Decision Characteristics Underlying Non-Suicidal Self-Injury in Patients with Major Depressive Disorder

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ABSTRACT

Non-suicidal self-injury (NSSI) behavior is significantly prevalent in both adolescents and psychiatric populations, with the highest risk observed in individuals with major depressive disorder (MDD). NSSI can be considered a result of risky decision-making in response to negative emotions, where individuals choose self-harm over other harmless alternatives, suggesting a potential decision-making deficit in NSSI individuals. This study delves into the complex relationship between NSSI and depression severity in decision-making and its cognitive underpinnings. We assessed decision behaviors in MDD patients with and without NSSI and healthy controls using the Balloon Analogue Risk Task, which involves risk-taking, learning, and exploration in uncertain scenarios. Using computational modeling, we dissected the nuanced cognitive dimensions influencing decision behaviors. A novel statistical method was developed to elucidate the interaction effects between NSSI and depression severity. Contrary to common perceptions, we found that individuals with NSSI behaviors were typically more risk-averse, but as depressive symptoms intensified, they began to perceive less risk and meanwhile behave more randomly. This research offers new insights into the cognitive aspects of NSSI and depression, underscoring the importance of recognizing the influence of comorbid mental disorders in deciphering the cognitive underpinnings of such behaviors, especially in the context of prevalent cross-diagnostic phenomena like NSSI behaviors.

INTRODUCTION

Non-suicidal self-injury (NSSI), prevalent in adolescents and psychiatric populations (Lim et al., 2019; Swannell et al., 2014), involves behaviors like deliberate cutting or burning, often used as a coping mechanism for intense emotional distress (Hasking et al., 2017; Perez et al., 2012; Wolff et al., 2019). Though distinct from suicidal behavior, NSSI is crucial to understand due to its strong association with future suicidal tendencies (Barrocas et al., 2011; Mars et al., 2019). Similar to suicidal actions, choosing to self-harm instead of engaging in more harmless coping solutions (e.g., talking to a friend, practicing mindfulness, or seeking professional counseling) reflects a maladaptive decision-making process. Our work, therefore, focuses on the decision characteristics of individuals with NSSI, aiming to identify the potentially multi-faceted cognitive dysfunctions behind NSSI decisions.

Despite the initial hypothesis linking higher impulsivity to NSSI, especially given its prevalence among adolescents, this connection has found little support in research that controls for psychiatric confounds (Dillahunt et al., 2022; Hamza et al., 2015). A more nuanced perspective considers risky decision-making, where individuals with NSSI evaluate various emotion-coping options, each with its own set of risks, rewards, and losses. These individuals effectively outweigh the emotional relief from self-harm against its negative consequences (e.g., pain, bleeding, and scarring), and prefer it over more harmless solutions. However, studies using standard risky decision tasks, such as the Iowa Gambling Task, have yielded inconsistent results in differentiating between NSSI and non-NSSI individuals (Dillahunt et al., 2022; Hamza et al., 2015). One reason for these mixed findings could be the inherent stochasticity of risky decision tasks, where different choices lead to variable experiences and thus exert different influences on subsequent decision behaviors, rendering simple behavioral measures less effective in capturing the complexity of individuals' decision characteristics. Furthermore, the frequent comorbidity of NSSI with conditions like depression (Chai et al., 2020; Wilkinson et al., 2011; Zubrick et al., 2017) adds another layer of complexity, potentially confounding the interpretation of the findings. For example, behavioral differences observed in such tasks might not solely reflect NSSI characteristics but also varying levels of depression among individuals. These limitations highlight the necessity of using more advanced methods to understand NSSI-related decision characteristics.

In the present study, we investigated individuals with major depressive disorder (MDD) exhibiting NSSI behavior (D+NSSI), contrasting them with MDD individuals without NSSI (D) and healthy controls (HC). Our approach involved the use of the

Balloon Analogue Risk Task (BART, Lejuez et al., 2002) alongside computational modeling to provide a comprehensive understanding of NSSI-related decision characteristics and their modulation by depression. The BART, which simulates real-world risk-taking behavior by requiring participants to pump a virtual balloon for potential rewards, assesses not only attitudes toward risk or loss, as widely known, but also delves into broader cognitive dimensions. These include participants' prior beliefs about risk, their learning from outcomes, and behavioral consistency under risk and uncertainty. Using computational modeling, we were able to disentangle these distinct cognitive dimensions from participants' decision behaviors, by estimating the model parameters for each group based on the hierarchical Bayesian method. Furthermore, we developed a novel statistical method to isolate the effects of NSSI, depression level, and their interaction on the model parameters. This allowed us to unravel the complex interplay of NSSI and depression in shaping individual decision characteristics, offering insights that are otherwise unattainable.

RESULTS

Demographic and clinical characteristics

A total of 241 participants were included in data analysis, including 142 healthy controls (HC), and 99 patients diagnosed with major depressive disorder (MDD), among them, 57 cases with comorbid NSSI (D+NSSI), while 42 without NSSI (D). Participants' gender, age, education year, self-reported NSSI history, self-rating anxiety and depression scales were recorded (Table 1). *Post hoc* tests revealed significant differences between any two groups in age, SAS and SDS, and between the depressed and healthy groups on years of education.

Table 1 Demographic and clinical characteristics

	Total (*N* = 241)	**HC (*N* = 142)**	**D (*N* = 42)**	**D+NSSI (*N* = 57)**	χ^2/F	***p*-value**
***N* by gender**					3.306	0.191
Male	78 (32.4%)	49 (34.5%)	16 (38.1%)	13 (22.8%)		
Female	163 (67.6%)	93 (65.5%)	26 (61.9%)	44 (77.2%)		
Age (year)	19.80±2.36	19.31±2.05	21.10±2.57	20.09±2.54	10.62	<0.001
Education year	13.49±2.11	13.11±1.77	14.43±2.49	13.75±2.36	7.231	<0.001
SAS	39.65±14.69	31.30±6.29	45.90±12.46	55.82±15.48	124.1	<0.001
SDS	45.29±16.86	34.85±8.00	51.90±11.56	66.42±13.96	200.2	<0.001

Note. Demographic or scale scores are in mean ± standard deviation. SAS: self-rating anxiety scale; SDS: self-rating depression scale.

Group Differences in Behavioral Measures

On each trial of BART (Figure 1A), participants saw a virtual balloon on the screen and need to decide whether to pump (to potentially increase reward points) or collect points and end the trial. Each pump could increase the balloon's size and thus the reward points by 1 but came with the risk that it may pop and nullify the points. Each trial thus presented a continual gamble between potential reward and loss. Each participant completed 60 trials of 30 red and 30 blue balloons, initially not knowing which color represented a higher risk. The color with higher risk would pop after 1 to 32 pumps ("32-balloon") while the lower-risk color after 1 to 128 pumps ("128-balloon"). The number of pumps that maximizes expected reward is respectively 16 and 64 for

the 32- and 128-balloons (Figure 1A, inset). Including these two different levels of risk in the experimental design allowed us to infer participants' prior beliefs and learning as well as their attitudes towards loss and risk from their pumping decisions.

Following the common practice of BART (Lejuez et al., 2002), a primary behavioral measure we used is participants' number of pumps in non-popping trials (denoted N_{pump}). Consistent with classical findings, for both levels of risk, participants pumped much less than the optimal number (Figure 1BC). Meanwhile, when we plot how the mean N_{pump} of each participant group changed over trials (Figure 1B), we can see differences between different groups as well as trends of learning, at least for the 128-balloons. A linear mixed-effect model (LMM) analysis was performed on N_{pump} to identify the effects of NSSI, MDD, balloon type, and trial number as well as their interactions. NSSI and balloon type had a significant interaction (b = –0.154, SE = 0.046, Satterthwaite's Method t= –3.33, p < 0.001), implying that participants with and without NSSI behaviors had different decision patterns for the two risk levels. Participants with and without MDD showed similar significant differences, participants with MDD pumped fewer for the 128-balloon condition (interaction of MDD with balloon type, b = –0.086, SE = 0.041, t = –2.11, p = 0.035). The learning effect across trial was evident in the interaction of balloon type and trial number (b = 0.306, SE = 0.02, t = 15.40, p < 0.001).

To provide a more comprehensive behavioral measurement for participants' decision characteristics in BART, we also calculated the standard deviation of N_{pump} across trials (denoted σ_{pump}) and the number of non-popping (i.e., reward gathered) trials (denoted N_{gather}) for each balloon type and participant group (Figure 1DE). Though LMM analysis could not be applied to these summary behavioral measures, mixed ANOVA showed a significant interaction between participant group by balloon type for σ_{pump} (F(2, 238) = 3.29, p = 0.039) and significant main effect of participant group for σ_{pump} (F(2, 238) = 3.54, p = 0.031) and N_{gather} (F(2, 238) = 5.07, p = 0.007), other than the obvious differences between different balloon types (F(1, 238) = 188.05, p < 0.001 for σ_{pump} and F(1, 238) = 679.85, p < 0.001 for N_{gather}).

Taken together, these behavioral measures of BART suggest that the HC, D, and D+NSSI groups had distinct decision patterns. But because all behavioral measures are the joint consequence of multiple cognitive components (e.g., learning, risk attitude, etc.), the underlying cognitive differences remained elusive. We will disentangle the cognitive dimensions below, with the help of computational modeling.

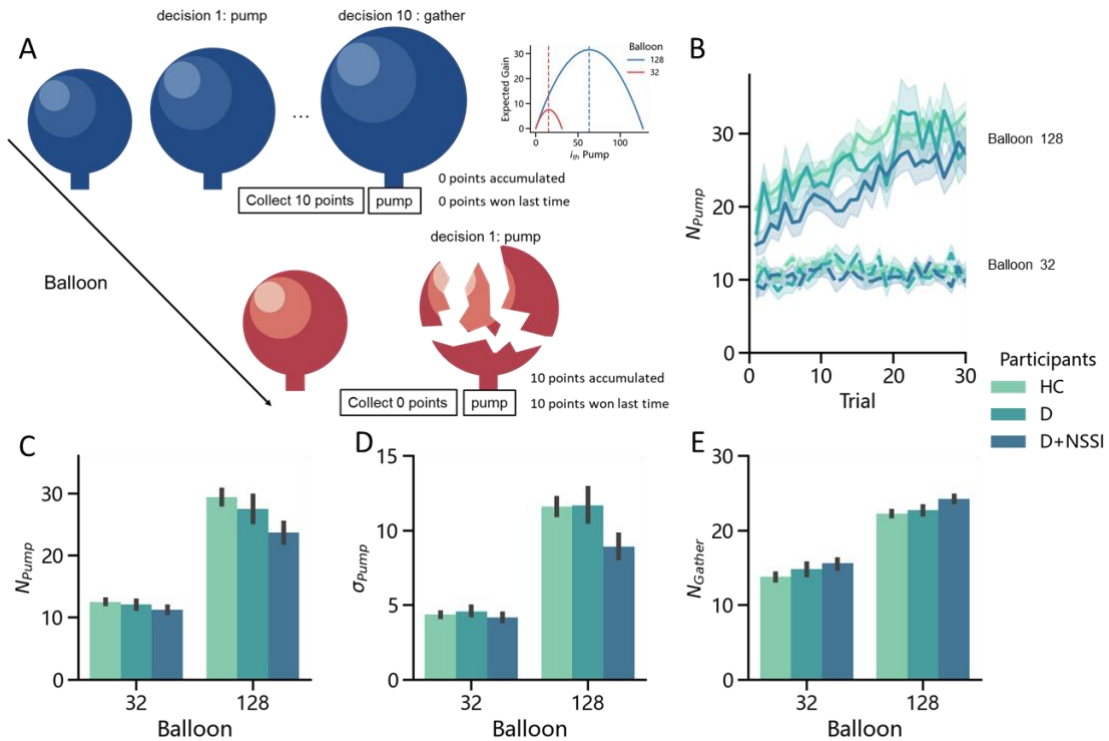

Figure 1. Balloon Analogue Risk Task (BART) and behavioral measures for the three groups of participants. A. Schematic representation of the BART, where at each moment participants choose to either pump the balloon to potentially accumulate one more reward point or to collect their accumulated points. If the balloon pops, the reward points accumulated for the balloon would be lost. The risk of balloon popping increases with each pump and varies with the color of the balloon. A new balloon starts after the old balloon popping or being collected. Each participant completed 30 red and 30 blue balloons (trials) in a random order. **Inset at top right**: Expected gain as a function of the number of pumps. The optimal numbers for the two balloon types (max pump before popping: 32 and 128), as indicated by the dashed vertical lines, are respectively 16 and 64. **B–E** plot the behavioral measures for the three groups of participants (*N* = 241). Color codes: light-green for the 142 healthy controls (HC), blue-green for the 42 participants with major depressive disorder (MDD) but no NSSI behavior (D), and dark-blue for the 57 participants with MDD and NSSI (D+NSSI). **B**. How the mean number of pumps in non-popping trials (N_{pump}) changed over trials. Curves in dashed lines and solid lines are respectively for the balloon types 32 and 128. Shadings denote 1 SE. **C**. Mean N_{pump} averaged across trials for each balloon type and participant group. **D**. Standard deviation of N_{pump} across trials (σ_{pump}) for each balloon type and participant group. **E**. The number of non-popping (i.e., reward gathered) trials (N_{gather}) for each balloon type and participant group. Error bars denote 1 SE.

Five Cognitive Dimensions Decomposed by the Computational Model

The computational model we used to fit participants' decision behaviors is an adaptation of the Exponential-Weight Mean–Variance (EWMV) model of Park et al. (2021), termed EWMV-VS (see Methods), which outperforms its precedent in predictive power and parameter recovery. As illustrated in Figure 2A, the model starts with an agent's initial belief about the likelihood of balloon popping (ϕ), which is updated with each successive trial based on the outcomes of previous balloons. This update is modulated by a learning rate (ξ), controlling the speed at which new information influences the agent's belief of balloon popping. Confronted with the choice to pump and potentially increase their tally by one point or to collect and secure their current pool of points, the agent evaluates this decision by considering the risk of popping and losing all accumulated points for the balloon. The model quantifies the agent's aversion to loss (λ) and their inclination towards risk (ρ) to calculate the expected utility of each pump, while the agent's propensity to stay consistent in their choices is represented by the parameter β. When fitted to participants' decision behaviors, the five parameters of the EWMV-VS model—prior belief of pop ϕ, learning rate ξ, choice consistency β, loss aversion λ, and risk preference ρ—can thus represent participants' characteristics on five distinct cognitive dimensions.

Some of these model parameters have intuitive behavioral implications, as indicated by the correlations between individual participants' model parameters and their behavioral measures (Figure 2B). For example, the average number of pumps in the initial trials of the 128-balloons, labeled "first 5 pumps", serves as a behavioral proxy for the model's parameter for prior belief of pop (ϕ). Similarly, "ΔN_{gather}", the differences in non-pop trials between the 128- and 32-balloons, is a behavioral reflection of the individual's learning rate (ξ), demonstrating how participants adjust their strategies based on experience. Though less intuitive or not unique to any specific parameter, the N_{pump}, σ_{pump}, and the standardized σ_{pump}/N_{pump}, are respectively closely related to loss aversion (λ), risk preference (ρ), and choice consistency (β).

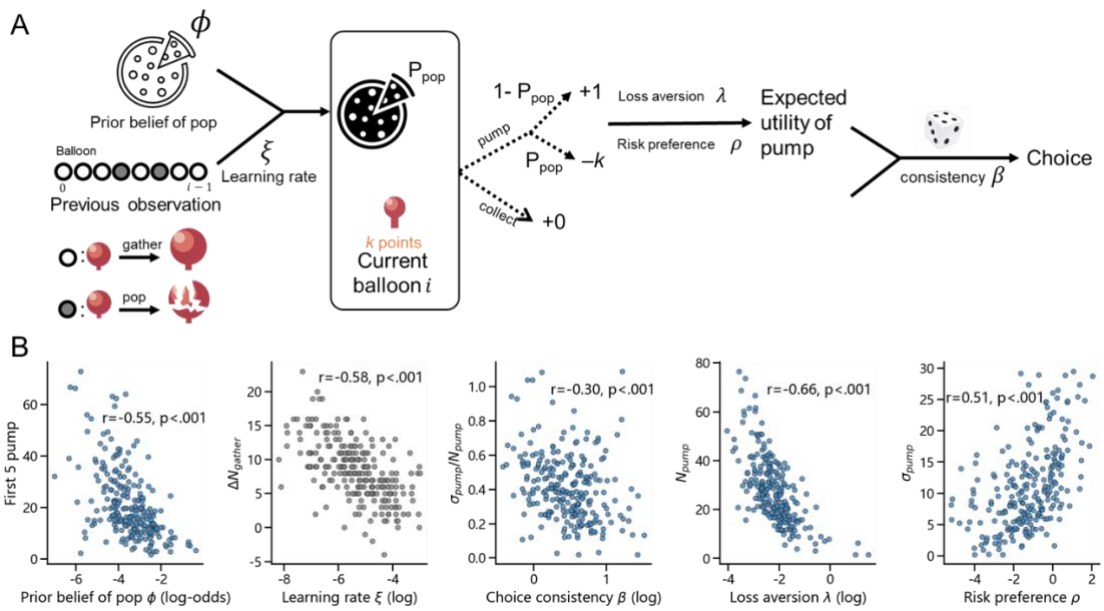

Figure 2. The computational model and its parameters' behavioral implications. A. Illustration of the computational model used to simulate participant decisions in BART. The model agent integrates its prior belief of balloon popping (ϕ) with previous observations up to the last trial (i.e., balloon $i-1$), resulting in the updated belief of P_{pop}. How fast the prior belief is wiped off by increasing observations is determined by the learning rate (ξ). For the current balloon i that has accumulated k points, the agent is now faced with the decision of either pumping to gain 1 more point but with a chance of P_{pop} losing all k points, or collecting the points. The agent's loss aversion (λ) and risk preference (ρ) contribute to its expected utility of pumping the balloon. The probability of choosing pumping is further modulated by the agent's choice consistency (β). **B**. Scatter plots showing how individuals' model parameters (prior belief of pop ϕ, learning rate ξ, choice consistency β, loss aversion λ, and risk preference ρ) correlated with their behavioral measures in the BART. "First 5 pump" refers to the mean number of pump in the first 5 trials of the 128-balloons, which reflects the individual's prior belief of pop. "ΔN_{gather}" refers to the difference in the number of reward-gathered trials (N_{gather}) between the 128- and 32-balloons, which reflects how much the individual learns from experience. The N_{pump} and σ_{pump}, as in Figure 1, respectively refer to the mean and standard deviation of the number of pumps, which and the combination of which are closely related to loss aversion, risk preference, and choice consistency. Data points are color-coded to indicate whether the behavioral measure is elicited from the 128-balloons (in gray-blue) or the difference between the 128- and 32-balloons (in gray). Each dot denotes one individual participant. The correlation coefficient (*r*) and p-value on each panel is based on Pearson's correlation.

Revealing Group-Level Cognitive Differences: Hierarchical Bayesian Modeling

To assess differences in each cognitive dimension across the three groups, we fit the EWMV-VS model to participants' decision behaviors using hierarchical Bayesian modeling (see Methods). Among the five parameters (Figure 3A), we observed significant group differences in the parameters of choice consistency and risk preference. In particular, when compared to participants with MDD but no NSSI behavior (i.e., the D group), the D+NSSI group exhibited a higher choice consistency (difference M = 0.22, 95% HDI [0.02, 0.44]). The D+NSSI group also had a lower risk preference than the healthy control group (difference M = –0.75, 95% HDI [–1.5, –0.002]), indicating a more cautious approach to risk-taking.

These findings, rooted in our model analysis, echo the behavioral patterns described earlier, specifically the reduced variability in the number of pumps (σ_{pump}) among the D+NSSI group (Figure 1D). While behavioral data alone might suggest this decreased variation could stem from diminished learning, implying more uniform behavior from early to late trials, our model-based analysis mostly rules out this possibility.

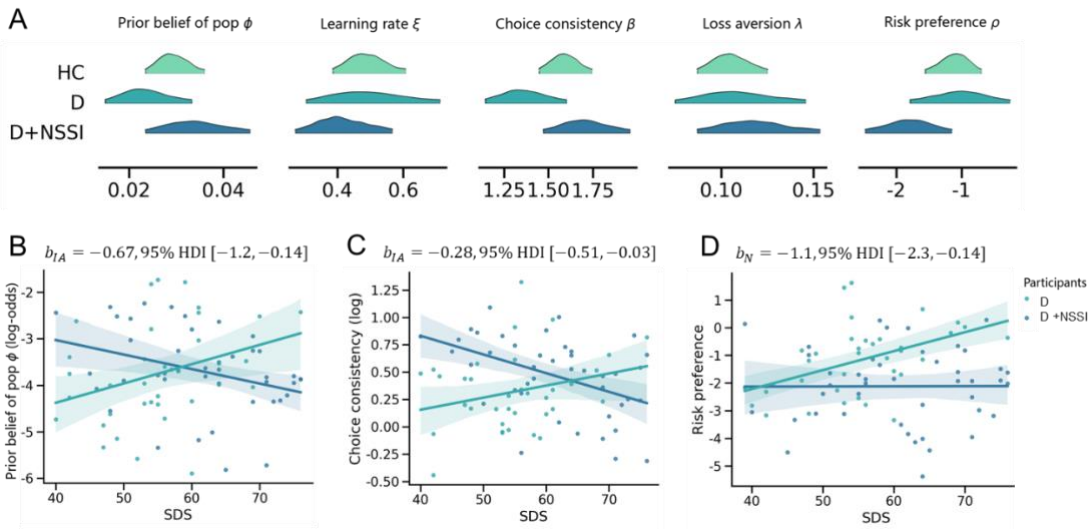

Figure 3. Estimated model parameters for different participant groups. A. The 95% highest density interval (HDI) of the posterior density of the group-level model parameters estimated from hierarchical Bayesian model fitting. Significant differences between groups were found for choice consistency (β) and risk preference (ρ). See text. **B–D** show the joint effects of NSSI and depression severity (as measured by the Self-Rating Depression Scale, SDS) on model parameters, where the participants in analysis

were limited to the D and D+NSSI groups with an overlapping range of SDS. Each dot denotes one individual participant. The shading on the regression line denotes the 95% HDI. **B**. Interaction (b_{IA}) between NSSI and SDS on prior belief of pop (ϕ). Higher depression severity was associated with a lower belief in pop likelihood for the NSSI group, while the reverse for the non-NSSI group. **C**. Interaction (b_{IA}) between NSSI and SDS on choice consistency (β). Higher depression severity was associated with less consistent choices in the NSSI group, while the reverse for the non-NSSI group. **D**. Main effect of NSSI (b_N) for risk preference (ρ). The NSSI group was less tolerant of risk than the non-NSSI group.

Unraveling NSSI and Depression Interplay: Effects-on-Parameters Analysis

We noted that the D+NSSI group had a significantly higher depression severity than the D group (as indicated by the SDS score in Table 1), despite both groups being diagnosed with MDD. To distinguish the impact of NSSI from depression severity, we combined two strategies. First, we selected from the D and D+NSSI groups the participants whose SDS fell into an overlapping range (*N* = 81, with 37 D and 44 D+NSSI). Second, we developed a novel Effects-on-Parameters Analysis (EPA, see Methods), which includes NSSI, SDS, and their interaction as linear predictors of the EWMV-VS model's parameters in hierarchical Bayesian modeling, providing a granular view of their joint effects on individuals' decision characteristics.

By applying EPA to the 81 participants' decision data, we found that NSSI was still associated with a decrease in risk preference (M = –1.1, 95% HDI [–2.3, –0.14]), even when depression severity was controlled (Figure 3D). NSSI and SDS jointly influenced the prior belief of pop and choice consistency in a more complicated way, showing as interaction effects. Specifically, the prior belief of pop increased with SDS for participants without NSSI but decreased with SDS for those with NSSI behaviors (Figure 3B; M = –0.28, 95% HDI [–0.51, –0.03]). Choice consistency rose with SDS among participants without NSSI but fell among those with NSSI (Figure 3C; M = –0.67, 95% HDI [–1.2, –0.14]).

In other words, participants with NSSI behaviors were more averse towards risk in general. However, as their depressive symptoms became more severe, they appeared to perceive the environment as less risky and were more random in their choices.

DISCUSSION

In the present study, we investigated the decision characteristics of MDD patients with or without NSSI behavior in BART (Lejuez et al., 2002), a classic decision-making task that involves learning and exploration as well as risk-taking. In addition to model-free behavioral measures, we used computational modeling to elicit five different cognitive phenotype from individuals' decision behaviors, providing a comprehensive understanding of NSSI-related decision characteristics and their modulation by depression. We found that the presence of NSSI behaviors is associated with a general aversion to risk. However, as depressive symptoms escalate, individuals with NSSI tend to perceive their environment as less risky and are more variable in their choices, potentially resulting in greater behavioral unpredictability.

Concerning the decision characteristics related to NSSI, little consensus has been reached (Allen et al., 2019; Hamza et al., 2015), partly because confounds like depression were frequent in previous studies (Sauder et al., 2016). Our finding that individuals with NSSI behaviors are more risk-averse instead of more "impulsive" as commonly perceived is consistent with that of Dillahunt et al. (2022). They studied adolescents with and without self-injury history who were otherwise almost matched in their clinical profile, showing that those with self-injury history made less pumps in BART, seeming to be "risk-averse". In our study, computational modeling allows us to extend beyond such behavioral observation and to precisely identify the cognitive phenotype that leads to the specific behavioral phenomenon, excluding alternative explanations such as an aversion to loss or failure to learn from the environment.

The Effects-on-Parameters analysis we developed further enables us to disentangle the effects of NSSI and depression severity and to uncover interaction effects on the model parameters. The prior belief of risk and choice consistency are the two cognitive dimensions that are influenced by such interactions. The former determines an individual's inclination to explore uncertain options, while the latter is related to the tendency of random exploration (Wilson et al., 2014). Together, our results suggest that when their depressive symptoms deepen, while individuals without NSSI may reduce their exploration of the environment, those with NSSI may even increase their exploration, which can be risky behaviors under some occasions.

Such intricate interplay between NSSI and depression may have led to the controversial results documented in previous studies (Hamza et al., 2015). It emphasizes the need for a comprehensive approach to isolating the influence of comorbid mental disorders, in order to decipher the cognitive underpinnings of decision behaviors in individuals with NSSI behaviors.

In conclusion, NSSI behaviors manifest a general aversion to risk. While, as depressive symptom severity increases, individuals perceive a decrease in environmental risks and demonstrate more unpredictable behavior. This suggests a complex interaction between depressive symptoms and NSSI behaviors in decision-making. Overestimating risks in unfamiliar environments diminishes the likelihood of exploring alternative means to cope with emotions, and depression amplifies engagement in risky behaviors.

METHODS

Participants

From April 2022 to Sept 2023, we recruited 101 outpatients or inpatients diagnosed with depression from Peking University Sixth Hospital, including 58 cases with NSSI (D+NSSI) and 42 cases without NSSI (D) behaviors. Additionally, 157 healthy controls (HC) were recruited from two universities. The study had been approved by the Institutional Review Board of Peking University Sixth Hospital and all participants provided informed consent.

Fifteen participants from the HC group were excluded due to a history of NSSI behavior. Furthermore, one participant from the HC group and one from the D+NSSI group were excluded for consistently inflating the balloons to the same extent in the decision task. One participant from the D group was excluded for data missing. As a result, a total of 241 participants were included in the final data analysis.

D+NSSI participants had to have engaged in NSSI behaviors for at least once in the previous 12 months, whereas D participants had no history of self-injury. Additional criteria for inclusion were: a) Individuals aged 16 to 25 years old; b) those diagnosed with major depressive disorder according to the International Classification of Diseases, Tenth Edition (ICD-10). Exclusion criteria included: a) patients engaging in suicidal self-injury; c) current diagnosis of other mental disorders such as pervasive developmental disorders, psychotic disorders, manic episodes, substance dependence, or obsessive-compulsive disorders; and d) presence of severe and unstable physical illness.

Psychiatric Assessment

The Zung self-rating anxiety scale (SAS) and the Zung self-rating depression scale (SDS) (Biggs et al., 1978) were used to assess depression and anxiety levels in this investigation, and raw scores were used.

Task and Design

In the Balloon Analogue Risk Task (BART) shown in Figure 1A, each trial presents participants with a virtual balloon on their computer screen. Participants can press a specific key to “pump” the balloon, which adds one point to their prize pool for each pump. However, every pump also carries a risk of causing the balloon to pop. If the balloon pops, the points in the prize pool for that balloon are lost, and the trial ends. Thus, participants must choose between pumping the balloon to potentially increase

their reward point or collecting the accumulated points to conclude the trial safely. The total points collected across all trials would be converted into monetary compensation at the end of the experiment.

Each participant completed 30 trials with red balloons and 30 with blue balloons, presented in a random order. The two different colors represent two levels of risk of popping, corresponding to different optimal numbers of pumps to maximize expected reward (see Inset in Figure 1A). One color of balloon is associated with an equal chance of popping on any pump between the 1st and the 32nd ("32-balloon"), while the other between the 1st and 128th ("128-balloon"). In the illustration of Figure 1A, red balloons are 32-balloons and blue balloons are 128-balloons. The real color-risk correspondence was counterbalanced between participants. Participants were not informed the probability of popping or which balloon would be riskier, and therefore had to learn from their own experience in the experiment.

The experiment consisted of three blocks of 20 trials: the first block was a randomized mix of 10 red and 10 blue balloon trials, and the subsequent two blocks consisted of 20 trials of each balloon color. The order of the last two blocks was counterbalanced across participants. In total, it took approximately 10 minutes.

Statistical Analysis

We conducted the following linear mixed-effects model (LMM) analysis on the number of pumps N_{pump} in the non-popping trials to test the potential influence of major depressive disorder (D) and NSSI behavior (NSSI) on participants' decision.

$$N_{pump} \sim 1 + \text{Balloon} * h * D * \text{NSSI} + (1 + h|\text{paticipant}) \quad (1)$$

where Balloon stands for the balloon type (0 for "32-balloon" and 1 for "128-balloon"), h is the index of the balloon in the experiment, D and NSSI are the dummy variables of major depressive disorder and NSSI behavior, and $(\cdot\,|\text{paticipant})$ denotes the random-effects terms. Data were normalized on the group level before entering LMMs. All the LMMs were implemented in R 4.0.3.

Computational Modeling

The computational model we used to fit participants' decision behaviors in BART (illustrated in Figure 2A) is an adaptation of the Exponential-Weight Mean–Variance (EWMV) model of Park et al. (2021). Below we first introduce the basic modeling idea and specific assumptions of EWMV, and then our adaptation—EWMV with variance standardization (EWMV-VS).

Basic modeling idea. After comparing a comprehensive set of computational models they constructed for BART, Wallsten et al. (2005) found that human participants' behaviors in BART are best captured by a model with three key assumptions for the belief updating and decision processes: 1) the agent believes that the probability of balloon popping could vary with balloon colors but is constant across different pumps for the same color of balloon, 2) the agent updates the probability of pop before each trial based on previous experience with popping and successful inflating, and 3) each agent has specific attitudes towards loss or risk. Following this stream of assumptions, Park et al. (2021) further proposed the EWMV model, which has closely-related mathematical forms and a comparable predictive power, but whose parameters can be more reliably recovered from human behavior, thus allowing for a more accurate characterization of individual differences.

EWMV. According to the EWMV model, the agent starts with a specific prior probability (parameter ϕ) for balloon popping, and updates its belief based on the numbers of popping and successful inflating previously observed for the balloons that matched the color of the current balloon. In the agent's belief updating process, the relative weights for the prior probability and experience are approximated by exponential weighting functions:

$$p_h = \phi \exp\left(-\xi \sum_{h'=1}^{h-1} m_{h'}\right) + \left(1 - \exp\left(-\xi \sum_{h'=1}^{h-1} m_{h'}\right)\right) P_{h-1}. \tag{2}$$

Here p_h denotes the pop probability per pump for the *h*-th balloon in its color, ξ is the parameter for learning rate. With $m_{(\cdot)}$ denoting the number of pumps for a specific balloon indicated by the subscript, $\sum_{h'=1}^{h-1} m_{h'}$ is the total number of pumps made to all previous $h-1$ balloons in the same color. For these $h-1$ balloons, P_{h-1} is the observed pop probability per pump:

$$P_{h-1} = \frac{\sum_{h'=1}^{h-1} d_{h'}}{\sum_{h'=1}^{h-1} m_{h'}}, \tag{3}$$

where d_h indicates whether balloon h finally popped (1) or not (0).

Suppose the agent has pumped the current balloon for k times, accumulating k points. At this moment, pumping corresponds to a gamble with probability $1-p_h$ to gain 1 more point but probability p_h to lose the k points; collecting is to win or lose nothing. To decide whether to pump or to collect the accumulated points, the agent calculated the expected utility of pumping relative to collecting:

$$U_{h,k} = [(1-p_h) - p_h \lambda k] + \rho p_h (1-p_h)(1+\lambda k)^2. \tag{4}$$

The first part of the equation, $[(1-p_h)-p_h\lambda k]$, is the sum of expected gain and expected subjective loss, with loss scaled by the loss aversion parameter λ, that is, how many units of gain one unit of loss equals to. The second part is the risk discounting term, with the variance of the gamble multiplied by the risk preference parameter ρ.

The agent's probability of choosing pumping is a softmax function of this expected utility:

$$r_{h,k} = \frac{1}{1+e^{-\beta U_{h,k}}}, \tag{5}$$

where the parameter β characterizes choice consistency. The final choice of pumping or collecting is a Bernoulli random variable based on $r_{h,k}$.

EWMV with variance standardization. When the probability of balloon popping is relatively small (e.g., 1/32 and 1/128), there could be strong correlation between the mean and variance terms in the computation of expected utility (Eq. 4). As a result, the risk preference parameter ρ cannot be accurately estimated. Similar issues would still occur if the risk preference parameter is incorporated in expected utility not as the scaling factor of variance but through the more classical form of a utility function (Krefeld-Schwalb et al., 2022; Olschewski et al., 2022). To alleviate this issue, we adopt the standardization method (Olschewski et al., 2022) to perform variance standardization on the expected utility:

$$U_{h,k} = \frac{[(1-p_h)-p_h\lambda k]+\rho p_h(1-p_h)(1+\lambda k)^2}{\sqrt{p_h(1-p_h)}(1+\lambda k)}. \tag{6}$$

The standardized $U_{h,k}$ is then entered into Eq. 5 to obtain the probability of choosing pumping. Similar to EWMV, there are five free parameters in our EWMV-VS model: prior belief of popping ϕ, learning rate ξ, choice consistency β, loss aversion λ, and risk preference ρ.

Model Fitting. Hierarchical Bayesian modeling was used for parameter estimation, which allows more accurate estimation of group-level effects. The model parameters were estimated from participants' choice data using the Markov Chain Monte Carlo method, implemented by the PyMC package (version 5.9.2) on python 3.11. Four independent chains were run, each with 1000 samples after an initial burn-in of 1000 samples, which resulted in a good convergence of $\hat{R} \leq 1.01$ for all estimated parameters. The 95% highest density intervals (HDI) were calculated for the group-level effects.

Effects-on-Parameters Analysis. To assess the joint effects of NSSI and depression severity on individuals' decision characteristics, we developed an Effects-

on-Parameters Analysis (EPA). Specifically, we built a hierarchical Bayesian model based on EWMV-VS, where each of the five parameters of EWMV-VS is generated from a linear combination of NSSI, SDS, and their interaction term. The 15 coefficients were then estimated from participants' choice data via hierarchical Bayesian modeling as described above.

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