suicidal intent emerges. These findings provide new insights into the putative dynamics underpinning STB, and offer potential markers for the early prediction, screening, detection, and prevention of suicidal behavior. These results would explain the observed increase in risk-taking behavior in STB such as substance use, early onset of sexual intercourse and physical fighting independent of psychiatric diagnosis.

Several limitations are worth mentioning. First, our cross-section findings are of correlational nature. Causal relationships remain to be tested in a longitudinal study. Second, although we assumed that increased risky behavior in STB was suboptimal, the current task was not suited to test this, given the task design of random feedback for gambling option. Future work in learning paradigms, where optimality is well defined, may be better suited to test earnings-based links to STB. Third, despite replicating our main results in an independent dataset (n=747), the modest S^- subgroup size (n=25) has a limited statistical power. Next, we did not evaluate the noise in our estimate e.g., by assessing the test-retest reliability on the task parameters and it is indeed possible that parameter estimate is somehow noisy.

To conclude, this study examined cognitive and affective computational mechanisms underlying increased risk behavior in adolescent patients with suicidal thoughts and behaviors. Given very limited predictive abilities of suicide from previous risk-factor investigations(8), our study offers a potential new perspective of mood, at the core of STB, and reveals a relationship between low mood sensitivity to certain reward and an increased risk behavior in STB and possibly suggesting dysfunctional dopaminergic and serotoninergic systems. Our findings suggest that computational measures may capture variance related to suicidal tendency in adolescents and thus may be relevant for future work on early identification and prevention of suicidality.

Data availability

All data produced in the present study are available upon reasonable request to the authors.

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supplementary materials

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Peer reviews

Reviewer #1 (Public review):

Summary:

The authors use a gambling task with momentary mood ratings from Rutledge et al. and compare computational models of choice and mood to identify markers of decisional and affective impairments underlying risk-prone behavior in adolescents with suicidal thoughts and behaviors (STB). The results show that adolescents with STB show enhanced gambling behavior (choosing the gamble rather than the sure amount), and this is driven by a bias towards the largest possible win rather than insensitivity to possible losses. Moreover, this group shows a diminished effect of receiving a certain reward (in the non-gambling trials) on mood. The results were replicated in a general online sample where participants were divided into groups with or without STB based on their self-report of suicidal ideation on one question in the Beck Depression Inventory self-report instrument. The authors suggest, therefore, that adolescents diagnosed with depression or anxiety with decreased sensitivity to certain rewards may need to be monitored more closely for STB due to their increased propensity to take risky decisions aimed at (expected) gains (such as relief from an unbearable situation through suicide) regardless of the potential losses. However, such a result was only found in the clinical sample and cannot be generalized more broadly based on the current findings.

Strengths:

- The study uses a previously validated task design and replicates previously found results through well-explained model-free and model-based analyses.

- Sampling of adolescents at high risk can help target early preventative diagnoses and treatments for suicide.

● Replication of the results in an online cohort increases confidence in the findings.

● The models considered for comparison are thorough and well-motivated. The chosen models allow for teasing apart which decision and mood sensitivity parameters relate to risky decision-making across groups based on their hypotheses.

● Novel finding of mood (in)sensitivity to non-risky rewards and its relationship with risk behavior in STB.

Weaknesses:

● Sample size of 25 for S- group is low-powered, which is explicitly mentioned as a study limitation.

● Modeling in the mediation analysis focused on predicting risk behavior in this task from the model-derived bias for gains and suicidal symptom scores. Thus, the implications of this work are more relevant to a basic-science understanding of the etiology of suicidal behavior than they are useful as a predictor of suicidal behavior, and it is not clear that a psychiatrist or psychologist could use this task to potentially determine who is at higher risk of attempting suicide and must be more closely monitored. Indeed, relationships between task parameters and behavior and suicidal behavior was limited to the clinical sample with a diagnosis of depression or anxiety disorder, and did not extend to the online sample. Therefore, the claim that these findings provide "computational markers for general suicidal tendency among adolescents" is unwarranted.

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Reviewer #2 (Public review):

Summary:

This article addresses a very pertinent question - what are the computational mechanisms underlying risky behaviour in patients having attempted suicide. In particular, it is impressive how the authors find a broad behavioral effect whose mechanisms they can then explain and refine through computational modeling. This work is important because currently, beyond previous suicide attempts, there has been a lack of predictive measures. This study is the first step towards that: understanding the cognition on a group level. Before then being able to include it in future predictive studies (based on the cross-sectional data, this study by itself cannot assess the predictive validity of the measure).

Strengths:

- Large sample size

- Replication of their own findings

- Well-controlled task with measures of behaviour and mood + precise and well-validated computational modeling

Questions, based on revised manuscript and replies to other reviewers:

(1) Replies to reviewers in general: Bayes Factors have been added, it would be good to also use common verbal terms to describe them (e.g. 'anecdotal', 'moderate' etc). For example, my reading of table S8 would be that for gambling rate there is only anecdotal evidence that it does not relate to PSWQ, BDI, and moderate evidence it does not relate to TAI.

(2) Reply to reviewer 1 Q2 (Predicting STB):

For the regression predicting suicidal ideation, it seems to me that what you did was a regression STB ~ gambling behaviour + approach + mood? Could you clarify? I had expected as a test of whether the task can predict STB risk something slightly different - a cross-validation (LOO or maybe 5-fold in the large sample): STB ~ gambling behaviour + approach [parameter from model] + mood [parameter from model]; and then computing in the left out participants: predicted STB. Then checking correlation between STB and predicted STB. This would allow testing whether the diverse task measures together predict STB (with the caveat, that it's cross-validated, rather than hold-out sample, unless you could train on one sample (in lab) and test on the other (online).

(3) Reply to reviewer 2 Q1 (parameter recovery): I'm looking at S3, it seems to still show only the scatter plots and not the correlation matrices, which are now added as text notes. Can you actually show these matrices? An off-diagonal correlation of 0.63 appears quite high. I think it needs to be discussed exactly which parameters those are, and whether that impacts the interpretation of the results.

(4) Reply to reviewer 3 Q3 (mood model): I would have imagined that the response would involve changing the mood equations (equation 8 main text) to include a term for whether the participant gambled or not, independent of the gamble value.

https://doi.org/10.7554/eLife.108002.3.sa2

Reviewer #3 (Public review):

This manuscript investigates computational mechanisms underlying increased risk-taking behavior in adolescent patients with suicidal thoughts and behaviors. Using a well-established gambling task that incorporates momentary mood ratings and previously established computational modeling approaches, the authors identify particular aspects of choice behavior (which they term approach bias) and mood responsivity (to certain rewards) that differ as a function of suicidality. The authors replicate their findings on both clinical and large-scale non-clinical samples.

The main problem, however, is that the results do not seem to support a specific conclusion with regard to suicidality. The S+ and S- groups differ substantially in the severity of symptoms, as can be seen by all symptom questionnaires and the baseline and mean mood, where S- is closer to HC than it is to S+. The main analyses control for illness duration and medication but not for symptom severity. The supplementary analysis in Figure S11 is insufficient as it mistakes the absence of evidence (i.e., $p > 0.05$) for evidence of absence. Therefore, the results do not adequately deconfound suicidality from general symptom severity.

The second main issue is that the relationship between an increased approach bias and decreased mood response to CR is conceptually unclear. In this respect, it would be natural to test whether mood responses influence subsequent gambling choices. This could be done either within the model by having mood moderate the approach bias or outside the model using model-agnostic analyses.

Additionally, there is a conceptual inconsistency between the choice and mood findings that partly results from the analytic strategy. The approach bias is implemented in choice as a categorical value-independent effect, whereas the mood responses always scale linearly with the magnitude of outcomes. One way to make the models more conceptually related would be to include a categorical value-independent mood response to choosing to gamble/not to gamble.

The manuscript requires editing to improve clarity and precision. The use of terms such as "mood" and "approach motivation" is often inaccurate or not sufficiently specific. There are

also many grammatical errors throughout the text.

Claims of clinical relevance should be toned down, given that the findings are based on noisy parameter estimates whose clinical utility for the treatment of an individual patient is doubtful at best.

Comments on revisions:'

The authors adequately addressed my comments and I find the manuscript substantially strengthened.

https://doi.org/10.7554/eLife.108002.3.sa1

Author response:

The following is the authors' response to the previous reviews

> ***eLife Assessment***
>
> *This valuable study combined careful computational modeling, a large patient sample, and replication in an independent general population sample to provide a computational account of a difference in risk-taking between people who have attempted suicide and those who have not. It is proposed that this difference reflects a general change in the approach to risky (high-reward) options and a lower emotional response to certain rewards. Evidence for the specificity of the effect to suicide, however, is incomplete, which would require additional analyses.*

We thank the editors and reviewers for this important assessment. Based on clinical interviews, we included patients with and without suicidality (S^+ and S^- groups). However, in line with suicidal-related literature (e.g., Tsypes et al., 2024), two groups also differed substantially in the severity of symptoms (see Table 1). To address the request for evidence on specificity to suicidality beyond general symptom severity, we performed separate linear regressions to explain in gambling behaviour, value-insensitive approach parameter (β_{gain}), and mood sensitivity to certain rewards (β_{CR}) with group as a predictor (1 for S^+ group and 0 for S^- group) and scores for anxiety and depression as covariates. Results remained significant after controlling anxiety and depression (*ps* < 0.027; Table S8). Given high correlations among anxiety and depression questionnaires (rs > 0.753, *ps* < 0.001), we performed Principal Components Analysis (PCA) on the clinical questionnaire to extract the orthogonal components, where each component explained 86.95%, 7.09%, 3.27%, and 2.68% variance, respectively. We then performed linear regressions using these components as covariates to control for anxiety and depression. Our main results remained significant (*ps* < 0.027; Table S9). We believe that these analyses provide evidence that the main effects on gambling and on mood were specific to suicide.

Moreover, as Reviewer 3 pointed out, these "absence of evidence" cannot provide insights of "evidence of absence". Although we median-split patients by the scores of general symptoms (e.g., depression and anxiety-related questionnaires) and verified no significant differences in these severities (Figure S11), we additionally conducted Bayesian statistics in gambling behavior, value-insensitive approach parameter, and mood sensitivity to certain rewards. BF_{01} is a Bayes factor comparing the null model (M_0) to the alternative model (M_1), where M_0 assumes no group difference. $BF_{01} > 1$ indicates that evidence favors M_0. As can be seen in Table S7, most results supported null hypothesis, suggesting that general symptoms of anxiety and depression overall did not influence our main results. Overall, we believe that these analyses provide compelling evidence for the specificity of the effect to suicide, above and beyond depression and anxiety.

Beyond these specific findings, this work highlights the broader utility of computational modelling and mood to better understand behavioral effect, showing how to use both mood and choice data to better comprehend a psychiatric issue.

Please see Tables S7, S8, S9 and our revisions below:.

Page 17:

"Within patients, this group effect on gambling rate remained significant after controlling for sex, illness duration, family history, diagnosis, and various medications use (*ps* < 0.05), as well as general symptoms (e.g., depression and anxiety; $p = 0.024$; also see Figure S11, Table S7 and Table S8). Given high correlations among anxiety and depression questionnaires (rs > 0.753, (*ps* < 0.001), we performed Principal Components Analysis (PCA) to extract main components, where each component explained 86.95%, 7.09%, 3.27%, and 2.68% variance, respectively. To further control for anxiety and depression, linear regression using these components as covariates revealed that the group effect on gambling rate remained significant ($p = 0.024$; Table S9)."

Pages 18-19:

"Within patients, this group effect on the approach parameter remained significant after controlling for sex, illness duration, family history, diagnosis, and various medications use (*ps* < 0.05), as well as general symptoms (e.g., depression and anxiety; $p = 0.027$; also see Figure S11, Table S7 and Table S8). Linear regression using PCA components as covariates revealed that the group effect on approach parameter remained significant ($p = 0.027$; Table S9)."

Page 21:

"Within patients, this group effect on βCR remained significant after controlling for gambling rate, earnings, mood-related outcome effect, mood drift effect, sex, illness duration, family history, diagnosis, and various medications use (ps < 0.032), as well as general symptoms (e.g., depression and anxiety; p = 0.001; also see Figure S11, Table S7 and Table S8). Linear regression using PCA components as covariates revealed that the group effect on this mood parameter remained significant (p = 0.001; Table S9)."

Page 27:

"Beyond these specific findings, this work highlights the broader utility of computational modelling and mood to better understand behavioral effect, showing how to use both mood and choice data to better comprehend a psychiatric issue."

> ***Public Reviews:***
>
> ***Reviewer #1 (Public review):***
>
> *Summary:*
>
> *The authors use a gambling task with momentary mood ratings from Rutledge et al. and compare computational models of choice and mood to identify markers of decisional and affective impairments underlying risk-prone behavior in adolescents with suicidal thoughts and behaviors (STB). The results show that adolescents with STB show enhanced gambling behavior (choosing the gamble rather than the sure amount), and this is driven by a bias towards the largest possible win rather than insensitivity to possible losses. Moreover, this group shows a diminished effect of receiving a certain reward (in the non-gambling trials) on mood. The results were replicated in an undifferentiated online sample where participants were divided into groups with or without STB based on their self-report of suicidal ideation on one question in the Beck Depression Inventory*

> *self-report instrument. The authors suggest, therefore, that adolescents with decreased sensitivity to certain rewards may need to be monitored more closely for STB due to their increased propensity to take risky decisions aimed at (expected) gains (such as relief from an unbearable situation through suicide), regardless of the potential losses.*
>
> *Strengths:*
>
> *(1) The study uses a previously validated task design and replicates previously found results through well-explained model-free and model-based analyses.*
>
> *(2) Sampling choice is optimal, with adolescents at high risk; an ideal cohort to target early preventative diagnoses and treatments for suicide.*
>
> *(3) Replication of the results in an online cohort increases confidence in the findings.*
>
> *(4) The models considered for comparison are thorough and well-motivated. The chosen models allow for teasing apart which decision and mood sensitivity parameters relate to risky decision-making across groups based on their hypotheses.*
>
> *(5) Novel finding of mood (in)sensitivity to non-risky rewards and its relationship with risk behavior in STB.*
>
> *Weaknesses:*
>
> *(1) The sample size of 25 for the S- group was justified based on previous studies (lines 181-183); however, all three papers cited mention that their sample was low powered as a study limitation.*

We thank the Reviewer for rising this concern. We agree that the sample size for S^- group (n=25) is modest, and the prior studies we cited also acknowledged limited power. We wanted to point out that we obtained a comparable sample size to a prior study. In the revision, we therefore updated the section to justify this sample size in which we acknowledge the limited power of our study in the limitation section. Please see our clarification below:

Page 32:

"Third, despite replicating our main results in an independent dataset (n=747), the modest S^- subgroup size (n=25) has a limited statistical power."

> *(2) Modeling in the mediation analysis focused on predicting risk behavior in this task from the model-derived bias for gains and suicidal symptom scores. However, the prediction of clinical interest is of suicidal behaviors from task parameters/behavior - as a psychiatrist or psychologist, I would want to use this task to potentially determine who is at higher risk of attempting suicide and therefore needs to be more closely watched rather than the other way around (predicting behavior in the task from their symptom profile). Unfortunately, the analyses presented do not show that this prediction can be made using the current task. I was left wondering: is there a correlation between beta_gain and STB? It is also important to test for the same relationships between task parameters and behavior in the healthy control group, or to clarify that the recommendations for potential clinical relevance of these findings apply exclusively to people with a diagnosis of depression or anxiety disorder. Indeed, in line 672, the authors claim their results provide "computational markers for general suicidal tendency among adolescents", but this was not shown here, as there were no models predicting STB within patient groups or across patients and healthy controls.*

Thank you for these thoughtful comments. Our study focuses on why adolescent patients with suicidality have increased risk behavior, aiming to provide a mechanism-based target for suicide prevention. Therefore, our dependent variable in the mediation model was gambling

behavior. We also agree that the clinically relevant question is whether suicidality can be predicted from task-derived behavior/parameters. We thus used risky behavior and the potential mental parameters to predict STB. Linear regressions showed that gambling behavior, as well as the value-insensitive approach parameter, can predict suicidal symptom scores among patients (former: β = 9.189, t = 2.004, p = 0.048; latter: β = 5.587, t = 2.890, p = 0.005). In healthy controls, these predictions failed (gambling behavior: β = 1.471, t = 0.825, p = 0.411; approach: β = 0.874, t = 1.178, p = 0.241). These results suggest that clinical relevance of these findings apply exclusively to people with a diagnosis of depression or anxiety disorder. We found same patterns for the mood parameter (mood sensitivity to certain rewards: patients: β = -28.706, t = -2.801, p = 0.006; healthy controls: β = -2.204, t = -0.528, p = 0.599). In sum, we believe that our statement of "computational markers for general suicidal tendency among adolescents" is reasonable now. Please see our revisions below:

Page 17:

"Furthermore, linear regression showed that gambling rate can predict the current suicidal ideation score (BSI-C, β = 9.189, t = 2.004, p = 0.048) among patients, but not among HC (β = 1.471, t = 0.825, p = 0.411), suggesting that gambling behavior has patient-specific predictive utility for suicidal symptoms."

Page 19:

"Furthermore, linear regression showed that approach parameter can predict the current suicidal ideation score (β = 5.587, t = 2.890, p = 0.005) among patients, but not among HC (β = 0.874, t = 1.178, p = 0.241), suggesting that value-insensitive approach parameter has patient-specific predictive utility for suicidal symptoms."

Page 21:

"Furthermore, linear regression showed that mood sensitivity to CR can predict the current suicidal ideation score (β = -28.706, t = -2.801, p = 0.006) among patients, but not among HC (β = -2.204, t = 0.528, p = 0.599), suggesting that mood sensitivity to CR has patient-specific predictive utility for suicidal symptoms."

> *(3) The FDR correction for multiple comparisons mentioned briefly in lines 536-538 was not clear. Which analyses were included in the FDR correction? In particular, did the correlations between gambling rate and BSI-C/BSI-W survive such correction? Were there other correlations tested here (e.g., with the TAI score or ERQ-R and ERQ-S) that should be corrected for? Did the mediation model survive FDR correction? Was there a correction for other mediation models (e.g., with BSI-W as a predictor), or was this specific model hypothesized and pre-registered, and therefore no other models were considered? Did the differences in beta_gain across groups survive FDR when including comparisons of all other parameters across groups? Because the results were replicated in the online dataset, it is ok if they did not survive FDR in the patient dataset, but it is important to be clear about this in presenting the findings in the patient dataset.*

Thank you for raising the important issue of multiple testing and for asking us to clarify exactly which tests were covered by the FDR procedure. In the clinical dataset we conducted a large number of inferential tests (χ^2, t-tests, ANOVAs, regressions) spanning: (i) group differences in demographic/clinical characteristics; (ii) sanity checks (e.g., anxiety/depression questionnaires); (iii) primary hypotheses (e.g., group differences in risky behavior); (iv) model-based analyses (parameter checks and between-group contrasts); and (v) control/sensitivity analyses. Post-hoc t-tests were performed only when the three-group ANOVA was significant. This yielded >150 p-values. FDR was applied using all these p-values. Please see Supplementary Note 8.

> *(4) There is a lack of explicit mention when replication analyses differ from the analyses in the patient sample. For instance, the mediation model is different in the two samples: in the patient sample, it is only tested in S+ and S- groups, but not in healthy controls, and the model relates a dimensional measure of suicidal symptoms to gambling in the task, whereas in the online sample, the model includes all participants (including those who are presumably equivalent to healthy controls) and the predictor is a binary measure of S+ versus S- rather than the response to item 9 in the BDI. Indeed, some results did not replicate at all and this needs to be emphasized more as the lack of replication can be interpreted not only as "the link between mood sensitivity to CR and gambling behavior may be specifically observable in suicidal patients" (lines 582-585) - it may also be that this link is not truly there, and without a replication it needs to be interpreted with caution.*

Thank you for these important comments. This study focused on cognitive and affective computational mechanisms underlying increased risky behavior in STB. Accordingly, we compared patients with STB (S^+) with patients without STB (S^-) and healthy controls (HC) to examine the effects of STB on risky behavior. Therefore, group comparison, instead of dimensional measure of suicidal symptoms by Beck Scale for Suicidal Ideation, can answer our research questions directly.

To enhance consistency between the clinical and replication datasets, we included all participants in each dataset when performing the mediation analysis. Given that S^- and HC did not differ in gambling behavior or the approach parameter in the clinical dataset, we merged these two groups. In the replication dataset, to mirror the S^+ vs. S^- contrast used clinically, we categorized the general sample into S^+ and S^- based on BDI item 9. The mediation results remained significant in both datasets (the clinical dataset: a×b = 0.321, 95% CI = [0.070, 0.549], p = 0.016; the replication dataset: a × b = 0.143, 95% CI = [0.016, 0.288], p = 0.031), suggesting that STB is associated with increased risk behavior via stronger approach motivation.

We also acknowledge the non-replication of the correlation between gambling behavior and mood sensitivity to certain rewards in the online sample. While this pattern might indicate that the link is specific to suicidal patients, it may also reflect sample-specific or unstable effects; thus, we now state this explicitly and interpret the finding with caution. Please see our revisions below:

Page 15:

“We next verified our results in an independent dataset, including the same task and BDI questionnaire in 747 general participants （500 females; age: 20.90±2.41）[46]. One item in BDI involves the measurement of STB. In item 9 of BDI, participants chose one option that describes them best: Option 1, “I don't have any thoughts of killing myself.”; Option 2, “I have thoughts of killing myself, but I would not carry them out.”; Option 3, “I would like to kill myself.”; Option 4, “I would kill myself if I had the chance.”. In line with the current definition of S^+/S^- in the clinical dataset, we identified S^+ group as choosing Option 2, 3, or 4, while participants selecting Option 1 were categorized as S^- group.”

Page 19:

“Given significant correlations between group, approach parameter, and gambling rate for gain trials (ps < 0.017), we further conducted a mediation analysis with the assumption of the mediating effect of approach motivation of suicidality on the risk behavior. Given that we aimed to test the effect of STB, with S^- and HC as controls, and given that S^- and HC did not differ in gambling behavior or in the approach parameter, we merged these two groups for the mediation analysis. Results supported our hypothesis (a×b = 0.321, 95% CI = [0.070, 0.549],

p = 0.016; Figure 2C), confirming that suicidal thoughts and behavior increase risk behavior through stronger approach motivation."

Page 26:

"However, we did not observe any significant correlation between mood sensitivity to CR and gambling behavior (ps > 0.389), which suggests that the link between mood sensitivity to CR and gambling behavior may be specifically observable in suicidal patients. Alternatively, this non-replicated result may also reflect sample-specific or unstable effects, which needs to be interpreted with caution."

> *(5) In interpreting their results, the authors use terms such as "motivation" (line 594) or "risk attitude" (line 606) that are not clear. In particular, how was risk attitude operationalized in this task? Is a bias for risky rewards not indicative of risk attitude? I ask because the claim is that "we did not observe a difference in risk attitude per se between STB and controls". However, it seems that participants with STB chose the risky option more often, so why is there no difference in risk attitude between the groups?*

Thank you for pointing out the ambiguity. In our manuscript, "motivation" and "risk attitude" are defined at the computational level. Following prior work with this task Rutledge et al., (2015, 2016), we decompose observed gambling into (i) value-dependent valuation parameters that capture risk attitude (e.g., risk aversion and loss aversion, which scale the subjective value of outcomes), and (ii) value-insensitive, valence-dependent biases that capture approach/avoidance motivation. Accordingly, a higher gambling rate does not imply a change in risk attitude per se: it can arise from an increased value-insensitive approach bias even when risk-attitude parameters are comparable between groups which is what we observe for S^+ vs. controls. We have clarified this point in the computational modeling section.

Pages 12-13:

"Please note that a higher gambling rate does not imply a change in risk attitude per se: it can arise from an increased value-insensitive approach bias even when risk-attitude parameters are comparable between groups. Risk attitude is indeed conceptualized in economics as the curvature of the utility function (i.e., the subjective value) of the objective outcomes, with concave curves associated with risk aversion, and convex curves associated with risk seeking [54,56]. By contrast, the approach or avoidance bias apply to all the value. A possible interpretation of the approach bias is that participant approach the option with the highest possible gain (the lottery) in the gain frame; the avoidance bias would then reflect a tendency to systematically avoid the highest potential losses (the lottery) in the loss frame."

> ***Reviewer #2 (Public review):***
>
> *Summary:*
>
> *This article addresses a very pertinent question: what are the computational mechanisms underlying risky behaviour in patients who have attempted suicide? In particular, it is impressive how the authors find a broad behavioural effect whose mechanisms they can then explain and refine through computational modeling. This work is important because, currently, beyond previous suicide attempts, there has been a lack of predictive measures. This study is the first step towards that: understanding the cognition on a group level. This is before being able to include it in future predictive studies (based on the cross-sectional data, this study by itself cannot assess the predictive validity of the measure).*
>
> *Strengths:*

> *(1) Large sample size.*
>
> *(2) Replication of their own findings.*
>
> *(3) Well-controlled task with measures of behaviour and mood + precise and well-validated computational modeling.*
>
> *Weaknesses:*
>
> *I can't really see any major weakness, but I have a few questions:*
>
> *(1) I can see from the parameter recovery that the parameters are very well identified. Is it surprising that this is the case, given how many parameters there are for 90 trials? Could the authors show cross-correlations? I.e., make a correlation matrix with all real parameters and all fitted parameters to show that not only the diagonal (i.e., same data is the scatter plots in S3) are high, but that the off-diagonals are low.*

Thank you for raising these thoughtful concerns. The current task consisted of 90 choices and 36 mood ratings. There were 5 choice parameters and 4 mood parameters. The apparently strong identifiability is not unexpected, as 90 choice trials and 36 mood ratings are comparable to those in prior computational modeling literature (Blain & Rutledge, 2022).

As suggested, we computed cross-scorrelations between all generating ("true") and recovered ("fitted") parameters. The resulting matrix showed high diagonal (choice winning model: rs > 0.91; mood winning model: rs > 0.90) and low off-diagonal (choice winning model: abs(rs) < 0.63; mood winning model: abs(rs) > 0.40) correlations, further supporting parameter recovery. Please see Supplementary Pages 2-3.

"Parameter recovery: Figure S3 shows good parameter recovery for both choice and mood winning model (choice: rs > 0.91, *ps* < 0.001; intraclass coefficients > 0.78; mood: rs > 0.90, *ps* < 0.001; intraclass coefficients > 0.86). Moreover, we computed cross-correlations between all generating ("true") and recovered ("fitted") parameters. The resulting matrix showed high diagonal (choice winning model: rs > 0.91; mood winning model: rs > 0.90) and low off-diagonal (choice winning model: abs(rs) < 0.63; mood winning model: abs(rs) > 0.40) correlations, further supporting parameter recovery."

Page 10：

"The numbers of choice trials and mood ratings were comparable to those in prior computational modeling studies [34,35]."

> *(2) Could the authors clarify the result in Figure 2B of a correlation between gambling rate and suicidal ideation score, is that a different result than they had before with the group main effect? I.e., is your analysis like this: gambling rate ~ suicide ideation + group assignment? (or a partial correlation)? I'm asking because BSI-C is also different between the groups. [same comment for later analyses, e.g. on approach parameter].*

Thank you for pointing out the lack of clarity. We performed group difference analysis and correlation of suicidal ideation analysis, separately. We first performed group difference analysis to test our hypothesis of STB effects. We then conducted correlational analysis to further specify our findings.

> *(3) The authors correlate the impact of certain rewards on mood with the % gambling variable. Could there not be a more direct analysis by including mood directly in the choice model?*

Thank you for this insightful suggestion. As suggested, we tried to integrate mood into choice models by adding mood bias component(s) in line with previous literature (Vinckier et al.,

2018). The first model (mcM1) assumes that mood biases choice, building on cM3 (the winning choice model). cmM2 further separated the mood bias parameter into two components according to participants' choices.

$$P_{\text{gamble}} = \frac{1-\beta_{\text{val}}}{1+e^{-\mu\left(U_{\text{gamble}}-U_{\text{certain}}+\beta_{\text{Mood}}\, z\,\text{Mood}\right)}} + \beta_{\text{val}} \text{ if } \beta_{\text{val}} \geq 0$$

$$P_{\text{gamble}} = \frac{1+\beta_{\text{val}}}{1+e^{-\mu\left(U_{\text{gamble}}-U_{\text{certain}}+\beta_{\text{Mood}}\, z\,\text{Mood}\right)}} \text{ if } \beta_{\text{val}} < 0$$

$$\beta_{\text{val}} \begin{cases} \beta_{\text{gain}}, & \text{gain trials}, \\ \beta_{\text{loss}}, & \text{loss trials}. \end{cases}$$

However, model comparison using BIC supported cM3 (Table S6), that is, without consideration of mood in choice modeling. This can be due to the lack of block design in our experimental design unlike e.g., Vinckier et al., (2018) and Eldar & Niv, (2015). Please see Supplementary Note 6.

> *(4) In the large online sample, you split all participants into S+ and S-. I would have imagined that instead, you would do analyses that control for other clinical traits. Or, for example, you have in the S- group only participants who also have high depression scores, but low suicide items.*

Thank you for this insightful suggestion. Following prior suicide-related literature (Tsypes et al., 2024), we controlled for depression by including them as covariates. Note that depression scores were derived from our established bifactor model (Wang et al., 2025), which decomposed depression from the anxiety. These results remained largely significant (*ps* ≤ 0.050), except a marginally significant effect of group on gambling behavior ($p = 0.059$). Despite a trend, this effect with covariates of depression-related questionnaires is strong in our clinical cohort ($p = 0.024$; Table S8). This suggests that the link between suicidality and risky behavior persists above and beyond general depressive symptoms.

Please see our clarifications below:

Page 26:

"After controlling for depression severity using our established bifactor model (see ref 60 for details), these results remained significant (*ps* ≤ 0.050), except a marginally significant effect of group on gambling behavior ($p = 0.059$). Despite a trend, this effect with covariates of depression-related questionnaires is strong in our clinical cohort ($p = 0.024$; Table S8). This suggests that the link between suicidality and risky behavior persists above and beyond general depressive symptoms."

> ***Reviewer #3 (Public review):***
>
> *This manuscript investigates computational mechanisms underlying increased risk-taking behavior in adolescent patients with suicidal thoughts and behaviors. Using a well-established gambling task that incorporates momentary mood ratings and previously established computational modeling approaches, the authors identify particular aspects of choice behavior (which they term approach bias) and mood responsivity (to certain rewards) that differ as a function of suicidality. The authors replicate their findings on both clinical and large-scale non-clinical samples.*
>
> *(1) The main problem, however, is that the results do not seem to support a specific conclusion with regard to suicidality. The S+ and S- groups differ substantially in the severity of symptoms, as can be seen by all symptom questionnaires and the baseline and mean mood, where S- is closer to HC than it is to S+. The main analyses control for illness duration and medication but not for symptom severity. The supplementary analysis in Figure S11 is insufficient as it mistakes the absence of evidence (i.e., p > 0.05)*

> *for evidence of absence. Therefore, the results do not adequately deconfound suicidality from general symptom severity.*

Thank you for this important comment. Based on clinical interviews, we included patients with and without suicidality (S^+ and S^- groups). However, in line with suicidal-related literature (e.g., Tsypes et al., 2024), two groups also differed substantially in the severity of symptoms (see Table 1). To address the request for evidence on specificity to suicidality beyond general symptom severity, we performed separate linear regressions to explain in gambling behaviour, value-insensitive approach parameter (β_{gain}), and mood sensitivity to certain rewards (β_{CR}) with group as a predictor (1 for S^+ group and 0 for S^- group) and scores for anxiety and depression as covariates. Results remained significant after controlling anxiety and depression (*ps* < 0.027; Table S8). Given high correlations among anxiety and depression questionnaires (rs > 0.753, *ps* < 0.001), we performed Principal Components Analysis (PCA) on the clinical questionnaire to extract the orthogonal components, where each component explained 86.95%, 7.09%, 3.27%, and 2.68% variance, respectively. We then performed linear regressions using these components as covariates to control for anxiety and depression. Our main results remained significant (*ps* < 0.027; Table S9). We believe that these analyses provide evidence that the main effects on gambling and on mood were specific to suicide.

As pointed out, these "absence of evidence" cannot provide insights of "evidence of absence". Although we median-split patients by the scores of general symptoms (e.g., depression and anxiety-related questionnaires) and verified no significant differences in these severities (Figure S11), we additionally conducted Bayesian statistics in gambling behavior, value-insensitive approach parameter, and mood sensitivity to certain rewards. BF_{01} is a Bayes factor comparing the null model (M_0) to the alternative model (M_1), where M_0 assumes no group difference. $BF_{01} > 1$ indicates that evidence favors M_0. As can be seen in Table S7, most results supported null hypothesis, suggesting that general symptoms of anxiety and depression overall did not influence our main results. Overall, we believe that these analyses provide compelling evidence for the specificity of the effect to suicide, above and beyond depression and anxiety.

Please see Table S7, S8 &S9 and our revisions below.

Page 17:

"Within patients, this group effect on gambling rate remained significant after controlling for sex, illness duration, family history, diagnosis, and various medications use (*ps* < 0.05), as well as general symptoms (e.g., depression and anxiety; *p* = 0.024; also see Figure S11, Table S7 and Table S8). Given high correlations among anxiety and depression questionnaires (rs > 0.753, *ps* < 0.001), we performed Principal Components Analysis (PCA) to extract main components, where each component explained 86.95%, 7.09%, 3.27%, and 2.68% variance, respectively. To further control for anxiety and depression, linear regression using these components as covariates revealed that the group effect on gambling rate remained significant (*p* = 0.024; Table S9)."

Pages 18-19:

"Within patients, this group effect on the approach parameter remained significant after controlling for sex, illness duration, family history, diagnosis, and various medications use (*ps* < 0.05), as well as general symptoms (e.g., depression and anxiety; *p* = 0.027; also see Figure S11, Table S7 and Table S8). Linear regression using PCA components as covariates revealed that the group effect on approach parameter remained significant (*p* = 0.027; Table S9)."

Page 21:

"Within patients, this group effect on βCR remained significant after controlling for gambling rate, earnings, mood-related outcome effect, mood drift effect, sex, illness duration, family history, diagnosis, and various medications use (ps < 0.032), as well as general symptoms (e.g., depression and anxiety; p = 0.001; also see Figure S11, Table S7 and Table S8). Linear regression using PCA components as covariates revealed that the group effect on this mood parameter remained significant (p = 0.001; Table S9)."

> *(2) The second main issue is that the relationship between an increased approach bias and decreased mood response to CR is conceptually unclear. In this respect, it would be natural to test whether mood responses influence subsequent gambling choices. This could be done either within the model by having mood moderate the approach bias or outside the model using model-agnostic analyses.*

Thank you for this important suggestion. As suggested, one interesting question was whether mood responses influence subsequent gambling choices and how to model them. First, we median-split mood responses (except the final rating) to compare gambling rate. Results showed a trend for less gambling rate in higher mood (t = -1.971, p = 0.050). However, there was no significant group difference (F = 0.680, p = 0.507). Second, with the assumption that mood biases choice, we constructed mcM1 based on cM3 (the winning choice model). Based on our finding of the negative correlation between mood sensitivity to certain rewards and gambling rate in S^+, we separated β_{Mood} parameter into $\beta_{\text{Mood-CR}}$ and $\beta_{\text{Mood-GR}}$ (cmM2). Model comparison using BIC supported cM3 (Table S6), that is, without consideration of mood in choice modeling. This can be due to the lack of block design in our experimental design unlike e.g., Vinckier et al., (2018) and Eldar & Niv, (2015). Please see Supplementary Note 6.

> *(3) Additionally, there is a conceptual inconsistency between the choice and mood findings that partly results from the analytic strategy. The approach bias is implemented in choice as a categorical value-independent effect, whereas the mood responses always scale linearly with the magnitude of outcomes. One way to make the models more conceptually related would be to include a categorical value-independent mood response to choosing to gamble/not to gamble.*

We apology for the unclear statement. The approach bias is implemented in choice as a continuous value-independent effect, ranging from -1 to 1.

$$P_{\text{gamble}} = \frac{1-\beta_{\text{val}}}{1+e^{-\mu(U_{\text{gamble}}-U_{\text{certain}})}} + \beta_{\text{val}} \text{ if } \beta_{\text{val}} \geq 0 \tag{5}$$

$$P_{\text{gamble}} = \frac{1+\beta_{\text{val}}}{1+e^{-\mu(U_{\text{gamble}}-U_{\text{certain}})}} \text{ if } \beta_{\text{val}} < 0 \tag{6}$$

$$\beta_{\text{val}} \begin{cases} \beta_{\text{gain}}, & \text{gain trials}, \\ \beta_{\text{loss}}, & \text{loss trials}. \end{cases} \tag{7}$$

It was true that the mood responses always scale with the magnitude of outcomes, since mood ratings were request after the outcomes. Therefore, mood parameters and the approach bias were both continuous.

We also attempted to integrate mood into choice modelling. See Response 2 for Reviewer 3 for details.

> *(4) The manuscript requires editing to improve clarity and precision. The use of terms such as "mood" and "approach motivation" is often inaccurate or not sufficiently specific. There are also many grammatical errors throughout the text.*

Thank you for this important suggestion. We have now explained motivation and mood in the Introduction section and the computational modeling section. Please see our clarifications below:

Pages 3-4:

"A growing literature indeed shows that risky behavior can be far better explained after adding value-insensitive approach and avoidance components to prospect theory [18,19], that is by including a decision bias in favor of the highest gain (approach) and another decision bias against the lowest loss (avoidance), above and beyond options value difference. This class of models highlights the important role of value-insensitive motivational components in decision making in addition to risk attitude-driven valuation (e.g., loss/risk aversion) [20]."

Page 5:

"Although mood is thought to persist for hours, days, or even weeks [30–33], momentary mood, measured over the timescale in the laboratory setting, represents the accumulation of the impact of multiple events at the scale of minutes [30,32,34–38]. Momentary mood external validity is demonstrated e.g., through its association with depression symptoms [37]. Mood is different from emotions, which reflect immediate affective reactivity and is more transient (e.g., from surprise to fear) [31–33,39]."

We have corrected grammatical errors throughout the manuscript.

> *(5) Claims of clinical relevance should be toned down, given that the findings are based on noisy parameter estimates whose clinical utility for the treatment of an individual patient is doubtful at best.*

Thank you for this comment. We agree that we did not evaluate the noise in our estimate e.g., by assessing the test-retest reliability on the task parameters, which is outside the scope of the study, and it is indeed possible that parameter estimate is somehow noisy. Therefore, we tone down the clinical relevance of our results. Please see our revision below:

Page 32:

"Next, we did not evaluate the noise in our estimate e.g., by assessing the test-retest reliability on the task parameters and it is indeed possible that parameter estimate is somehow noisy."

> ***Recommendations for the authors:***
>
> ***Reviewer #1 (Recommendations for the authors):***
>
> *(1) Title: I believe "aberrant mood dynamics" is both too general and overstating the results of this study, which did not measure mood dynamics longitudinally. "Aberrant" is also overly pathologizing. I would suggest sticking more directly to the results, for instance, "Insensitivity of momentary mood to non-risky rewards in adolescent suicidal patients".*

Thank you for this suggestion. We have now corrected it.

> *(2) Abstract: in line 61, "Our study uncovers the cognitive and affective mechanisms" suggests that these are the only ones, and you uncovered them. Of course, there could be more mechanisms contributing to risk behavior in STB, so I would suggest removing the word "the" or adding "one of the".*

Thank you for this suggestion. We have now corrected it.

> *(3) One major weakness of this study is that suicidal thoughts and behaviors were not assessed via a clinical instrument such as the Columbia Suicide Severity Rating Scale - this should be mentioned upfront.*

Thank you for this comment. According to medical records and information from family and friends by the researcher and psychiatrists, patients with suicidal thoughts and behaviors were categorized as suicidal group (S^+), while patients without suicidal thoughts and behaviors were identified as control group (S^-). Note that medical records and information were recorded from clinical interviews where the psychiatrists were vigilant for signs of suicidal ideation and inquired about suicidal-related thoughts and behaviors from both the patients and their families. Therefore, the current group operation was possibly comparable to Columbia Suicide Severity Rating Scale.

> *(4) Table 1: female/male are sex, not gender (gender is man/woman/transgender/non-binary).*

Thank you for this suggestion. We have now corrected it.

> *(5) Equation 1: It would be good to clarify what happens in gain-only or loss-only trials (the other value is then 0, but this can be clarified as it is not technically a loss or a gain).*

Thank you for this suggestion. We have now corrected it. Please see below for our revision:

Page 12:

"Please note that V_{gain} is 0 in gain trials and V_{loss} is 0 in loss trials."

> *(6) Figure 1E: The model prediction is not informative here. Given the linear regression model, there is no other option except that the mean prediction would overlap with the mean empirical measurement (unless the model was specified incorrectly). The same is true in Figure 2A.*

Thank you for this suggestion. We have now removed plots for model prediction.

> *(7) Figure 1G: There was no analysis of the differences between groups in terms of earnings, given that the ANOVA was not significant. Still, if the claim is that risky behavior is sometimes suboptimal in this task, it would be good to show that there is a correlation between, say, symptoms of STB across groups and 1) risky behavior and 2) earnings.*

Thank you for this insightful comment. In the patient cohort, risky behavior (gambling rate)—but not earnings predicted the current suicidal ideation score (BSI-C, $\beta = 9.189$, $t = 2.004$, $p = 0.048$; earnings, $\beta = 0.001$, $t = 0.582$, $p = 0.562$). The lack of association for earnings is consistent with the task design, in which there is no stable optimal policy and payouts are only a coarse proxy for decision quality. Future work in learning paradigms, where optimality is well defined, may be better suited to test earning-based links to STB. We have clarified this point below:

Page 32:

"Second, although we assumed that increased risky behavior in STB was suboptimal, the current task was not suited to test this, given the task design of random feedback for

gambling option. Future work in learning paradigms, where optimality is well defined, may be better suited to test earnings-based links to STB."

> *(8) Line 290: "beta_gain: -1-1" is unclear. I believe you meant beta_gain \in [-1,1].*

Thank you for this suggestion. We have now corrected it to make it clear.

> *(9) The gain and loss biases are modeled as minimum and maximum probabilities for choosing the gamble. This is a legitimate choice for value-agnostic biases, but it is not the traditional choice (as far as I know). I wonder if the same results would hold with the more traditional formulation of the bias as an added constant to the utility of the gamble, i.e., p(gamble) = 1/(1+ exp(-mu(U_gamble + beta_gain - U_certain)). I believe in this case, you would also not have to specify different equations for positive or negative biases, or to limit the bias to the range of [-1,1] (indeed, the bias would be in reward-equivalent units).*

Thank you for this suggestion. The winning choice model we used here was consistent with previous literature (Rutledge et al., 2015 & 2016), which decomposed the decision process into risk-attitude-driven valuation (e.g., loss and risk aversion) and value-insensitive motivational components. These approach/avoidance parameters are a decision bias in favor of the highest gain (approach) and another decision bias against the lowest loss (avoidance), above and beyond options value difference.

As suggested, we also compared the traditional bias choice model. Model comparison did not support this. Please see Supplementary Page 4.

> *(10) Also, for equations 5-8, it seems that 5-6 are identical to 7-8 except for the use of beta_gain versus beta_loss. You might want to consider simplifying by putting beta in the equations and specifying in the text that, depending on the trial type (loss or gain), the relevant beta is used.*

Thank you for this suggestion. We have now simplified it. Please see our revision below:

$$P_{\text{gamble}} = \frac{1-\beta_{\text{val}}}{1+e^{-\mu(U_{\text{gamble}}-U_{\text{certain}})}} + \beta_{\text{val}} \text{ if } \beta_{\text{val}} \geq 0 \tag{5}$$

$$P_{\text{gamble}} = \frac{1+\beta_{\text{val}}}{1+e^{-\mu(U_{\text{gamble}}-U_{\text{certain}})}} \text{ if } \beta_{\text{val}} < 0 \tag{6}$$

$$\beta_{\text{val}} \begin{cases} \beta_{\text{gain}}, & \text{gain trials}, \\ \beta_{\text{loss}}, & \text{loss trials}. \end{cases} \tag{7}$$

> *(11) It is not clear what equations are applied to mixed trials in cM3.*

Sorry for the confusion. We have now clarified this point.

Page 12:

"Approach/avoidance parameters are not applied to in mixed trials."

> *(12) Model comparison: the mood models are nested within each other (e.g., mM3 can be derived from mM1 by setting beta_EV = beta_RPE). In this case, model comparison can use the likelihood ratio test instead of BIC, which can be too conservative (and therefore does not support the extra beta parameter for RPE, different from previous results in the literature). I wonder if a likelihood ratio test would lead to results more in line with previous findings with this task?*

Thanks for this suggestion. We agree that mM1 (CR+EV+RPE) and mM3 (CR+GR) are nested. However, our model space also included unnested models, such as mM5 ($CR+GR_{better}+GR_{worse}$). Therefore, it was not reasonable in our model space to use likelihood ratio tests.

> *(13) Line 346: The replication sample is described as "healthy participants," however, their health (or mental health) status was not assessed, and they may as well have mental health concerns. I would suggest calling this a general sample or an undifferentiated sample - but not a healthy sample.*

Sorry for the confusion. We have now corrected this phrase.

> *(14) Line 363: "in addition to the replication of previous findings in the validation dataset" is unclear. Are those tests not two-tailed?*

Sorry for the unclear statement. In the replication analyses, we used one-tailed t-tests because the direction of the effect was revealed on the clinical dataset. Please see our clarification below:

Page 15:

“For the replication of previous findings in the validation dataset, we used one-tailed tests in line with our clinically motivated directional hypothesis.”

> *(15) Line 372: "validating our group manipulation" - the presented work does not have a manipulation. Maybe you meant "validating our grouping of participants"?*

Thank you for this suggestion. We have now corrected it to make it clear.

> *(16) Figure 2B: It is not clear how the data were binned for illustration purposes only, and why this binning is necessary (I have not seen it in other papers) - presenting the data from each subject and the correlation line with error margins (as is done here) should be sufficient.*

Thank you for flagging this. For illustration only, we binned the data proportional to group sizes: in the patient sample (S^- n = 25; S^+ n = 58; ≈1:2), we displayed 3 bins for S^- and 6 bins for S^+. We agree that binning is not necessary; all statistics were computed on raw, unbinned data. The binned panel was included solely for visualization, consistent with our prior work (Blain et al., 2023).

> *(17) Table 2: delta BIC should be presented per subject (that is, divided by the number of subjects in each group), as the groups are of different sizes, so as presented now, the columns are not comparable across groups.*

Thank you for the helpful suggestion. Our goal in Table 2 is not to compare ΔBIC magnitudes across groups, but to identify the winning model within each group. The ΔBICs are aggregated at the group level solely to rank models for that group. Dividing by the number of participants would rescale each group’s column by a constant and would therefore not affect the within-group ranking or the conclusion that cM3 is the best model in all groups. For this

reason, we retain the current presentation and interpret each column within group rather than across groups.

> *(18) Line 640 - the effect of expectations and prediction errors on mood was not only shown in healthy people, but also in people with depression (Rutledge et al., 2007, https://pubmed.ncbi.nlm.nih.gov/28678984/)*

Thank you for this comment. Indeed, Rutledge et al., (2017) showed evidence for CR+EV+RPE mood model in adult people with depression. However, our study recruited adolescents with depression or anxiety, given that adolescent period might provide a developmental window for opportunities for early intervention of suicidality. Therefore, it is also possible that the current winning model was specific to adolescents. Please see our clarifications below:

Page 28:

"It is also possible that the current winning model was specific to adolescents. Given that Rutledge et al., (2017) supported the "CR-EV-RPE model" in adults with depression, our study with adolescent populations may suggest a developmental change for mood sensitivities."

> *(19) Supplemental material: Is the R2 section about R-squared? Perhaps you can use superscript on the 2 to make that clearer? For Figure S2, how was model recovery determined? Should I interpret the confusion matrix as suggesting that the winning model for each and every simulated subject was the generating model, or was the winning model determined for the whole simulated population in each of the 100 simulations? Traditionally, confusion matrices use the former measure, but the results of 100% recoverability make me suspect the latter was used here. In Figure S3, should we not be looking at simulated parameters and recovered parameters? What are "real parameters" here?*

Thank you for these important comments. We now consistently denote the coefficient of determination as R^2 (with a superscript 2) throughout the manuscript and Supplementary Materials.

For the model recovery analysis in Figure S2, we have clarified that the confusion matrix is computed at the population level. Specifically, for each of the 100 simulations we generated a full dataset under each candidate model, fit all models to that dataset, and selected the winning model based on group-level model evidence (BIC). Each cell in the confusion matrix therefore reflects the proportion of simulations in which model *j* was selected as the best-fitting model when the data were generated by model *i*. This operation was reasonable because the decision of the winning model is made on the population-level dataset rather than on individual subjects.

In Figure S3, the term "real parameters" referred to the parameters used to generate the simulated data. To avoid confusion, we now relabel these as "simulated (generating) parameters" and explicitly describe the figure as showing the relationship between simulated (generating) parameters and recovered parameters. Please see Supplementary Pages 2-3:

"Model recovery： We generated 100 simulated datasets for each model (3 choice models and 8 mood models) using the fitted parameters of each model as the ground truth. Each dataset contained 201 trials and included 3 (or 8) sets of simulated data corresponding to the respective models. For each simulated dataset, we then fit all models and determined the winning model at the population level based on group-level BIC, yielding a confusion matrix in which each entry represents the proportion of simulations in which model *j* was selected as the best-fitting model when the data were generated by model *i*. As shown in Figure S2, all models are highly identifiable, indicating excellent recovery performance for both the choice and mood models."

"Parameter recovery: Figure S3 shows good parameter recovery for both choice and mood winning model (choice: rs > 0.91, *ps* < 0.001; intraclass coefficients > 0.78; mood: rs > 0.90, *ps* < 0.001; intraclass coefficients > 0.86). Moreover, we computed cross-correlations between all generating ("generating") and recovered ("fitted") parameters. The resulting matrix showed high diagonal (choice winning model: rs > 0.91; mood winning model: rs > 0.90) and low off-diagonal (choice winning model: abs(rs) < 0.63; mood winning model: abs(rs) > 0.40) correlations, further supporting parameter recovery."

> *Typos:*
>
> *(1) Line 90: original → originate*
>
> *(2) Line 596-598 - the same phrase is repeated twice.*
>
> *(3) Line 616: on the other word → hand.*

Sorry for the mistakes. We have now corrected them throughout the manuscript.

> ***Reviewer #2 (Recommendations for the authors):***
>
> *For people unfamiliar with interpersonal theory or motivational-volitional model, or three-step theory (lines 105-106), could you briefly explain the key idea of mood and suicide before going to the decision-making tasks? And from this, maybe motivate the predictions in your task? In particular, in the abstract and introduction, the phrasing could be a bit more concise and simpler. In the abstract, sentences were sometimes quite long. In the introduction, some paragraphs are somewhat repetitive. In the discussion, there were some typos.*

Thank you for these suggestions. We have now explained the key idea of mood and suicide before going to the decision-making tasks in the introduction, which can be seen below:

Pages 4-5:

"Contemporary theories of suicide converge on the idea that STB is initially caused by low mood experience. The interpersonal theory of suicide proposes that suicidal desire arises when people simultaneously feel socially disconnected ("thwarted belongingness") and like a burden on others ("perceived burdensomeness"), experiences that are tightly linked to chronically low mood [25]. The motivational–volitional model [26] and the three-step theory [27,28] similarly emphasize that when negative mood and feelings of defeat or entrapment are experienced as inescapable, they can give rise to suicidal ideation, and that the progression from ideation to suicide attempts depends on additional factors such as reduced fear of death, increased pain tolerance, and a tendency to act impulsively under intense affect. Some official organizations, e.g., National Institute of Mental Health, have also listed mood problems as warning signals [8]. Interestingly, within the framework of decision making under uncertainty, gambling on lotteries with a revealed outcome has been found to induce high mood variance [29], providing an opportunity to assess the relationship between deficient mood and increased gambling decisions in STB."

We have also refined the wording and corrected typos throughout the manuscript.

> ***Reviewer #3 (Recommendations for the authors):***
>
> *(1) Since many readers might only read the abstract, it is important that it is both informative and accurate. I have two suggestions in this respect. First, for the abstract to be more informative, it may be helpful to indicate already there that these are value-insensitive approach-avoidance parameters, in the sense that they favor/disfavor the gamble regardless of the potential outcomes' magnitude or probability. This issue is also*

> *present throughout the text, where the phrases "approach and avoidance motivation" are referred to as if they have established and precise computational definitions. In my view, these terms could just as easily be interpreted as parameters that multiply the value of potential gains or losses, which is not what the authors mean. It would be helpful to clarify this terminology.*

Thank you for these suggestions. In line with previous literature (Rutledge et al., 2015 & 2016), approach and avoidance motivation are indeed defined at the computational level, referring to a decision bias in favor of the highest gain (approach) and another decision bias against the lowest loss (avoidance), above and beyond options value difference. We have cited these papers in the manuscript. We also make it clear to further clarify approach and avoidance parameters in the abstract and introduction. Please see our revisions below:

Page 2 (Abstract):

"Using a prospect theory model enhanced with value-insensitive approach-avoidance parameters revealed that this rise in risky behavior resulted only from a heightened approach parameter in S^+."

"Altogether, model-based choice data analysis indicated dysfunction in the approach system in S^+, leading to greater propensity for gambling in the gain domain regardless of the lottery expected value."

Page 3 (Introduction):

"A growing literature indeed shows that risky behavior can be far better explained after adding value-insensitive approach and avoidance components to prospect theory [18,19], that is by including a decision bias in favor of the highest gain (approach) and another decision bias against the lowest loss (avoidance), above and beyond options value difference. This class of models highlights the important role of value-insensitive motivational components in decision making in addition to risk attitude-driven valuation (e.g., loss/risk aversion) [20]."

> *(2) The statement "our study uncovers the cognitive and affective mechanisms contributing to increased risk behavior in STB" is overstating the findings, as the study may have uncovered some contributing mechanisms, but likely not all of them. Removing the word "the" would fix this issue.*

Thank you for this suggestion. We have now corrected it.

> *(3) Since mood is typically defined as lasting hours, it's inappropriate to refer to ratings that only reflect the last few trials as self-reports of mood. To be sure, I view the distinction between emotions and moods as quantitative, not qualitative, so I do not think there is a problem studying the former to understand the latter, but to avoid confusion, the terminology should follow common usage.*

Thank you for this suggestion. We follow previous work and operational definitions regarding mood (Rutledge et al., 2014, Eldar & Niv, 2015, Vinckier et al., 2018). Emotion is usually a very brief response to a specific stimulus (Emanuel & Eldar, 2023), e.g., leading to rapid changes like surprise then fear. In contrast, mood is defined as a diffuse state that is not specific to one stimulus. Here, we operationally and computationally define mood as an affective state reflecting the recent history of safe and gamble outcomes. We now clarify that point in the main text. Please see our revision below:

Page 5:

"Although mood is thought to persist for hours, days, or even weeks [30–33], momentary mood, measured over the timescale in the laboratory setting, represents the accumulation of the impact of multiple events at the scale of minutes [30,32,34–38]. Momentary mood external

validity is demonstrated e.g., through its association with depression symptoms [37]. Mood is different from emotions, which reflect immediate affective reactivity and is more transient (e.g. from surprise to fear) [31–33,39]."

> *(4) Line 78: The phrases "increase in risk attitude", "decrease in loss attitude", and "decrease in value-independent choice biases" are unclear to me in terms of their directionality. An attitude might be avoidant or embracing. If it is the former then increasing it would decrease risk-taking.*

Thank you for pointing out the ambiguity. We have now corrected them throughout the manuscript. Please see our revision below:

Page 4:

"We therefore hypothesized that heightened approach motivation, or weakened avoidance motivation, would account for increased risk behavior in STB."

> *(5) Line 125: I was not sure why one would expect the mood response to gamble-related quantities (EV and RPE) to be lower in STB and not higher.*

Sorry for the typo. We hypothesized that mood would respond more strongly to gambling-related quantities expected value (EV) and reward prediction error (RPE)—in adolescents with STB than in controls, given prior evidence that STB is associated with greater risk-taking.

> *(6) The text could use proofreading, as there are many typos. These are from the first 100 lines alone:*
>
> *(a) Abstract: regardless the lotteries -> regardless of the lotteries'.*
>
> *(b) Line 78: it remains whether.*
>
> *(c) Line 80: can each -> each can.*
>
> *(d) Line 90: may original from.*

Sorry for the mistakes. We have now corrected them throughout the manuscript.

> *(7) The rationale for focusing on the S+ group for mood model comparison is incorrect. The purpose is to identify parameters that vary as a function of suicidality, and for that, the S- group is just as important.*

Thank you for this comment. We agree that the S^- group is as important as the S^+ group. A direct comparison was complicated because the winning mood models differed (S^+: mM3; S^-: mM5; Table 3). To ensure comparability, we checked results from both model specifications (mM3 and mM5). The conclusions were convergent: mood sensitivity to certain rewards (CR) was lower in S^+ than in S^- (see Fig. 3 for mM3 and Fig. S8 for mM5).

> *(8) There appears to be a contradiction between the inclusion criteria, which include having experienced suicidal thoughts and behaviors, and the definition of the S- group as not having suicidality.*

Thank you for pointing out this mistake. The corrected version of inclusion criteria can be seen on Page 7:

"Patients were included if they met the following criteria: 1) both the researcher and psychiatrists agreed on their group classification; 2) they had a current diagnosis of major depressive disorder (MDD; unipolar depression), generalized anxiety disorder (GAD), or bipolar disorder with depressive episodes (BD), confirmed by two experienced psychiatrists using the Structured Clinical Interview for DSM-IV-TR-Patient Edition (SCID-P, 2/2001 revision;

see Supplementary Note 1 for details)；3) they were between 10 and 19 years of age; 4) they had no organic brain disorders, intellectual disability, or head trauma; 5) they had no history of substance abuse; 6) they had no experience of electroconvulsive therapy."

> *(9) It would be helpful to specify whether mood modeling was based on objective or subjective values, and why.*

Thank you for this helpful suggestion. We have now clarified whether mood modeling was based on objective or subjective values, and why. Specifically, we constructed two model families: one in which mood was driven by objective monetary outcomes (objective values) and one in which mood was driven by subjective values derived from each participant's fitted choice model (subjective values). We then used the VBA_groupBMC function in the VBA toolbox to perform family-wise model comparison, with 8 candidate mood models within each family. Consistent with previous literature, the objective-value family provided a clearly superior fit to the data (exceedance probability, EP = 1.000). Based on this result and for parsimony, we report and interpret the mood modeling results from the objective-value family in the main text. We have clarified this point in Supplementary Note 9.

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