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Diminishing loss sensitivity during risky decision-making among male individuals with gambling disorder

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FULL-LENGTH REPORT

ABSTRACT

Background and aims: Gambling disorder (GD) poses severe impacts on both individuals and society. Impairment in risky decision-making is a key behavioral characteristic of GD, but the underlying cognitive processes of these deficits remain unclear. *Methods:* A total of 100 male participants with GD and 59 healthy controls were recruited to complete psychological assessments and the Balloon Analog Risk Task. Since GD involved abnormal loss evaluation, we developed a novel cognitive model incorporating diminishing loss sensitivity and revealed the processes underlying the risk-taking behaviors with hierarchical Bayesian analysis. *Results:* Participants with GD exhibited stronger loss aversion ($H_1 = 50.00$, $p < 0.001$, $\eta^2 = 0.325$) but faster-diminishing loss sensitivity ($H_1 = 24.60$, $p < 0.001$, $\eta^2 = 0.152$), regardless of severity. The faster-diminishing loss sensitivity can explain the deficits in the overall performance of risky decision-making ($H_1 = 6.79$, $p = 0.009$, $\eta^2 = 0.039$; $\beta = 206.81$, 95% HDI [135.13, 278.49], $t_{93} = 5.66$, $p < 0.001$, Cohen's $d = 0.565$). Overconfident prior belief ($H_1 = 8.58$, $p = 0.003$, $\eta^2 = 0.050$) and higher updating rate ($H_1 = 7.91$, $p = 0.005$, $\eta^2 = 0.049$) were observed among participants with GD. Slower diminishing loss sensitivity was negatively correlated with higher non-planning impulsiveness ($R = -0.24$, $p = 0.015$). *Discussion and Conclusions:* This research provides novel perspectives on cognitive processes underlying the risky decision-making of GD, highlighting the role of diminishing loss sensitivity during loss evaluation and its clinical implications, which inspire future research on assessment and therapy for GD.

KEYWORDS

hierarchical Bayesian modeling, gambling disorder, risky decision-making, balloon analog risk task, diminishing sensitivity, loss aversion

INTRODUCTION

Gambling disorder and risky decision-making

Gambling disorder (GD), characterized by a persistent and recurrent pattern of gambling causing distress or impairment, is the first behavioral addiction recognized in the *Diagnostic and Statistical Manual of Mental Disorders, 5th Edition* (DSM-5) (Potenza et al., 2019). It affects 0.2–5.3% of adults globally and causes significant impairments in cognition, emotion, and social functioning, with profound negative consequences for individuals and society (Hodgins, Stea, & Grant, 2011; Potenza et al., 2019). Impairment of risky decision-making is an important behavioral characteristic of GD and is associated with the key symptoms of GD, including impulsivity and craving (Brand et al., 2005; Ciccarelli, Griffiths, Cosenza, Nigro, & D'Olimpio, 2020; Clark et al., 2013; Gelskov, Madsen, Ramsøy, & Siebner, 2016;

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Ioannidis, Hook, Wickham, Grant, & Chamberlain, 2019; Mallorquí-Bagué, Mestre-Bach, & Testa, 2023; Ochoa et al., 2013). Previous studies using cognitive tasks, such as the Cambridge Gambling Task (Yazdi et al., 2019) and the Iowa Gambling Task (Zois et al., 2014), supported this conclusion of impairments in risky decision-making in GD. However, other studies have failed to find significant differences in metrics of risk-taking performance compared with the control group (Kovács, Richman, Janka, Maraz, & Andó, 2017; Linnet, 2013). These inconsistencies may stem from a lack of focus on the cognitive processes underlying the risky decision-making of GD. Thus, further investigation into these processes could help clarify these discrepancies.

Defects in the cognitive processes underlying risky decision-making in GD

Currently, there are various theoretical perspectives, including risk-taking propensity (Fujimoto et al., 2017), prior confidence (Hoven, Hirmas, Engelmann, & van Holst, 2023), cognitive flexibility (Wiehler & Peters, 2024), exploration-exploitation balance (Wiehler, Chakroun, & Peters, 2021), and loss evaluation (Zhang & Clark, 2020), on the defects in the cognitive processes underlying risky decision-making in GD.

Regarding risk-taking propensity, the risk foraging theory suggests that individuals with GD tend to exhibit a higher preference for risky behaviors in situations where they should have been risk-averse (Fujimoto et al., 2017; Lucas et al., 2023; Spurrier & Blaszczynski, 2014). Prior confidence is defined as a positive prior belief in the outcome of risky choices. Previous studies indicate that individuals with GD often exhibit overconfidence in their choices during risky decision-making (Brevers et al., 2014; Goodie, 2005; Hoven et al., 2023). And the above two dimensions are not isolated, since studies have shown that risk propensity can be influenced by prior knowledge or confidence in the risk-taking outcome (Erdman et al., 2025; Xue, Lu, Levin, & Bechara, 2010). In recent years, computational modeling of decision-making behavior has further revealed abnormalities in cognitive flexibility and the exploration-exploitation balance in GD (Wilkinson et al., 2023). Abnormalities in cognitive flexibility, characterized by decreased learning or updating rates in reinforcement learning tasks, are considered to be related to aberrant risky decision-making behaviors in gambling (Brand et al., 2005; de Ruiter et al., 2009; Perandrés-Gómez, Navas, van Timmeren, & Perales, 2021; van Timmeren, Daams, van Holst, & Goudriaan, 2018; Wiehler & Peters, 2024). In terms of the exploration-exploitation balance, previous experimental results suggest that individuals with GD tend to rely more on choices that have already yielded rewards, indicating more habitual rather than goal-directed decision-making (Hales, Clark, & Winstanley, 2023; Wiehler et al., 2021).

Loss evaluation is the main concern of the prospect theory (Kahneman & Tversky, 1979), the widely accepted theory of risky decision-making, and decreased loss aversion has been proposed as a cognitive mechanism for GD (Genauck et al., 2017; Takeuchi et al., 2016). Additionally, according to the principle of diminishing sensitivity in the advanced version of prospect theory (Tversky & Kahneman, 1992), loss evaluation also involves diminishing sensitivity to loss, which may represent an important mechanism in GD risky decision-making but lacks empirical evidence (Zhang & Clark, 2020). Notably, previous studies have also shown that loss evaluation was correlated with impulsivity (Cáceres & San Martín, 2017; Jiang et al., 2024) and craving (Skinner & Aubin, 2010), as the core symptoms of addiction.

Incorporating the findings above, the abnormal risky decision-making in GD may involve multiple cognitive processes. However, previous studies usually focus on isolated aspects, and conflicting experimental results have been reported (Hoven, Luigjes, & van Holst, 2024; Takeuchi et al., 2016). Therefore, it is critical to systematically investigate these multiple cognitive processes involved in risky decision-making in GD.

Cognitive modeling based on the Balloon Analog Risk Task

Cognitive computational modeling based on the Balloon Analog Risk Task (BART) has been developed to uncover various cognitive processes involved in risky decision-making (Wallsten, Pleskac, & Lejuez, 2005). The BART is a widely used tool for assessing risk decision-making in real-world contexts (Lejuez et al., 2002; Wang et al., 2022). In the BART, participants make a series of risky decisions: each pump has the potential to either inflate the balloon and add to the accumulated reward or pop it, forfeiting all potential gains from that trial. Compared to similar risk decision-making tasks, such as the Iowa Gambling Task (Aram et al., 2019), BART does not involve gambling-related visual stimuli, thus avoiding the influence of cue-induced craving on decision-making behavior (Sui, Zhang, Yuan, & Rao, 2024). The original metrics of BART include total score, exploded balloons, and the adjusted pumps (mean pumps of the unexploded balloons) (Lejuez et al., 2002). Previous research has found elevated adjusted pumps in individuals diagnosed with GD by DSM-5, demonstrating a heightened risk-taking propensity (Ciccarelli, Malinconico, Griffiths, Nigro, & Cosenza, 2016), while another study showed no significant change in the same metric with a relatively smaller sample size (Bonini, Grecucci, Nicolè, & Savadori, 2018). Our prior research used a relatively large sample size of individuals with GD and found that individuals with GD had a lower total score of BART, whereas exploded balloons and adjusted pumps showed no significant difference from that of healthy controls (Zhong, Liu, et al., 2025). Nevertheless, a detailed elucidation of the cognitive and neurobiological processes underlying these behavioral performances is warranted.

Cognitive computational modeling has allowed a more comprehensive understanding of the underlying cognitive processes involved in risky decision-making (Park, Yang, Vassileva, & Ahn, 2021). Researchers can build corresponding models based on the cognitive processes of interest and compare parameter differences across different populations with hierarchical Bayesian analysis (Veenman, Stefan, & Haaf, 2023). Cognitive computational modeling of the BART has been employed in the empirical research on psychiatric disorders (Liu et al., 2022; Lu et al., 2024). For instance, a previous study applied the exponentially weighted mean-variance (EWMV) model and discovered reduced loss aversion and choice consistency among participants diagnosed with bipolar disorder comorbid with substance use disorder (Lasagna et al., 2022). Another study applied a four-parameter model (Wallsten et al., 2005) and found that individuals with methamphetamine use disorder exhibited impaired outcome evaluation when exposed to addiction cues (Sui et al., 2024). A recent study also found increased risk-taking tendencies in individuals with alcohol use disorder using the EWMV model (Yuan et al., 2024). Given that cognitive computational modeling based on BART has successfully highlighted abnormalities in various mental disorders, it is possible to explore the cognitive processes driving risk decision-making abnormalities in GD utilizing this approach.

Aim of the study

Our previous work has characterized behavioral anomalies on the BART in individuals with GD (Zhong, Liu, et al., 2025). Herein, this study further examined the various cognitive processes underlying risky decision-making tendencies in individuals with GD. Notably, based on the characteristics of the population with GD, we incorporated the dimension of diminishing loss sensitivity into the loss evaluation process of the EWMV model employed by previous studies mentioned above (Lasagna et al., 2022; Yuan et al., 2024), leaving the interpretation of all other parameters unchanged. Firstly, we tested whether the new model with 6 dimensions successfully fits the behavioral data of risk decision-making in GD. Secondly, we compared the differences in the dimensions of risk decision-making cognitive processes between healthy controls (HC), the group with GD, and the subgroups of participants with GD. Furthermore, we explored the correlations between abnormal cognitive processes and clinical characteristics in GD.

METHODS

Participants

A total of 103 participants with GD were recruited from Shanghai Mental Health Center, Shanghai, China. All of them are male. Three of them were excluded due to incomplete responses to all items of the psychological assessment. These participants with GD had gambled at least once within the previous year and were diagnosed with GD using the DSM-5 criteria. Fifty-nine HC participants were recruited.

The inclusion criteria for participants with GD were: aged 18–60, with 9 or more years of education, able to complete the questionnaire assessment and behavioral tests; meeting the DSM-5 diagnostic criteria for GD; normal vision and hearing, or in the normal range after correction; agreeing to cooperate in completion of follow-up assessments. The exclusion criteria for the study were: suffering from severe cognitive dysfunction, like a history of traumatic brain injury, cerebrovascular disease, epilepsy, etc.; with history of psychotic disorder, bipolar disorder, alcohol or drug dependence or mental disorders caused by medications; with the use of cognitive-promoting medicines in the last 6 months, and impaired intelligence (IQ < 70); with other psychoactive substance abuse or dependence during the previous 5 years (except nicotine). Inclusion criteria for HC were: aged 18–60 years; 9 or more years of education, able to complete the questionnaire assessment and behavioral tests; with no history of any psychiatric disorders and an absence of gambling-related habits, such as purchasing lottery tickets; with a score of less than 5 on the South Oaks Gambling Screen (SOGS) (Zhou et al., 2025) quantifying gambling behavior and with no diagnosed GD by DSM-5; normal vision or hearing or corrected in the normal range. The exclusion criteria are the same as those for GD.

In line with previous studies, the subgroup of GD is divided according to DSM-5: Mild (4–5 symptoms), moderate (6–7 symptoms), and severe (8–9 symptoms) (Rash, Weinstock, & Van Patten, 2016).

Psychological assessment

The Visual Analog Scale (VAS) was used to assess the craving level for gambling (Mallorquí-Bagué et al., 2023). The impulsivity trait was measured by the validated Chinese version of the 30-item Barratt Impulsiveness Scale (BIS) (Huang, Li, Fang, Wu, & Liao, 2013). See the Supplementary Materials for detailed information on the assessments.

Task and design

The BART employed in our study is modified by narrowing the balloon inflation range and validated, which is more similar to the risky decision-making circumstances of gambling (Liu et al., 2022; Rao, Korczykowski, Pluta, Hoang, & Detre, 2008; Salatino et al., 2022). A schematic representation of BART is shown (Fig. 1A). See the Supplementary Materials for detailed information on the task and design.

Computational modeling

Based on four recently published computational cognitive models, including the reparametrized Bayesian Sequential Risk-taking model (BSR model) (Park et al., 2021; Wallsten et al., 2005), the scaled target learning model (STL model) (Zhou, Myung, & Pitt, 2021), the Exponential-Weight model (EW model) (Park et al., 2021), the EWMV model (Park et al., 2021), we proposed the Exponential-Weight Mean-Variance model with simply linear combined mean and variance (EWMV-SLC model) and employed hierarchical Bayesian modeling for analysis. The EWMV-SLC model introduces one additional parameter, ζ (diminishing loss sensitivity), compared to EWMV, with all other parameters sharing identical meanings. Lower ψ denotes the

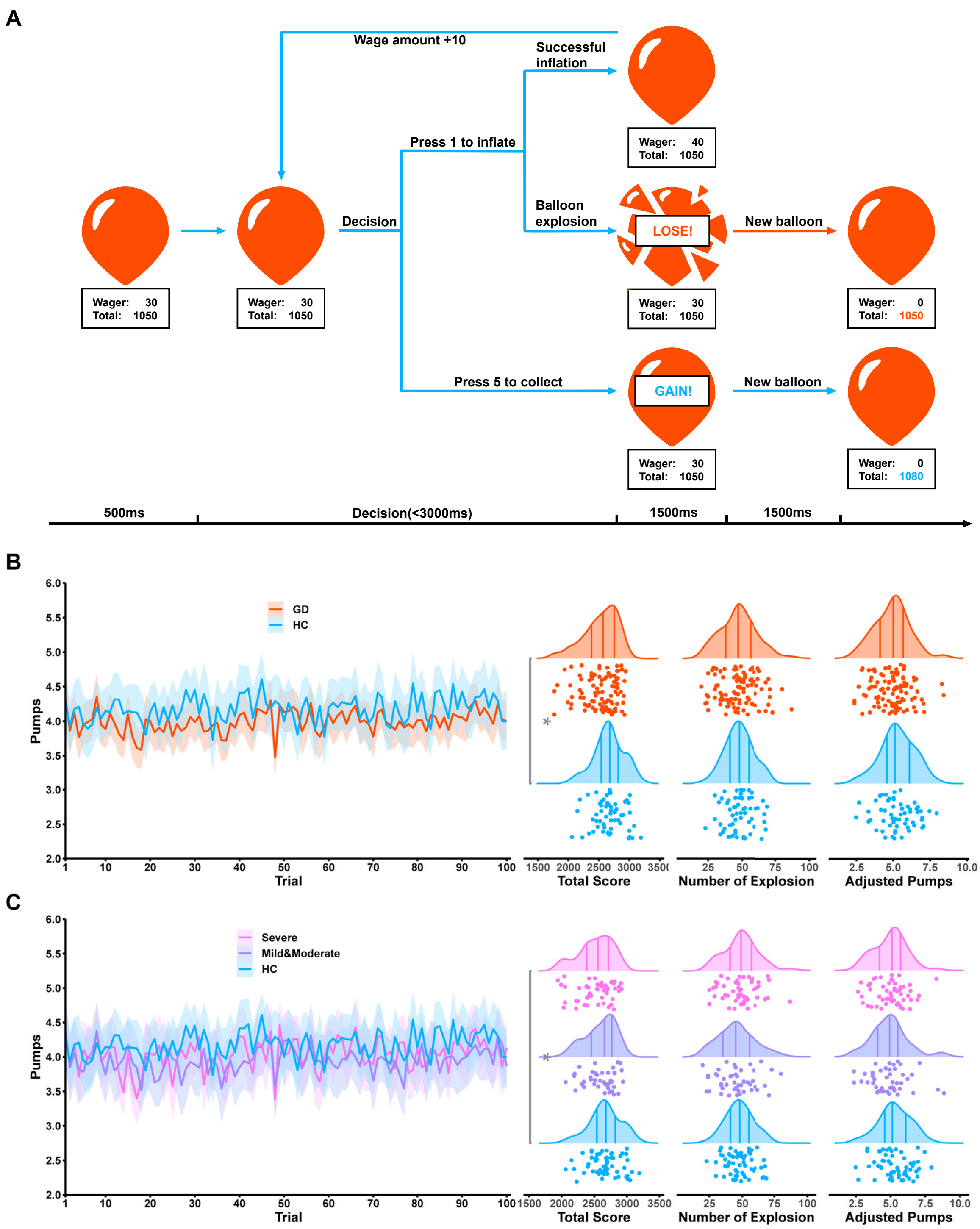

Fig. 1. Task design, observed behavior and group difference of classic behavioral parameters

(A) Procedure of the BART. During the task, participants should decide the number of pumps of each balloon to optimize their total rewards without prior knowledge of the underpinning mechanism of balloon explosion. In each BART trial, participants see a virtual balloon on the center of the white screen, where they can press "1" to inflate the balloon or "5" to stop inflating. The balloon will be inflated automatically if the participants fail to press "1" or "5" on the keyboard within 3 s. If the participant chooses to inflate the balloon and the balloon does not explode, the potential reward of the balloon increases by 10, but the probability of exploding and loss also increases. But if the balloon explodes after pumps, the points of the balloon are nullified and no rewards are received. If participants stop inflating, they will gain the reward associated with the balloon

(B–C) Trial-by-trial number of pumps of each group and group difference of classic behavioral parameters. Total Score: Points at the end of the task; Number of Explosion: The number of exploded balloons during the task; Adjusted Pumps: The average pumps of unexploded balloons. On the left part of the plot, lines show the mean pumps and ribbons denote 95% confidence interval. On the right part, vertical lines denote the medians and quartile numbers, and dots show the individuals' parameters. *: $p < 0.05$

overconfidence in the task at the beginning of the task. Lower η means a slower update of the belief on the possibility of the balloon bursting, indicating cognitive flexibility. Higher ρ indicates a stronger willingness to take risks. Higher τ means higher exploitation tendency, namely choice consistency. Lower λ denotes less aversion to loss in the tasks. Note that ζ lower than 1 means a diminishing loss sensitivity, while ζ higher than 1 means an increased loss sensitivity. The relatively lower ζ indicates relatively faster-diminishing loss sensitivity or slower-increasing loss sensitivity when ζ is higher than 1. Therefore, to avoid confusion, we did not distinguish the relationship between ζ and 1 in this study and simply interpreted lower ζ as a relatively faster-diminishing loss sensitivity. See the Supplementary Materials for detailed information on model-fitting.

Statistical analysis

Quantitative continuous model parameters were compared across groups with one-way analyses of variance (ANOVAs) followed by Tukey correction when comparing three or more groups for normally distributed data. Outliers in the behavioral test were detected before group comparison and correlation analysis by the Median Absolute Deviation (MAD) method for non-normally distributed data and the standard deviation method for normally distributed data, with data points exceeding 3 MAD or standard deviation from the median or mean value removed (Leys, Ley, Klein, Bernard, & Licata, 2013). All data were normalized at the group level before comparison, and data that could not be normalized were compared with the Kruskal-Wallis test followed by the Dunn test with the Holm correction. The normality of the data above was determined by the Shapiro-Wilk test. The significance cut-off for this study was set at 0.05. All data above were cleaned and visualized with the tidyverse (version 2.0.0) (Wickham et al., 2019) in R (version 4.1.3), and statistical analyses were implemented with rstatix (version 0.7.2) (Kassambara, 2023) and MASS (version 7.3-55) for robust regression (Venables & Ripley, 2002) in R (version 4.1.3).

Ethics

All participants provided informed consent before their participation and the study protocol was approved by the Institutional Review Board, Shanghai Mental Health Center (2022–18).

RESULTS

Demographic and clinical characteristics

One hundred and fifty-nine participants were analyzed, including 100 males diagnosed with GD and 59 age- and education-matched male HC. Based on DSM-5, participants with GD are subdivided into mild (9 participants), moderate (37 participants), and severe (54 participants) groups. Since the sample size of the mild group was relatively low and their total scores showed no significant difference from the moderate group ($n_{\mathrm{mild}} = 8$, $n_{\mathrm{moderate}} = 36$, $Z = -1.47$, $p_{\mathrm{Holm}} = 0.429$, $r = -0.221$), they were combined into a group (Mild & Moderate group). The similarity between the two population groups has also been documented in previous studies (Mide, Arvidson, & Gordh, 2023). Significantly higher levels of impulsivity were shown in the group with GD (Table 1), in line with previous studies (Ioannidis et al., 2019; Ruiz de Lara & Perales, 2020; Zhong et al., 2024). Descriptive statistics of all groups including the mild group are shown in Table S2.

Behavioral performance

Consistent with the common analysis of the BART (Lejuez et al., 2002), the total points, the number of exploded balloons and the adjusted pumps (mean pumps of the unexploded balloons) were compared among groups (Fig. 1B and C). The total score of the group with GD was significantly lower compared to the HC group ($n_{\mathrm{GD}} = 95$, $n_{\mathrm{HC}} = 57$, $H_1 = 6.79$, $p = 0.009$, $\eta^2 = 0.039$), while the number of exploded balloons ($n_{\mathrm{GD}} = 100$, $n_{\mathrm{HC}} = 59$, $F_{1,\,157} = 0.10$, $p = 0.753$, $\eta^2 = 0.001$) and the adjusted pumps ($n_{\mathrm{GD}} = 99$, $n_{\mathrm{HC}} = 59$, $F_{1,\,156} = 3.82$, $p = 0.052$, $\eta^2 = 0.024$) showed no significant difference. In the subgroup level, the total score of the severe group was significantly lower than the HC group ($n_{\mathrm{Severe}} = 50$, $n_{\mathrm{Mild\&Moderate}} = 42$, $n_{\mathrm{HC}} = 57$, $H_2 = 7.20$, $p = 0.027$, $\eta^2 = 0.036$; $Z = 2.68$, $p_{\mathrm{Holm}} = 0.007$, $r = 0.260$), and the other two exhibited no significance (Number of exploded balloons: $n_{\mathrm{Severe}} = 54$, $n_{\mathrm{Mild\&Moderate}} = 46$, $n_{\mathrm{HC}} = 59$, $F_{2,\,156} = 0.97$, $p = 0.382$, $\eta^2 = 0.012$; Adjusted pumps: $n_{\mathrm{Severe}} = 54$, $n_{\mathrm{Mild\&Moderate}} = 46$, $n_{\mathrm{HC}} = 59$, $F_{2,\,156} = 1.46$, $p = 0.236$, $\eta^2 = 0.018$).

Computational modeling

Model selection among groups. To clarify the cognitive processes underlying behavioral patterns, behavioral data from all groups underwent hierarchical Bayesian analysis with 5 competing models. Among 5 competing models, EWMV-SLC demonstrated a statistically significant superiority within the group with GD, and its Expected Log-predictive Density (ELPD) did not show a significant divergence from that of the optimal model across all other groups (Fig. 2). Thus, EWMV-SLC was considered the most suitable model for all groups and was thus selected for subsequent analysis. Both the posterior prediction check (Figure S2) and parameter recovery (Figure S3) demonstrated robust performance.

The EWMV-SLC model decomposed participants' cognitive processes in risky decision-making into 6 dimensions (Fig. 3A) (see Methods for details). The interpretation of the modeling parameters was partially validated by their Pearson correlation with intuitive behavioral measures (Fig. 3B).

Group differences revealed by hierarchical Bayesian modeling and comparison. Among the 6 dimensions, prior belief, updating rate, loss aversion and diminishing loss sensitivity exhibited significant differences between the group with GD and HC (Fig. 3C). Specifically, significant

Table 1. Demographic and clinical characteristics of participants

Dependent measure	Total, $N = 159$	HC, $n = 59$	GD, $n = 100$ Total, $n = 100$	Mild & Moderate, $n = 46$	Severe, $n = 54$	F/H	p	η^2
Age, Years								
Mean (SD)	30.84 (7.91)	31.71 (9.91)	30.33 (6.45)	30.78(5.86)	29.94 (6.95)	–	–	–
Median [Min, Max]	29 [20, 60]	28 [20, 60]	29.5 [20, 59]	30 [20, 53]	29 [20, 59]	–	–	–
2-Group Comparison	–	–	–	–	–	$H_1 = 0.28$	0.595	0
3-Group Comparison	–	–	–	–	–	$H_2 = 1.48$	0.476	0
Education, Years								
Mean (SD)	14.96 (3.25)	15.27 (4.49)	14.77 (2.23)	14.93 (1.84)	14.63 (2.52)	–	–	–
Median [Min, Max]	16 [6, 24]	16 [6, 24]	15 [6, 19]	15 [10, 18]	15.5 [6, 19]	–	–	–
2-Group Comparison	–	–	–	–	–	$H_1 = 2.57$	0.109	0.010
3-Group Comparison	–	–	–	–	–	$H_2 = 2.60$	0.273	0.004
BIS Total Score								
Mean (SD)	82.78 (17.64)	69.20 (16.04)	90.79 (13.09)	88.50 (13.99)	92.74 (12.07)	–	–	–
Median [Min, Max]	84 [35, 118]	70 [35, 114]	90 [50, 118]	88 [50, 117]	92 [56, 118]	–	–	–
2-Group Comparison	–	–	–	–	–	$F_{1,\ 157} = 85.13$	< 0.001	0.352
3-Group Comparison	–	–	–	–	–	$F_{2,\ 156} = 44.00$	< 0.001	0.361
BIS: Attentional Impulsiveness								
Mean (SD)	25.99 (6.15)	22.47 (6.13)	28.06 (5.17)	27.50 (4.58)	28.54 (5.62)	–	–	–
Median [Min, Max]	27 [10, 41]	22 [10, 38]	28 [12, 41]	28 [13, 38]	29 [12, 41]	–	–	–
2-Group Comparison	–	–	–	–	–	$H_1 = 32.40$	< 0.001	0.200
3-Group Comparison	–	–	–	–	–	$H_2 = 32.80$	< 0.001	0.197
BIS: Motor Impulsiveness								
Mean (SD)	27.16 (6.75)	22.64 (6.11)	29.82 (5.61)	29.00 (6.37)	30.52 (4.82)	–	–	–
Median [Min, Max]	27 [12, 41]	23 [12, 40]	30 [12, 41]	29 [12, 41]	31 [20, 40]	–	–	–
2-Group Comparison	–	–	–	–	–	$F_{1,\ 157} = 56.79$	< 0.001	0.266
3-Group Comparison	–	–	–	–	–	$F_{2,\ 156} = 29.38$	< 0.001	0.274
BIS: Non-planning Impulsiveness								
Mean (SD)	29.64 (7.59)	24.08 (7.08)	32.91 (5.77)	32.00 (5.37)	33.69 (6.02)	–	–	–
Median [Min, Max]	30 [10, 46]	24 [10, 44]	33 [17, 46]	32 [17, 42]	34.5 [21, 46]	–	–	–
2-Group Comparison	–	–	–	–	–	$F_{1,\ 157} = 73.15$	< 0.001	0.318
3-Group Comparison	–	–	–	–	–	$F_{2,\ 156} = 37.66$	< 0.001	0.326
VAS Score								
Mean (SD)	–	–	3.65 (3.34)	3.07 (3.01)	4.15 (3.55)	–	–	–
Median [Min, Max]	–	–	2 [0, 10]	2 [0, 9]	3.5 [0, 10]	–	–	–
Group Comparison	–	–	–	–	–	$H_1 = 2.00$	0.158	0.010

HC: Health controls; GD: Gambling disorder; Mild & Moderate: Participants with mild and moderate gambling disorder; Severe: Participants with severe gambling disorder; BIS: Barret Impulsivity Scale; VAS: Visual Analog Scale for gambling craving; The 2-Group Comparison denotes to the comparison between HC and GD, while the 3-Group Comparison denotes to the comparison among HC, Mild & Moderate and Severe groups; Group Comparison of VAS Scores means the comparison between Mild & Moderate and Severe groups.

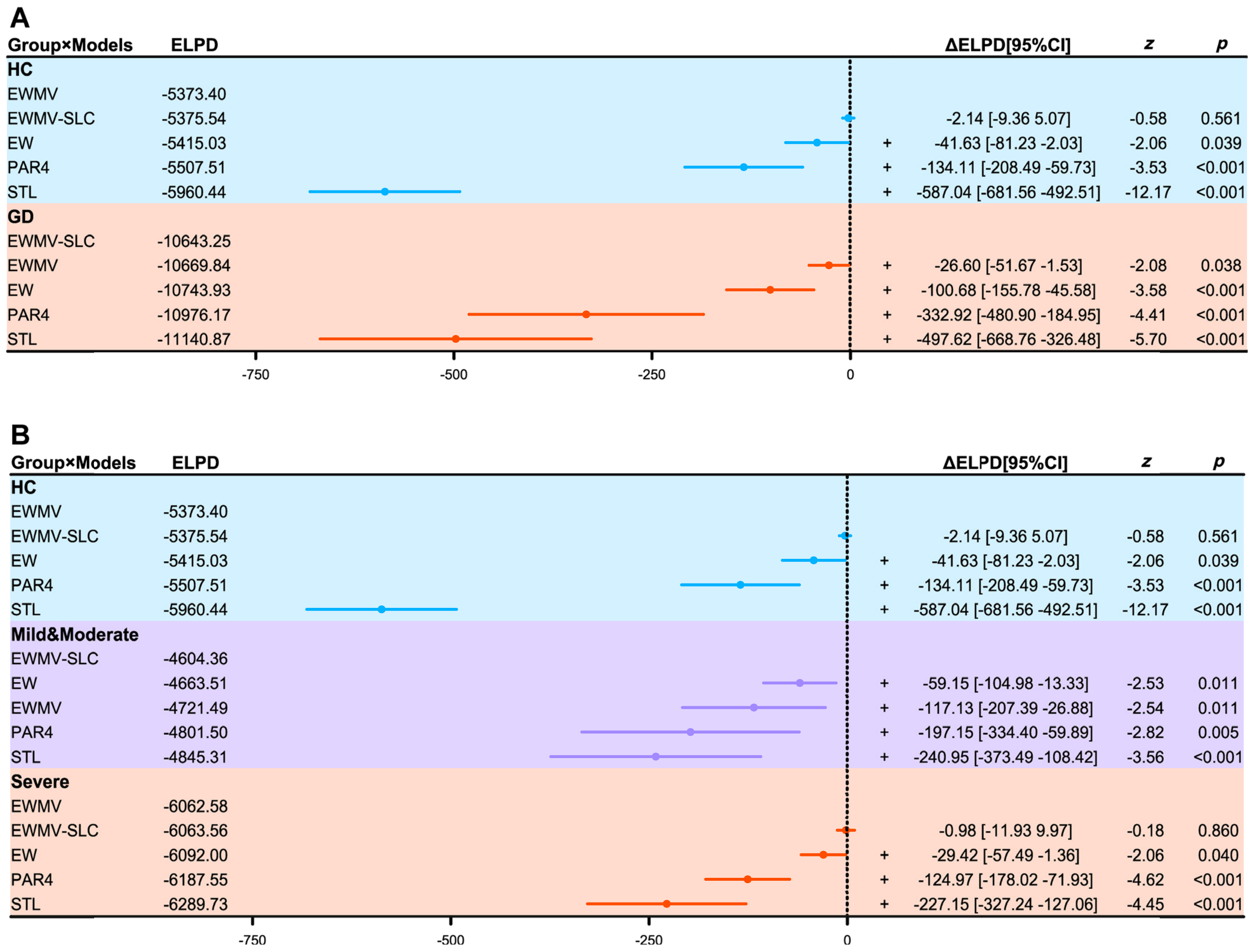

Fig. 2. Model comparison among all groups based on the *z*-score of the ELPD differences between models
(A-B) Hierarchical Bayesian analysis of 5 competing models for HC, GD and subgroups of GD. Dots and bars illustrate the predictions and confidence intervals for the difference of ELPD (ΔELPD). The model exhibiting the lowest ELPD is considered the optimal model for the group, with all other models subjected to comparative analysis. The significance of the differences is rigorously tested via *z*-score. +: $p < 0.05$

elevations in loss aversion (λ: $n_{GD} = 98$, $n_{HC} = 55$, $H_1 = 50.00$, $p < 0.001$, $\eta^2 = 0.325$) and faster-diminishing sensitivity to loss (ζ: $n_{GD} = 99$, $n_{HC} = 58$, $H_1 = 24.60$, $p < 0.001$, $\eta^2 = 0.152$) were observed, indicating stronger loss avoidance generally but faster-diminishing sensitivity to loss with the accumulation of potential loss. Besides, the group with GD expressed lower prior belief for the balloon bursting (ψ: $n_{GD} = 98$, $n_{HC} = 56$, $H_1 = 8.58$, $p = 0.003$, $\eta^2 = 0.050$) and a higher updating rate (η: $n_{GD} = 88$, $n_{HC} = 55$, $H_1 = 7.91$, $p = 0.005$, $\eta^2 = 0.049$). Risk-taking propensity (ρ: $n_{GD} = 93$, $n_{HC} = 59$, $H_1 = 0.03$, $p = 0.863$, $\eta^2 = 0$) and choice consistency (τ: $n_{GD} = 90$, $n_{HC} = 54$, $H_1 = 3.08$, $p = 0.080$, $\eta^2 = 0.015$) exhibited no significant difference between groups.

At the subgroup level (Figure S4), the prior beliefs and diminishing loss sensitivity in the severe and the Mild & Moderate groups were significantly lower than those of the HC group. Furthermore, the update rate of the severe group was higher than that observed in both the Mild & Moderate and HC groups. In terms of risk preference, the Mild & Moderate group exhibited a lower tendency towards risk-taking relative to the HC group, while the severe group displayed a higher inclination for risk. Notably, individuals with severe and mild-to-moderate GD showed heightened loss aversion compared to the HC, with the Mild & Moderate group demonstrating a relatively greater aversion to losses. There was no difference in the consistency of decision-making between groups. See Table S3 for detailed statistics.

Interpretations for behavioral performance by computational parameters. With the computational metrics of the six cognitive dimensions scaled, robust regression was used to quantify the contribution of each cognitive computational parameter to the overall behavioral task of each group (Fig. 3D). No considerable multicollinearity was detected in the robust regression models (Table S4). In all groups, ζ explained overall task performance well (HC: $\beta = 118.12$, 95% HDI [30.01, 206.23], $t_{52} = 2.63$, $p < 0.001$, Cohen's $d = 0.342$; Mild & Moderate: $\beta = 182.71$, 95% HDI [115.98, 249.45], $t_{39} = 5.37$, $p < 0.001$, Cohen's $d = 0.791$; severe: $\beta = 360.57$, 95% HDI [267.47, 453.66], $t_{47} = 7.59$, $p < 0.001$,

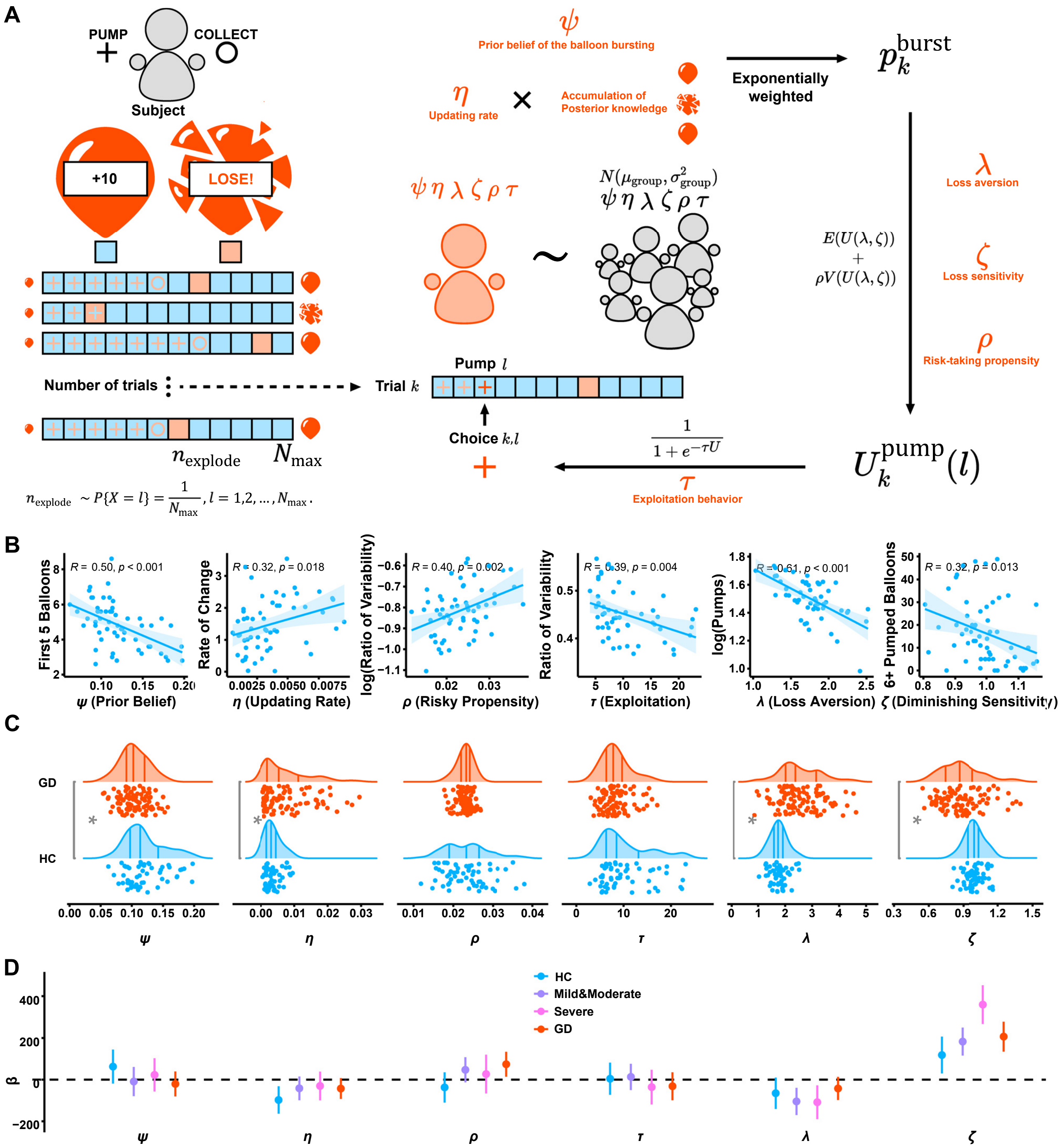

Fig. 3. Illustration of EWMV-SLC model, distribution of parameters and their mapping onto task performance

(A) Illustration of the underlying rule of BART and hierarchical Bayesian modeling for EWMV-SLC

(B) Correlations between behavioral and computational parameters in the HC group. First 5 balloons: average pumps of the first 5 balloons, indicating the prior belief of balloon bursting; Rate of change: the difference between the number of pumps of 11–20 balloons and 21–30 balloons to the optimal number of pumps (see Methods); Ratio of variability: ratio of variance and mean of the number of pumps; Pumps: number of pumps; 6+ pumped balloons: number of balloons pumped more than 6 times

(C) The posterior distribution for six computational parameters of the GD and HC groups. Vertical lines denote the medians and quartile numbers, and dots show the individuals' parameters. *: $p < 0.05$

(D) Regression coefficients of six cognitive domains on the total points of the BART. β: regression coefficient of the computational parameters

Cohen's d = 1.033; GD: β = 206.81, 95% HDI [135.13, 278.49], $t_{93} = 5.66$, $p < 0.001$, Cohen's $d = 0.565$), indicating that the overall task performance could be explained by diminishing loss sensitivity.

Correlation between clinical measures and parameters related to loss. To further investigate the clinical relevance of these findings, a Pearson correlation analysis was conducted between the two dimensions of loss evaluation and clinical scales that characterize addiction traits, namely, impulsivity (3 subfactors of BIS: Attentional Impulsiveness, Motor Impulsiveness, and Non-planning Impulsiveness) (Stanford et al., 2009) and craving (VAS). The Pearson correlation revealed that diminishing loss sensitivity exhibited a significant negative correlation with non-planning impulsiveness (Fig. 4).

DISCUSSION

Previous studies on GD have not simultaneously addressed loss aversion and diminishing loss sensitivity. Earlier research found that individuals with GD exhibit lower levels of loss aversion (Genauck et al., 2017), but other studies have highlighted heterogeneity in loss aversion (Takeuchi et al., 2016). In this study, we introduced the measure of diminishing loss sensitivity into the loss evaluation process of risky decision-making. We found that, although individuals with GD exhibit higher levels of loss aversion, their risk decision-making deficits are primarily due to faster-diminishing loss sensitivity. Incorporating loss sensitivity into the loss utility function may help resolve the controversy on the inconsistently measured loss aversion (Yechiam, 2019).

Consistent with previous research, individuals with GD exhibited an overconfident belief that the probability of a balloon bursting was relatively low (Brevers et al., 2014; Goodie, 2005; Hoven et al., 2023). No significant differences in risk preferences were observed across the population with GD, but subgroup analysis indicated that individuals with mild and moderate GD had lower risk tendencies than HC, while those with severe GD demonstrated higher risk preferences, suggesting potential heterogeneity in risk orientation (Sharman et al., 2019). A higher learning rate was observed in the population with GD, which contradicted findings from previous studies based on reversal learning tasks (Brevers et al., 2014; Goodie, 2005; Hoven et al., 2023). The possible reason was that our study did not differentiate between positive and negative reward learning rates and the observed increase in learning rate may be related to enhanced sensitivity to positive stimuli in individuals with GD (Suzuki et al., 2023). In summary, through hierarchical Bayesian cognitive modeling, we provided a more comprehensive explanation of how cognitive processes collectively cause risky decision-making dysfunction in GD.

The EWMV-SLC model incorporated the parameter of diminishing loss sensitivity, which held significant relevance in GD and performed well in both the HC and the group with GD. We compared this model with all previously published winning models to ensure its best alignment with the behavior of individuals with GD. In this study, to enhance the reliability of group comparisons, we performed model fitting and comparison for all groups based on ELPD, the widely used standard for hierarchical Bayesian model selection (Sivula, Magnusson, Alonzo Matamoros, & Vehtari, 2020). The model comparison results confirmed

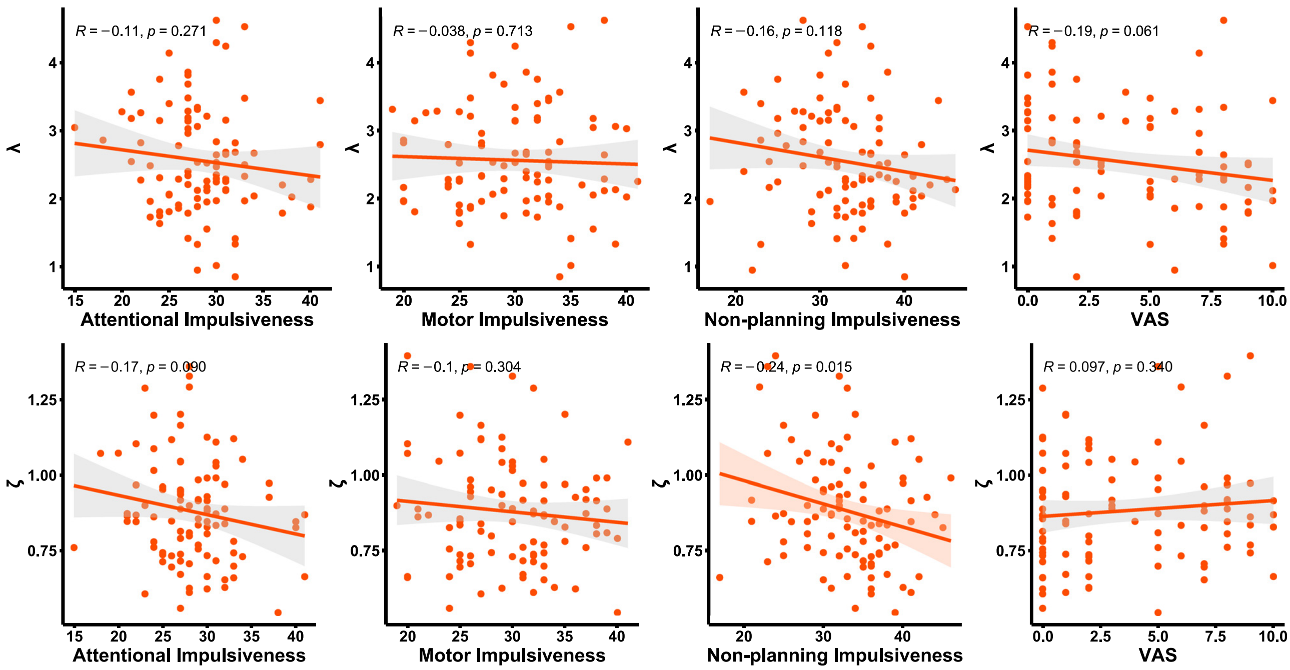

Fig. 4. Correlations between loss evaluation and clinical traits among GD
λ: loss aversion; ζ: diminishing loss sensitivity; VAS: Visual Analog Scale for gambling craving. Colored ribbon: p < 0.05

that the EWMV-SLC model showed no significant difference from the best-fitting EWMV model in HC, while the EWMV-SLC model outperformed other competing models in GD. These further supported the notion that diminishing loss sensitivity is indeed a key process driving the abnormal risk decision-making behaviors of GD.

Previous studies have indicated that impaired risky decision-making in GD is associated with impulsive traits (Hirmas & Engelmann, 2023) and craving (Takeuchi et al., 2016). Our research further revealed that reduced loss aversion in risk decision-making was linked to a stronger craving, while faster-diminishing loss sensitivity was associated with heightened impulsivity, specifically non-planning impulsiveness. In individuals with GD, diminishing loss sensitivity refers to the diminished responsiveness to potential monetary losses as risk increases, often without regard for the consequences to themselves or their families. Impulsivity is defined as the tendency to respond to external stimuli without considering the consequences, reflecting an individual's psychological traits (Gullo & Potenza, 2014), whereas non-planning impulsiveness is characterized by a disregard for consideration of future outcomes (Machado et al., 2024). Therefore, the impulsive behaviors exhibited by individuals with GD may result from a loss of sensitivity to potential negative outcomes, which may be caused by the non-planning impulsiveness. These inferences may represent the psychological mechanisms underlying the abnormal risk decision-making of GD and their clinical manifestations, offering valuable insights for cognitive-behavioral therapy (Andersland, Dow, Ginley, Whelan, & Pfund, 2025) and targeted neuromodulation (Zhong, Chen et al., 2025).

Our study still has certain limitations. Firstly, the participants with GD included in our study were predominantly moderate to severe cases, with fewer mild cases. Given the illicit status of gambling in China, coupled with limited healthcare accessibility in GD (Zhong et al., 2024) and the typically crisis-driven nature of help-seeking in gambling disorder (Bowden-Jones et al., 2022), only those with GD causing significant familial and social harm are likely to seek outpatient care. Additionally, due to the relative rarity of female individuals with GD (Hodgins et al., 2011), it is difficult to obtain large sample datasets of cognitive evaluation and experiments, and the findings in this study may not be generalized to female patients with GD.

Taken together, our study utilized hierarchical Bayesian cognitive modeling to analyze the cognitive processes underlying risk decision-making impairments in individuals with GD and found that diminishing loss sensitivity explained their abnormal risk decision-making. Furthermore, we identified correlations between loss evaluation features and impulsivity and craving in the population with GD: Higher non-planning impulsiveness is associated with diminishing loss sensitivity, while higher craving is associated with lower loss aversion. The abnormal psychological processes of GD revealed in this study may guide future cognitive-behavioral therapy and target neuromodulation.

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Data availability: The data from this study can be shared upon a reasonable request.

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SUPPLEMENTARY MATERIAL

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2025.00230.

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