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FULL-LENGTH REPORT

Reduced loss aversion in value-based decision-making and edge-centric functional connectivity in patients with internet gaming disorder

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ABSTRACT

Background and aims: Impaired value-based decision-making is a feature of substance and behavioral addictions. Loss aversion is a core of value-based decision-making and its alteration plays an important role in addiction. However, few studies explored it in internet gaming disorder patients (IGD). *Methods:* In this study, IGD patients (PIGD) and healthy controls (Con-PIGD) performed the Iowa gambling task (IGT), under functional magnetic resonance imaging (fMRI). We investigated group differences in loss aversion, brain functional networks of node-centric functional connectivity (nFC) and the overlapping community features of edge-centric functional connectivity (eFC) in IGT. *Results:* PIGD performed worse with lower average net score in IGT. The computational model results showed that PIGD significantly reduced loss aversion. There was no group difference in nFC. However, there were significant group differences in the overlapping community features of eFC[1]. Furthermore, in Con-PIGD, loss aversion was positively correlated with the edge community profile similarity of the edge[2] between left IFG and right hippocampus at right caudate. This relationship was suppressed by response consistency[3] in PIGD. In addition, reduced loss aversion was negatively correlated with the promoted bottom-to-up neuromodulation from the right hippocampus to the left IFG in PIGD. *Discussion and conclusions:* The reduced loss aversion in value-based decision making and their related edge-centric functional connectivity support that the IGD showed the same value-based decision-making deficit as the substance use and other behavioral addictive disorders. These findings may have important significance for understanding the definition and mechanism of IGD in the future.

KEYWORDS

loss aversion, value-based decision-making, Iowa gambling task, net score, edge-centric functional network, internet gaming disorder

INTRODUCTION

Playing internet games is a kind of leisure activity in our daily lives. There has been a substantial increase in playing internet games and related activities during the coronavirus (COVID-19) stay-at-home mandates and quarantines (King, Delfabbro, Billieux, & Potenza, 2020; Kiraly et al., 2020; Zha, Li, et al., 2022). However, compulsive uncontrolled, and excessive internet use could lead to problematic internet use such as the internet gaming disorder (IGD) for some individuals, particularly adolescents and young adults (D. King, Koster, & Billieux, 2019).

IGD is a behavioral addiction (Holden, 2001), that refers to excessive indulgence in online games and leads to consequences, including physical and psychological disorders, social impairments, and poor work performance (King & Delfabbro, 2018; Lukavska, 2018; Potenza, 2015). The IGD is currently in the Appendix of Section III of the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) as a non-substance disorder deserving further research. Recently, IGD has also been designated as an addictive disorder by the World Health Organization in the "Clinical Descriptions and Diagnostic Guidelines for ICD-11 Mental and Behavioral Disorders" (https://icd.who.int/dev11/l-m/en).

Impaired value-based decision-making is a feature of both substance-related disorders and pathological gambling (Diekhof, Falkai, & Gruber, 2008; Wiehler & Peters, 2015). Loss aversion is a central facet of value-based decision-making (Genauck et al., 2020) and is a concept developed by prospect theory, one of the most classic behavioral models of value-based decision-making, which means that people are more sensitive to the possibility of losing objects or money than the possibility of gaining the same objects or amounts of money (Tom, Fox, Trepel, & Poldrack, 2007). The Iowa Gambling Task (IGT) (Meshi, Elizarova, Bender, & Verdejo-Garcia, 2019) is one of the most common and popular paradigms used to assess value-based decision-making (Ahn et al., 2014; Ferraro et al., 2012; Fridberg et al., 2010; Vassileva et al., 2013). While there are a few studies have applied the IGT to investigate the group difference between IGD and healthy comparison participants and almost focused on the relative preferences for "advantageous" decks over "disadvantageous" decks (Lin, Wang, Sun, Ko, & Chiu, 2019; Metcalf & Pammer, 2014; Yao et al., 2015), this approach does not leverage the full potential of the IGT. Computational neuroscientists interested in the IGT have mainly focused their efforts on the value-based learning and decision-making components of the task (Ahn et al., 2014; Ferraro et al., 2012; Fridberg et al., 2010; Vassileva et al., 2013). A few previous studies using the PVL-DecayRI (Vassileva et al., 2013) or the PVL-Delta (Fridberg et al., 2010) models to study decision-making processes in the IGT in drug users. Consistent findings, both chronic (current) marijuana users (Fridberg et al., 2010) and polysubstance (former) users (Vassileva et al., 2013) showed reduced loss aversion compared to healthy control in the IGT. Few studies have investigated loss aversion in value-based decision-making in the IGD by using the IGT in conjunction with the computation model like the PVL-DecayRI or the PVL-Delta models. Recent neuroscientific researches showed that individual differences in loss aversion in substance use and behavioral addictive disorders were associated with the reward evaluation and processing network, including regions like the inferior frontal gyrus (IFG), hippocampus, and caudate (Genauck et al., 2017; Gianelli, Basso, Manera, Poggi, & Canessa, 2022; Quester & Romanczuk-Seiferth, 2015; Zha, Li, et al., 2022). However, it is currently unknown whether the IGD shows the same decision-making deficit.

Cognition and behavior stem from the interaction of brain networks, and the interactions between neural units are central to neurocognitive function research (Reid et al., 2019). Node-centric functional connectivity (nFC) is the traditional approach to investigating functional brain networks which emphasizes interactivity among pairs of nodes (Craddock et al., 2013; Rogers, Morgan, Newton, & Gore, 2007) and the nFC construct relies on forcing each brain node into one and only one community. Although the nFC has been useful in cognitive and network neuroscience (Di Martino et al., 2014; Fornito, Zalesky, & Breakspear, 2015), it cannot capture potentially meaningful features or patterns of inter-relationships among edges. And it divides brain regions into non-overlapping communities which conflicts with evidence that cognition and behavior require contributions from regions that span multiple node-defined communities and systems (Anderson, Kinnison, & Pessoa, 2013). Recently Faskowitz et al. proposed the edge-centric functional connectivity (eFC) to investigate functional brain networks that represent pairwise functional interactions among a network's edges (Faskowitz, Esfahlani, Jo, Sporns, & Betzel, 2020). In the eFC construct, overlapping community features are inherent and the definition of community comes closer to matching the brain's multifunctional nature (Faskowitz et al., 2020; Jo, Faskowitz, Esfahlani, Sporns, & Betzel, 2021; Jo, Zamani Esfahlani, et al., 2021). Therefore, the nFC and the eFC provide complementary insights into the organization and function of brain networks.

In this study, we hypothesized that the PIGD would exhibit worse performance (lower average net score) and reduce loss aversion in IGT. To better characterize the behavioral performance of IGT, including loss aversion, we used computational modeling approaches to disentangle the distinct neurocognitive processes. Furthermore, to reveal the possible neural mechanisms of reduced loss aversion in the PIGD, we examined whether the functional network of nFC and eFC altered in the IGT in the PIGD and whether loss aversion was associated with these functional network alterations.

METHODS

Participants

Forty-nine participants, including patients with the IGD (PIGD, $n = 27$) and their controls (Con-PIGD, $n = 22$), were recruited. The PIGD were recruited through the General Hospital of Beijing Military Region's Addiction Medicine Center. The Con-PIGD were recruited through advertisements from the Beijing local community. The PIGD met the DSM-5 criteria for internet gaming disorder (i.e., meet at least 5 of 9 criteria within a 12-month-period). Structured clinical interviews were conducted by two experienced psychiatrists for the diagnoses. See details in Supplemental Methods (SM).

Measures

Demographic variables. The survey assessed the subjects' age, education, and gender.

Clinical variables. The survey measured symptom severity of the internet game disorder, including the duration of internet gaming exposure (years), the longest once internet gaming exposure (hours), weekly internet gaming exposure (hours), and frequency of weekly internet gaming exposure.

The settings and the study protocol and procedure

We recruited the PIGD and the Con-PIGD to perform the IGT under functional magnetic resonance imaging (fMRI) and to complete some surveys. Behavioral measures included symptom severity of IGD, net-score and loss aversion acquired from the IGT. We calculated nFC (Luo, Liu, Jin, Chang, & Peng, 2021; Zha, Li, et al., 2022), eFC and overlapping community features of eFC. And we used the generalized mediation analysis and dynamic causal modeling (DCM) analysis. Finally, we used the machine learning methods to classify two groups. See details in SM.

The IGT. The IGT was the same as that we used in several studies (Fig. 1) (Li et al., 2020; Wang et al., 2017; Wei et al., 2018; Zha, Li, et al., 2022). Four decks labeled with A, B, C, and D. Decks C and D were the advantageous because they had a positive payoff in the long run, and decks A and B were the disadvantageous because they had a negative payoff in the long run. The performance of IGT was net score, which calculated by subtracting the total number of selections on decks AB from the total number of selections on decks CD (Christakou, Brammer, Giampietro, & Rubia, 2009). See details in SM.

The computational model. Based on the literature, we compare the most promising the IGT models involving loss aversion: the Prospect Valence Learning (PVL) model with delta learning rule (PVL-Delta) (Ahn, Busemeyer, Wagenmakers, & Stout, 2008), the PVL model with decay reinforcement learning rule (PVL-DecayRI) (Ahn, Krawitz, Kim, Busmeyer, & Brown, 2011). See details in SM.

The fMRI data acquisition and pre-processing. All MRI data were acquired using 3-T Siemens Magnetom Trio scanners in the Xuanwu Hospital Capital Medical University, Beijing. Pre-processing was similar to that used in a study (Zha et al., 2019; Zha et al., 2022) and was processed with the Analysis of Functional Neuroimages (Version AFNI_18.2.03) (Cox, 1996). See details in SM.

Functional network of nFC. Following previous studies, we defined nodes and calculated the nFC Matrix (Luo et al., 2021; Zha, Li, et al., 2022). Nodes were automatically divided by anatomical automatic labeling (AAL) parcellation (Tzourio-Mazoyer et al., 2002). nFC describes the spatio-temporal correlation between spatially distinct brain regions.

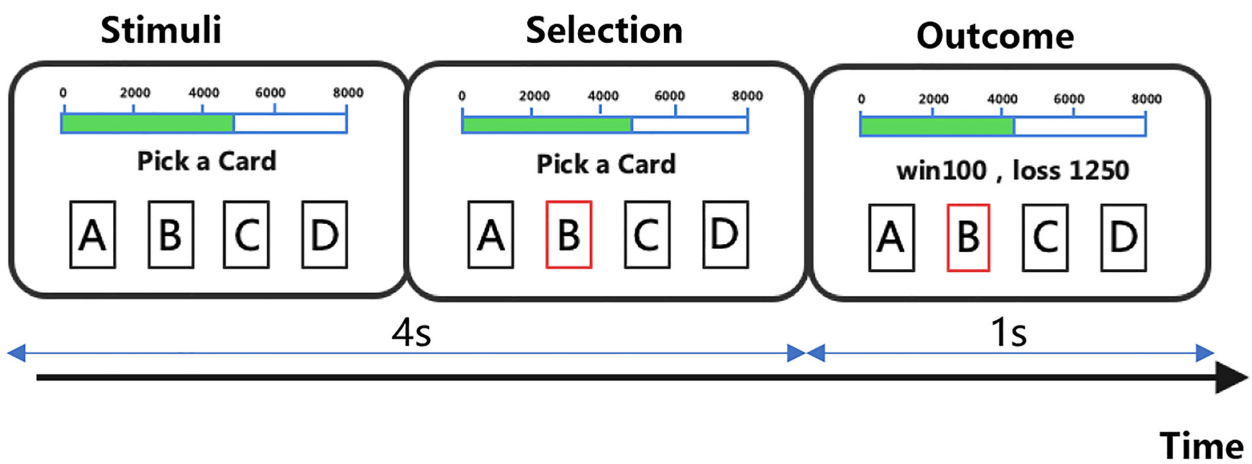

Fig. 1. **The Iowa gambling Task.** The task contained 180 trials, which were divided into three runs. There were three blocks for each run. There were 20 trials for each block, and the inter-block interval was a 30 s resting interval. Two phases were performed for each trial. The first phase was the selection phase in which participants were asked to select one of four decks within 4 s. The second phase was the outcome phase, in which the outcome was shown for 1 s. The decks were labeled with A, B, C, and D

Functional network of eFC. Overlapping community structural features are inherent in the eFC construct. Clustering the eFC matrix assigns each edge to a community. Each edge is associated with two brain regions (the nodes it connects). Thus, edge community assignments can be mapped back onto individual brain regions and, because every region is associated with $N-1$ edges, allow regions to simultaneously maintain a plurality of community assignments.

eFC matrix. Following the study, we calculated the eFC Matrix (Faskowitz et al., 2020). Nodes were the same as those in the nFC. The first step was to z-score each time series for all nodes. Next, for all pairs of nodes, we referred to the product of the elements-wise of their z-scored time series as 'edge time series', representing the magnitude of time-resolved co-fluctuation between node pairs. The final step was to calculate the element-wise product between pairs of edge time series, resulting in a set of co-fluctuation time series. See details in SM.

Overlapping community feature-Normalized entropy. Following a study (Faskowitz et al., 2020), the recommended modified k-means ($k = 10$, the clustering algorithm repeated 250 times) algorithm was applied to divide the eFC matrix into non-overlapping communities of co-fluctuating edges and then map the edge assignments back to a single node, yielding overlapping regional community assignments.

The normalized entropy indicates the distribution of edge community assignments and measures the extent to which region *i*'s community affiliations are distributed evenly across all communities or concentrated within a small number of communities. See details in SM.

Overlapping community features-Edge community profile similarity. We assigned each edge to a single community. These edge communities can be rearranged into the upper triangle of an N×N matrix, X, whose element x_{i-j} denoted the edge community assignment of the edge between nodes i and j. The i th column of X, edge community profile of nodes i, which we denote as $x_i = [x_{i-1}, \ldots, x_{i-N}]$, encodes the community labels of all edges in which node i participates.

From the X matrix, we extracted the edge community profile of nodes i and j and compared the edge community profile of nodes i and j by calculating the similarity of vectors x_i and x_j. Here, the edge community profile similarity of the edge between nodes i and j is the fraction of elements in both vectors with the same community label. That is:

$$S_{i-j} = \frac{1}{N-2} \sum_{u \neq i,j} \delta(x_{i-u}, x_{j-u})$$

Here, $\delta(x_{i-u}, x_{j-u})$ is the Kronecker delta and takes on a value of 1 when x_{i-u} and x_{j-u} were co-assigned to the same community but is 0 otherwise, and u is the third nodes. Note the normalization of over $N-2$ because we ignore the self-connection x_{i-i} and x_{j-j}. Repeating this comparison for all pairs of nodes generates the similarity matrix, $S = \{s_{i-j}\}$.

To understand which brain regions may be responsible for the group difference of the edge community profile similarity of the edge between nodes i and, S_{i-j}. We compared the edge community profile similarity of the edge between nodes i and j at each third brain nodes (u) and generated the edge community assignment similarity of the edge between nodes i and j at each third brain region (u), S_{i-u-j}.

All data were analyzed using MATLAB v2018a (MATLAB, MathWorks Inc., Natick, MA, PC), the Statistical Package for Social Science (SPSS v.22, Chicago, Illinois, PC), the Analysis of Functional Neuroimages (Version AFNI_18.2.03) (Cox, 1996), and the hBayesDM R package (Ahn, Haines, & Zhang, 2017) (https://cran.r-project.org/web/packages/hBayesDM/index.html).

Statistical analysis

We tested whether PIGD showed alterations in average net score, loss aversion, nFC, overlapping community features of eFC and effective connectivity. Correlations between loss aversion and overlapping community features of eFC networks were performed. Generalized mediation analysis of whether response consistency suppressed the association between loss aversion and overlapping community features of eFC networks in the PIGD. Calculated the effective connectivity using DCM analysis. Correlations between loss aversion and effective connectivity were also performed. Machine learning methods were used to test whether the loss aversion, overlapping community features of edge-centric functional networks, and effective connectivity could classify two groups. See details in SM.

Ethics

This study was approved by the Human Research Ethics Committee of the University of Science and Technology of China and the General Hospital of Beijing Military Region. Written informed consent was obtained from participants or their parents before the study. The research was conducted according to the principles of the Declaration of Helsinki.

RESULTS

Demographic results

There were no differences in demographic variables between groups. However, the PIGD significantly increased the symptom severity of the IGD (Table 1).

The IGT performance results

The average net score of the PIGD was significantly lower in the IGT ($t_{47} = 2.375, p = 0.022, , cohen's\ d\ = 0.680$, $95\ CI = [0.102, 1.259]$) (Fig. 2).

Computational modeling results

We used the Watanabe-Akaike Information Criterion (WAIC) (Watanabe, 2010) to compare the post-hoc fits of models (PVL-DecayRI model: $WAIC_{PIGD} = 7846.68$,

Table 1. Participants demographics and clinical variables

Demographics and Clinical Variables	Control-for-PIGD (n = 22)		PIGD (n = 27)		Test	p Value
	Mean	SD	Mean	SD		
Age, Years, Mean (SD)	20.500	3.098	19.704	3.244	$t_{47} = 0.872$	0.388
Education, Years, Mean (SD)	13.136	1.859	11.889	2.563	$t_{47} = 1.909$	0.062
Duration of Internet Gaming Exposure, years	0.511	0.933	2.676	1.827	$t_{47} = 5.041$	0.000
The longest Once Internet Gaming Exposure, hours	3.091	4.876	16.148	13.651	$t_{47} = 4.263$	0.000
Weekly Internet Gaming Exposure, hours	12.684	20.474	66.815	26.335	$t_{47} = 7.887$	0.000
Frequency of Weekly Internet Gaming Exposure	3.046	3.922	7.019	4.360	$t_{47} = 3.317$	0.002

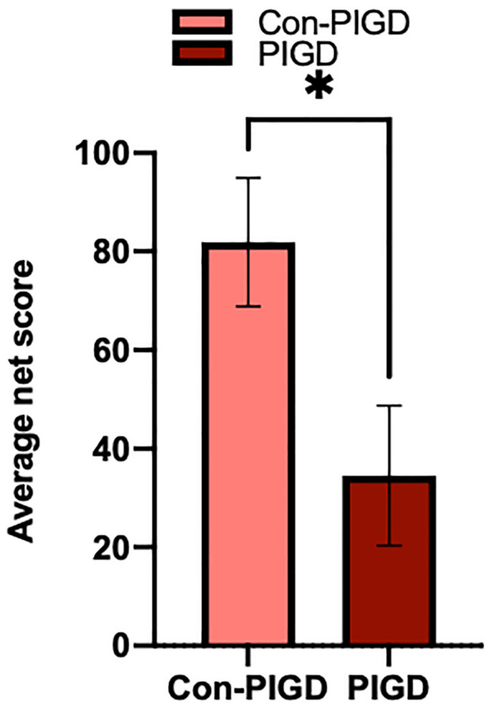

Fig. 2. **The performance of the IGT.** The average net score of the PIGD was significantly lower than that of the Con-PIGD in the IGT task. The error bars indicate the SEM. *: p<0.05

$WAIC_{Con-PIGD} = 5288.54$; PVL-Delta model: $WAIC_{PIGD} = 10573.7$, $WAIC_{Con-PIGD} = 7510.92$). Therefore, we chose second best-fit model, the PVL_DecayRI, to investigate loss aversion.

Loss aversion was significantly reduced in the PIGD ($t_{47} = 28.70, p<0.0001, cohen's\ d = 8.241, 95\ CI = [6.516, 9.968]$) (Fig. 3_a). The PIGD also showed reduced outcome sensitivity ($t_{47} = 14.81, p<0.0001, cohen's\ d = 4.253, 95\ CI = [3.241, 5.266]$) (Fig. 3_b). However, the remaining two parameters, response consistency and decay rate, were not significantly different between groups (Fig. 3_c, Fig. 3_d). The estimated loss aversion parameter in PVL-DecayRI model in our study is reliable, which can be replicated with PVL-delta model. Specifically, we also found significantly reduced loss aversion among PIGD compared to Con-PIGD ($t_{47} = 37.74, p<0.0001$, cohen's $d = 10.841, 95\ CI = [8.621, 13.100]$).

Simulations assess the accuracy of a model's predictions for the entire selection sequence based on the model parameters, independent of the subject's selection history. A posteriori prediction check can be used to evaluate whether the model produces valid predictions. The simulated data generated by the PVL-Decay model is similar to the real data of PIGD and Con-PIGD (Fig. 4_a, Fig. 4_b).

Results of the nFC

To test whether the PIGD altered the nFC network. We calculated the nFC of all node pairs and compared them between groups. To correct for the 4,005 independent tests, an alpha level of 1/4005 (p<0.0002) was used to declare significance for the local measures (Cocchi et al., 2012). As results, nFC weren't significantly different between groups.

Results of the overlapping community features of eFC networks

Overlap is inherent within the eFC construct. To capture the potentially meaningful overlapping community features of the eFC network, we measured the community overlap of the eFC at the level of individual brain regions (nodes) i.e., the normalized entropy.

We compared the normalized community entropy of each node between groups. To correct for the 90 independent tests, an alpha level of 1/90 (p<0.01) was used to declare significance for the local measures (Cocchi et al., 2012). We found that the normalized community entropy of the left triangle IFG was reduced significantly in the PIGD ($t_{47} = 2.643, p = 0.011, cohen's\ d = 0.759, 95\ CI = [0.177, 1.342]$) (Fig. 5_a, Fig. 5_b).

Furthermore, to investigate the internal overlapping community features of the left IFG at the level of the brain system, we calculated the average edge community profile similarity of all edges between the left IFG and all other nodes. Then compared the average edge community profile similarity of each edge between groups. To correct for the 89 independent tests, an alpha level of 1/89 (p<0.01) was used to declare significance for the local measure (Cocchi et al., 2012). As a result, the average edge community profile similarity of the edge between the left IFG and the right hippocampus ($S_{\text{left IFG–right hippocampus}}$) was reduced significantly in the PIGD ($t_{47} = 2.469, p = 0.011, cohen's\ d = 0.709, 95\ CI = [0.129, 1.289]$) (Fig. 5_c, Fig. 5_d).

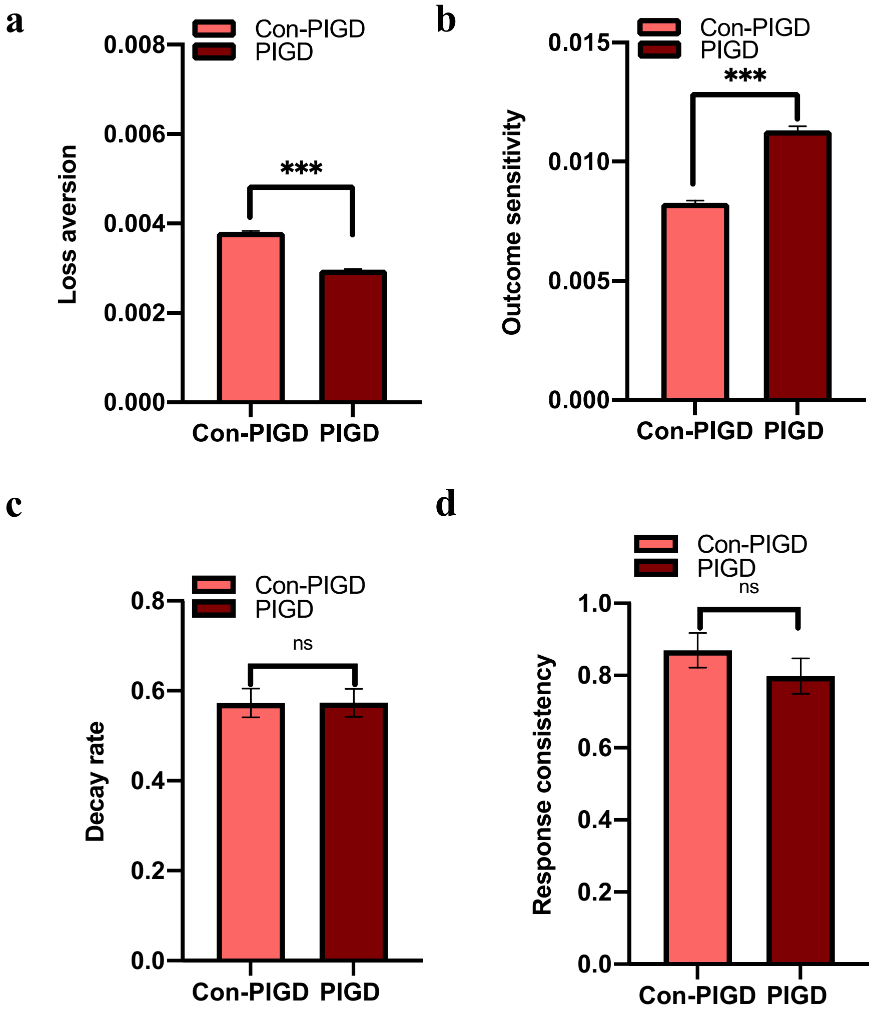

Fig. 3. **Behavioral modeling results. a.** The loss aversion parameter (λ) was significantly reduced in the PIGD. **b.** The outcome sensitivity parameter (α) was significantly reduced in the PIGD. **c-d.** The response consistency parameter (cons) and decay rate parameter (A), were not significantly different between the PIGD and the Con-PIGD. The error bars indicate the SEM. *: p<0.05; **: p<0.01; ***: p<0.001. ns: no significance

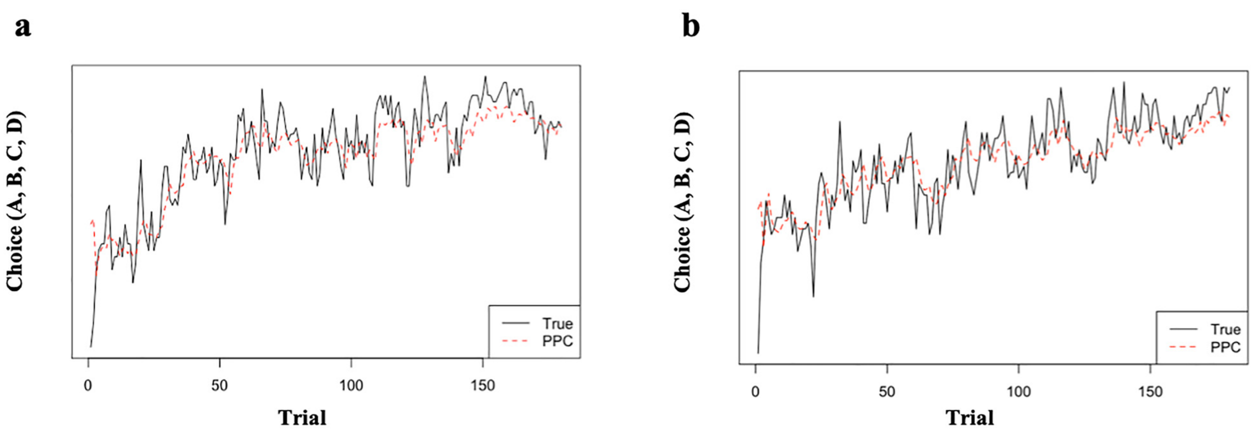

Fig. 4. **Posterior prediction checks (PPC) of the PVL-DecayRI model. a.** The posterior prediction checks for the Con-PIGD. **b.** The posterior prediction checks for the PIGD. Red dotted lines were simulated data and black lines were the true data. The simulated data were similar to the real data in both PIGD and Con-PIGD

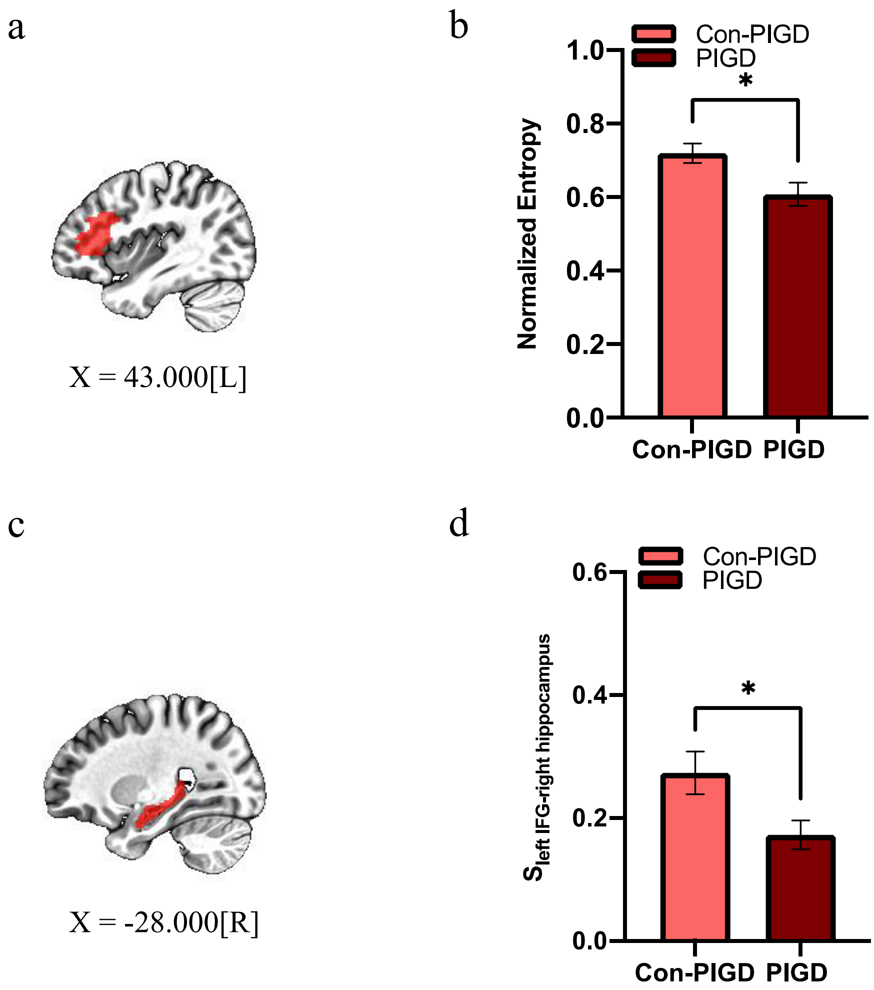

Fig. 5. **The Edge functional connectivity results. a.** The left triangle IFG was defined according to automated anatomical labeling (AAL) template labels. **b.** At the node level, the normalized community entropy within the left triangle IFG was significantly reduced in the PIGD compared to the Con-PIGD. **c.** The right hippocampus was defined according to the automated anatomical labeling (AAL) template labels. **d.** At the level of the brain system, the average edge community profile similarity of the edge between the left IFG and the right hippocampus ($S_{\text{left IFG–right hippocampus}}$) was significantly reduced in the PIGD compared to the Con-PIGD. The error bars indicate the SEM. *: p<0.05; **: p<0.01; ***: p<0.001; ns: no significance; R: right; L: left

To understand which nodes may be responsible for the group difference of the average edge community profile similarity of the edge between the left IFG and the right hippocampus ($S_{\text{left IFG–right hippocampus}}$). We compared the edge community profile similarity of the edge between the left IFG and the right hippocampus at each third node and found that the PIGD group showed significantly reduced edge community profile similarity of the edge between the left IFG and the right hippocampus at these nodes, including the right frontal inferior orbital gyrus $S_{\text{left IFG-right IFO-right hippocampus}}$ ($t_{47} = 2.948, p = 0.005, cohen's\ d = 0.846, 95\ CI = [0.259, 1.433]$) (Fig. 6_a), the right insular $S_{\text{left IFG-right insular-right hippocampus}}$ ($t_{47} = 2.551, p = 0.004,\ cohen's\ d = 0.869$, $95\ CI = [0.281, 1.458]$) (Fig. 6_b), the right caudate $S_{\text{left IFG-right caudate-right hippocampus}}$ ($t_{47} = 2.558, p = 0.014, cohen's\ d = 0.733, 95\ CI = [0.151, 1.315]$) (Fig. 6_c), the left amygdala $S_{\text{left IFG-left amygdala-right hippocampus}}$ ($t_{47} = 2.887, p = 0.006$, $cohen's\ d = 0.827, 95\ CI = [0.240, 1.413]$) (Fig. 6_d), the left hippocampus $S_{\text{left IFG-left hippocampus-right hippocampus}}$ ($t_{47} = 3.016, p = 0.004, cohen's\ d = 0.869, 95\ CI = [0.281, 1.458]$) (Fig. 6_e) the left frontal superior medial gyrus $S_{\text{left IFG-left MFG-right hippocampus}}$ ($t_{47} = 3.226, p = 0.002, cohen's\ d = 0.94$, $95\ CI = [0.347, 1.353]$) (Fig. 6_f).

Relationship between loss aversion and overlapping community features of edge-centric functional networks

What overlapping community features of the edge-centric functional networks are associated with loss aversion in the IGT? Follow-up correlation analysis indicated that in the Con-PIGD loss aversion was significantly positively correlated with $S_{\text{left IFG-right caudate-right hippocampus}}$ ($r = 0.596$, $p = 0.003$) (Fig. 7). However, there were no significant associations in the PIGD ($r = -0.016, p = 0.945$) (Fig. 7). Fisher r-to-z transformation were used to assess the significance of the difference between the two correlation coefficients. The PIGD and the Con-PIGD had a significantly

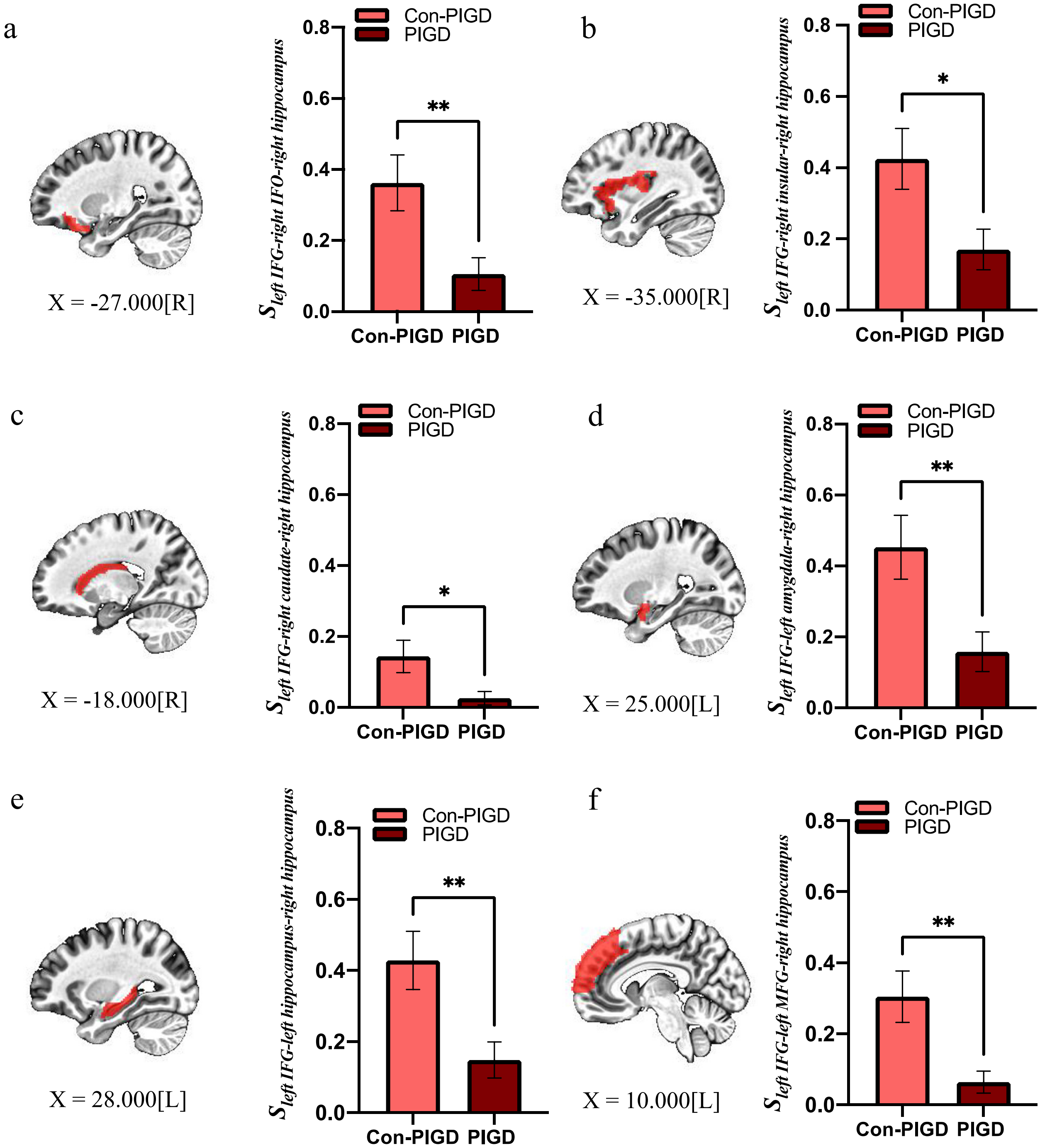

Fig. 6. **Edge community profile similarity of the edge between the left IFG and the right hippocampus at third nodes.** The PIGD group showed significantly reduced edge community profile similarity of the edge between the left IFG and the right hippocampus compared to the Con-PIGD at these nodes, including **a.** the right frontal inferior orbital gyrus ($S_{\text{left IFG-right IFO-right hippocampus}}$); **b.** the right insula ($S_{\text{left IFG-right insular-right hippocampus}}$); **c.** the right caudate ($S_{\text{left IFG-right caudate-right hippocampus}}$); **d.** the left amygdala ($S_{\text{left IFG-left amygdala-right hippocampus}}$)); **e.** the left hippocampus ($S_{\text{left IFG-left hippocampus-right hippocampus}}$); **f.** the left frontal superior medial gyrus ($S_{\text{left IFG-left MFG-right hippocampus}}$), which were defined according to the Automated Anatomical Labeling (AAL) template labels. The error bars indicate the SEM. *: p<0.05; **: p<0.01; ***: p<0.001. ns: no significance; R: right; L: left

different relationship between the $S_{\text{left IFG-right caudate-right hippocampus}}$ and the loss aversion the IGT ($z = 2.290, p = 0.022$) (Fig. 7). Loss aversion was linearly related to response consistency (Molins, Serrano, & Alacreu-Crespo, 2021). Response consistency was related to expected value and impulsivity (Lorains et al., 2014). To investigate whether response consistency mediated the suppressed association between loss aversion and the $S_{\text{left IFG-right caudate-right hippocampus}}$, we performed the generalized mediation analysis proposed by Wen et al. (Wen & Ye, 2014). As a result, the

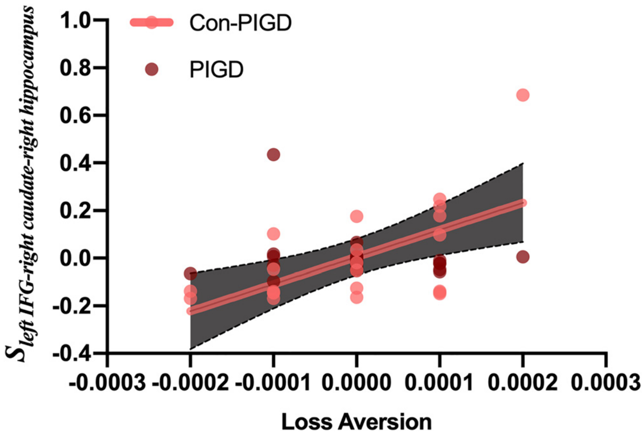

Fig. 7. **Relationship between the loss aversion and the $S_{\text{left IFG-right caudate-right hippocampus}}$.** Loss aversion was significantly positively correlated with the $S_{\text{left IFG-right caudate-right hippocampus}}$ in the Con-PIGD. However, there was no significant association in the PIGD. The dashed area in the panels shows the 95% confidence interval in the present study

response consistency was fully mediated the suppressed association between loss aversion and $S_{\text{left IFG-right caudate-right hippocampus}}$ in the PIGD $(a: 95\%\ CI\ [-0.761, -0.093], p = 0.002;\ b: 95\%\ CI\ [0.023, 0.765], p = 0.004; ab: 95\%\ CI\ [-0.405, -0.005], p = 0.106;\ c: 95\%\ CI\ [-0.263, 0.006], p = 0.199;\ c': 95\%\ CI\ [-0.129, 0.546], p = 0.420)$ (Fig. 8).

Result of the DCM

Whether changes in effective connectivity within loss-aversion-correlated overlapping community features of edge-centric functional networks was associated with loss aversion in the PIGD? We calculated the effective connectivity within these nodes 1) the left IFG; 2) the right hippocampus; and 3) the right caudate using the DCM. The PIGD significantly increased effective connectivity from the right hippocampus to the left IFG in the outcome phase ($t_{47} = 2.756$, $p = 0.008$, $cohen's\ d = 0.79$, $95\ CI = [0.207, 1.376]$). Correlation analysis indicated that loss aversion was significantly

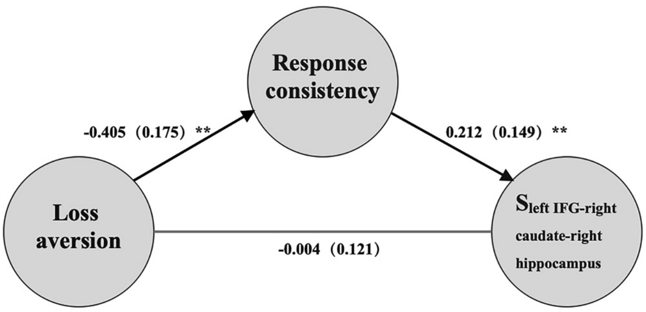

Fig. 8. **Generalized mediation result.** In the PIGD, the suppressed association between loss aversion and overlapping community features of the edge-centric functional network ($S_{\text{left IFG-right caudate-right hippocampus}}$) in the IGT was fully mediated by the response consistency. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

positively correlated with it $(r = -0.516, p = 0.006)$ in the PIGD. However, there was no significant association in the Con-PIGD $(r = -0.274, p = 0.218)$. And the Fisher r-to-z transformation result showed that there was no different relationship between groups $(z = -0.940, p = 0.347)$.

Results of machine learning classification

Machine learning methods were used to test whether the loss aversion, the $S_{\text{left IFG-right caudate-right hippocampus}}$, and the effective connectivity from the right hippocampus to the left IFG could classify the PIGD from the Con-PIGD. The area under the receiver operating characteristic curve (ROC_AUC) for classifying the PIGD versus Con-PIGD reached 0.85 (Fig. 9_a) and the accuracy of the classification reached 0.71, suggesting that loss aversion related behavioral and neuroimaging features provided a way to distinguish PIGD from Con-PIGD. We also performed a permutation test (permutation times = 1000) to validate this result and found that the accuracy of the classification mentioned above reached the top 1% in the random permutation distribution (permutation tests, 99th cutoff = 0.69, $p = 0.006$) (Fig. 9_b).

DISCUSSION

The present study results were consistent with our hypothesis. We found that the average net score of the IGT was significantly lower than that of the Con-PIGD, indicating that the PIGD group performed worse than the Con-PIGD in value-based decision-making. The PVL-DecayRI model was used to disentangle the underlying psychological processes involved in IGT performance. Consistent with our hypothesis, we observed a significantly reduced loss aversion in the PIGD group compared to the Con-PIGD group, suggesting that the reduced loss aversion may be a psychological mechanism for poor performance in value-based decision-making tasks. In addition, a study on value-based decision-making deficits also observed that gambling disorder and alcohol dependence exhibited reduced loss aversion compared to the healthy controls (Genauck et al., 2017). Therefore, our findings also suggested that the IGD, as a new behavioral addiction, is similar to other substance and other behavioral addictions, significantly reduced loss aversion in value-based decision-making.

Our study provided novel insights into the brain functional networks of the PIGD in the value-based decision-making from the perspective of the nFC and the eFC. nFC, is often interpreted as reflecting the time-averaged strength of “communication” between brain regions. Our findings demonstrated that reduced loss aversion in the PIGD is independent of the strength of communication in value-based decision making. eFC tracks how communication patterns evolve over time and ultimately assesses whether similar patterns are occurring in the brain simultaneously. Our findings showed the potential of the overlapping

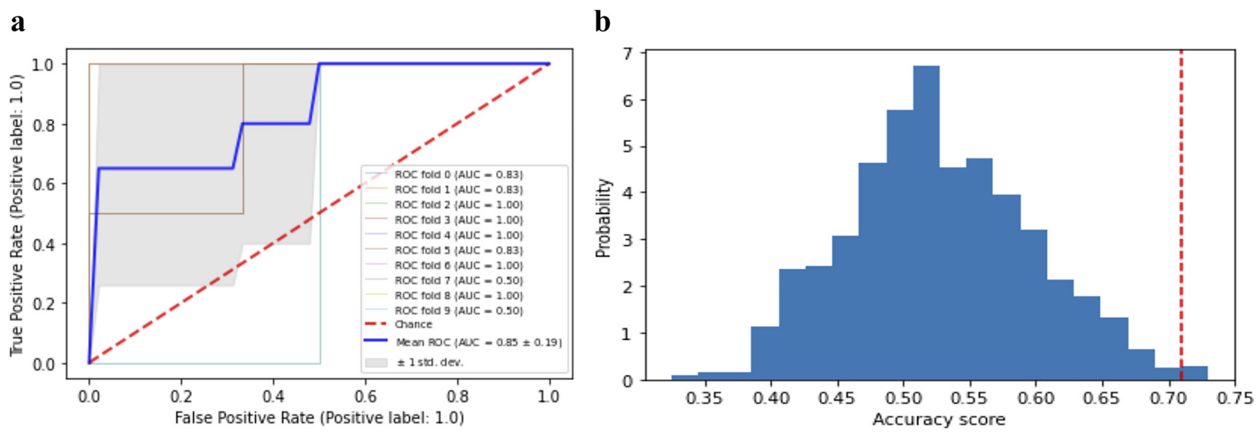

Fig. 9. **Machine learning classification results. a.** The area under the receiver operating characteristic curve (ROC_AUC) for classifying the PIGD versus Con-PIGD reached 0.85. Positive label: 1.0 means the result the classification prediction of PIGD and CON-PIGD was PIGD and counted it as 1. **b.** The permutation test result show that the accuracy of the classification mentioned above reached the top 1% in the random permutation distribution

community features to serve as biomarkers for the PIGD diagnosis. The edge community profile similarity of the edge between the left IFG and the right hippocampus at right caudate was significantly reduced in the PIGD, which suggested that function integration ability and diversity of the reward evaluation and processing network was reduced. The IFG mainly involved in the executive control processing of the sense of control over the gain/loss outcome and the evaluation of the gain/loss information (Friese, Binder, Luechinger, Boesiger, & Rasch, 2013; Lee, Chatzisarantis, & Hagger, 2016; Zhang, Hu, Wang, Wang, & Dong, 2020). The hippocampus participates in reward processing (Zarrindast, Nouri, & Ahmadi, 2007). The right caudate mainly involved in processing the magnitude of received losses (Volkow, Wang, Fowler, Tomasi, & Telang, 2011). Therefore, the left IFG, the right hippocampus, and the right caudate were part of an integral edge network involved in reward evaluation and processing. A possible mechanism is that response consistency suppressed the association between loss aversion and the overlapping community features of edge-centric reward evaluation and processing functional network. Response consistency measures the consistency of decision makers' choices with value expectations (Molins et al., 2021) and is related to impulsivity, which is common in IGD (Lorains et al., 2014; Zha et al., 2019). Furthermore, DCM result indicated that it may be due to the promoted bottom-up neuromodulation (right hippocampus to left IFG) in the PIGD. In other words, the motivation to obtain rewards represents a central feature of addictions and seems to be more pronounced with the PIGD. Meanwhile, the PIGD cannot process the sense of control over the gain/loss outcome and evaluate the gain/loss information well. This may be why the PIGD find it easy to indulge in the game and difficult to withdraw from playing games.

Our study has several theoretical implications. First, existing theories of IGD largely neglect decreased loss aversion in value-based decision-making. Reduced loss aversion in value-based decision-making also seems to be a general feature of IGD, like other addictive disorders (Balodis et al., 2012; Ersche et al., 2016; Fauth-Buhler & Mann, 2017; Yao et al., 2015; Yip et al., 2018). Therefore, more consideration of loss aversion in value-based decision-making might be valuable for both neurobiological and clinical research in IGD. Second, our results proposed an idea about IGD. IGD may not inhibit a specific cognitive function of the individual brain region, but by dispersing the edge network functions, thereby simultaneously processing multiple functional processes in a complex environment. Therefore, it is impossible to concentrate more resources on goal-directed cognitive control, such as value-based decision-making.

LIMITATIONS

First, the majority of the sample in the present study was male. Despite the fact that the ratio of female IGD patients in China is very low (Qi et al., 2016), we still tried to recruit some female patients. The ratio of female participants in the PIGD group was comparable with that in the healthy control groups. Second, loss aversion has not yet been used to directly compare the IGD to other addiction disorders. Future work is needed to directly investigate the similarities and differences in the loss aversion and related brain networks between behavioral and substance addiction. Third, IGT may not be the best paradigm to study loss aversion in value-based decision making. In order to deepen the research on loss aversion impairment in value-based decision-making of IGD, more other loss aversion related task paradigms and research methods would be adopted in the future research on loss aversion impairment in value-based decision-making of IGD. It may be helpful to further understand the mechanism of IGD and provide more evidence for the treatment of IGD.

CONCLUSION

PIGD performed worse in IGT. IGD, as a new behavioral addiction, is similar to the substance and other behavioral addictions, with significantly reduced loss aversion in value-based decision-making. The possible neural mechanism of reduced loss aversion in the PIGD was the reduction in communication patterns of the edge-centric reward evaluation and processing functional network (the left IFG, the right hippocampus, and the right caudate). Loss aversion, overlapping community features of the edge-centric reward evaluation and processing functional network (left IFG, right hippocampus, and right caudate), and bottom-up neuromodulation (right hippocampus to left IFG) in IGT may provide consistent and novel behavioral and neuroimaging evidence supporting loss aversion as a specific factor for distinguishing of PIGD from Con-PIGD. These findings may have important significance for understanding the definition and mechanism of IGD in the future.

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SUPPLEMENTARY MATERIAL

Supplementary data to this article can be found in a separate file: https://doi.org/10.1556/2006.2023.00014.

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