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RESEARCH REPORT

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Neural underpinnings of internet gaming addiction tendency: The role of the limbic network in reward/punishment sensitivity and risky decision-making alterations

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Abstract

Background and aims: Internet gaming addiction (IGA) is associated with altered reward/punishment sensitivity and risky decision-making. Nevertheless, the underlying neural mechanisms of such changes remain poorly understood. This study examined behavioral and neural predictors of IGA tendency with multiple datasets.

Design: Observational study.

Setting and participants: A total of 1142 university students [360 males and 782 females, mean (standard deviation) age of 18.75 (1.67) years] participated in the behavior-brain cross-sectional dataset (BBC). A subset of 303 BBC participants [71 males and 232 females, baseline mean age of 18.84 (1.72) years] participated in the behavior longitudinal dataset (BL).

Measurements: The Sensitivity to Punishment and Sensitivity to Reward Questionnaire (SPSRQ) assessed sensitivity to reward and punishment stimuli. The Internet Game Addiction Questionnaire assessed levels of addiction symptoms in the context of internet games. The Iowa Gambling Task (IGT) assessed risky decision-making behavior. Resting-state functional magnetic resonance imaging (MRI) data were preprocessed using standard pipelines and analyzed based on Yeo's seven-network parcellation template, with particular focus on the Limbic Network (LN) and its functional connectivity patterns. Statistical analyses included Spearman correlation, structural equation modeling and cross-lagged panel models.

Findings: Cross-sectional analyses revealed that the IGT net score (NS) was negatively associated with reward sensitivity (RS, rho = −0.181, $P = 0.022$), which was positively associated with punishment sensitivity (PS, rho = 0.125, $P < 0.001$). PS positively predicted IGA tendency ($\beta = 0.180$, $P < 0.001$). Additionally, LN strength exhibited a positive correlation with RS (rho = 0.077, $P < 0.001$) and a negative correlation with PS (rho = −0.045, $P = 0.090$). Moreover, the functional connectivity strength between LN and other functional networks was positively associated with RS. Longitudinal analyses demonstrated that (1) the IGT net score at the first time point (T1) negatively predicted RS at the second time point (T2, $\beta = -0.123$, $P = 0.031$), (2) RS at T1 positively predicted IGA tendency at T2 ($\beta = 0.100$, $P = 0.019$), (3) PS at T1 negatively predicted RS at T2 ($\beta = 0.085$, $P = 0.056$) and (4) LN strength at T1 directly predicted RS and PS at T1 (RS:

β = 0.126, P = 0.027; PS: β = −0.104, P = 0.064), as well as RS at T2 (β = 0.079, P = 0.080).

Conclusion: Internet gaming activity net score appears to be negatively correlated with reward sensitivity. Punishment sensitivity appears to be positively correlated with tendency toward internet gaming activity. There appears to be a positive correlation between reward sensitivity and punishment sensitivity.

KEYWORDS

functional magnetic resonance imaging (fMRI), internet gaming addiction tendency, limbic network, punishment sensitivity, reward sensitivity, risky decision-making

INTRODUCTION

Internet gaming has become popular in many societies [1]. Despite the various possible benefits of playing video games, their use can be highly rewarding, leading to people using them excessively and developing addiction-like symptoms in relation to video gaming [2, 3]. Consequently, the concept of internet gaming addiction (IGA) has garnered increased attention. IGA is a form of behavioral addiction characterized by a maladaptive dependence on internet games that manifests in typical addiction symptoms, such as salience, tolerance, conflict, inability to quit and loss of control [4, 5]. It is particularly prevalent among adolescents owing to their ongoing psychological development, rendering them more susceptible to the allure and adverse effects of internet gaming [6]. Studies have shown that IGA not only adversely impacts mental health, potentially leading to issues such as anxiety and depression [7, 8], but also alters brain function and structure [9, 10]. Nevertheless, as IGA lacks formal diagnosis with clear cut-offs and consensus criteria, we follow prior studies and treat it as a continuous concept—IGA tendency [11–13]. This approach avoids premature diagnosis using unverified standards and facilitates detecting neural and behavioral correlates before full IGA develops, supporting early intervention efforts.

Here, we seek to understand how IGA tendency unfolds by focusing on reward sensitivity and punishment sensitivity as key underlying mechanisms of addictive behaviors. This is because addictive behaviors, including internet-related addictive behaviors, may form through reward and punishment misjudgment [14, 15]. Reward sensitivity and punishment sensitivity impact an individual's response to positive or negative stimuli, respectively [16, 17]. These sensitivities are also closely tied to decision-making under risk [18], which is also an underlying cause of addictive behaviors [19]. Indeed, individuals with IGA often exhibit poor impulse control, high levels of psychological distress and cognitive deficits, including impaired decision-making abilities, characterized by weakened cognitive control, preference for immediate rewards and a disregard for potential punishment [11]. According to reinforcement sensitivity theory (RST) [20, 21], an individual's behavioral tendencies are modulated by their levels of reward and punishment sensitivity. Applied to video games, enhanced reward sensitivity can increase the motivation for gaming achievements, while reduced punishment sensitivity may diminish the awareness of negative consequences, perpetuating addictive behaviors [11, 22, 23].

Importantly, the limbic network (LN) modulates such sensitivities and risky behaviors. It does so through its core functions of emotional regulation, memory formation and reward processing [24]. Interacting dynamically with other networks, the LN plays a crucial role in IGA [25, 26]. The LN encompasses key brain regions involved in reward processing, emotional regulation and motivation, such as the prefrontal cortex, cingulate cortex, amygdaloid nuclear complex, limbic thalamus, hippocampal formation and nucleus accumbens [27, 28]. Consequently, changes in the functional connectivity within the LN can drive excessive sensitivity to gaming reward signals [29]. Neural activity patterns in the striatum and related areas within the LN differ when processing punishment (loss) versus reward (gain) signals [30], suggesting the subconscious processing of these signals and their translation into behavioral motivation via specific brain regions, such as the striatum and amygdala [31]. Moreover, the interplay of functional connectivity patterns between the LN and the salience network (primarily including the insula and anterior cingulate cortex) influences motivation and cognition, which can also impact addictive behaviors [32]. Disruptions in the functional connectivity of the reward network, particularly the ventral striatum, with the cognitive control network (mediated by the prefrontal cortex), may drive an imbalance between reward seeking and behavioral control in individuals with gaming disorders [33]. Therefore, abnormalities in the LN and its inter-network dialogs may represent important characteristics of the neuro-phenotype of IGA.

Despite existing research linking reward and punishment sensitivity, risky decision-making and IGA, gaps remain in our understanding of the interactive mechanisms and neural foundations of these relationships. Most studies thus far have used cross-sectional designs with separate emphases on behavioral or neural mechanisms, limiting the ability to form a more nuanced brain–behavior model of the contribution of reward/punishment sensitivity to IGA formation. The current study aims to bridge this gap by examining how reward and punishment sensitivity, alongside risky decision-making, influence IGA tendency in college students, while exploring the underlying neural mechanisms. Using a longitudinal design, we track behavioral changes in healthy young adults and analyze their dynamic relationship with IGA risk. Ultimately, this research seeks to elucidate the complex interplay among these factors, offering a robust theoretical and empirical foundation for understanding and addressing IGA tendency. Based

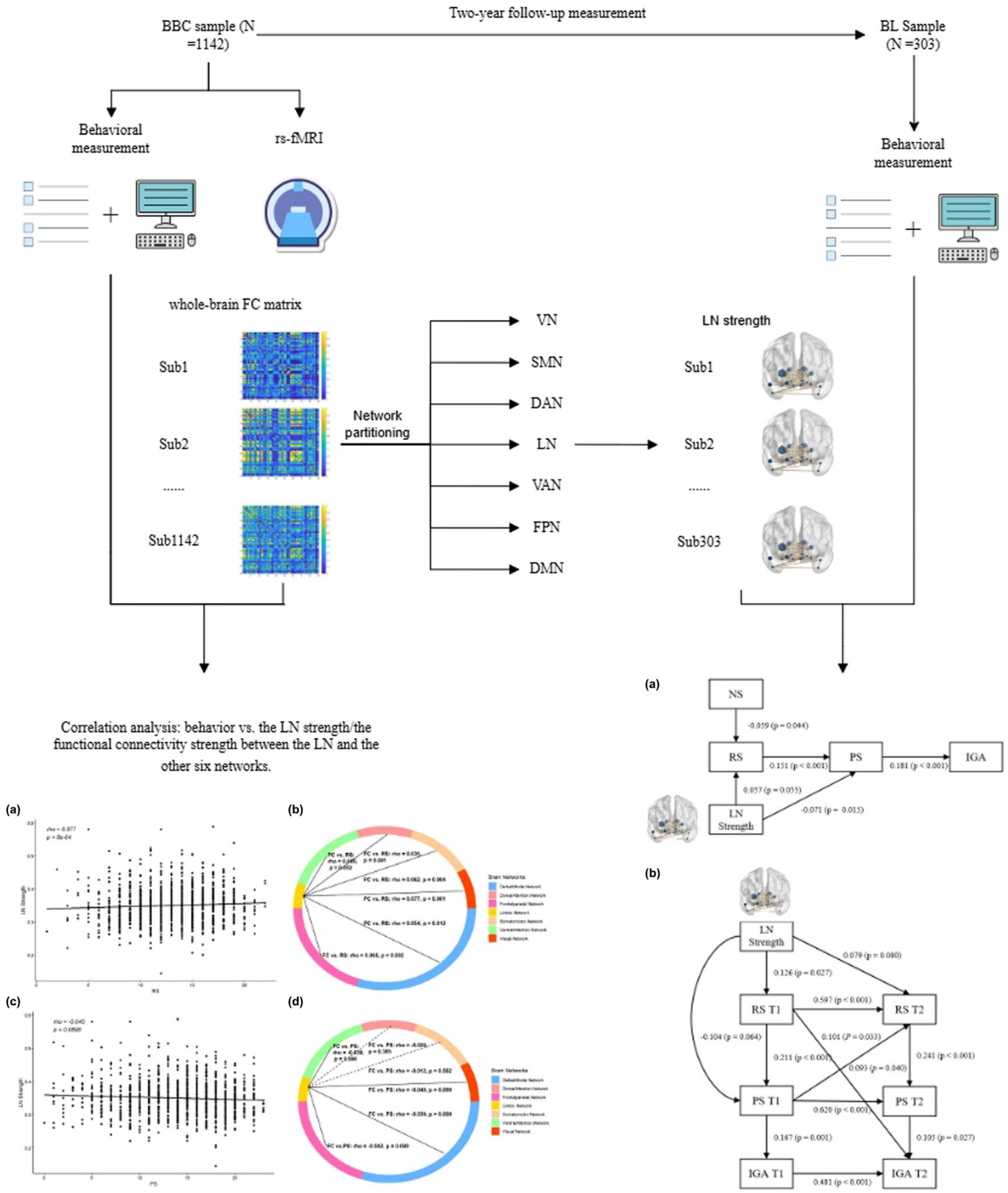

FIGURE 1 Framework for understanding the interplay between behavior and brain functional networks. BBC, behavior brain cross-sectional samples; BL, behavior longitudinal samples; DAN, dorsal attention network; DMN, default mode network; FC, functional connectivity; FPN, frontal parietal network; LN, limbic network; NS, net score on the Iowa gambling task; PS, punishment sensitivity; RS, reward sensitivity; SMN, somatomotor network; VAN, ventral attention network; VN, visual network.

on prior research, we hypothesize a positive association between reward and punishment sensitivity and both risky decision-making and IGA tendency. Additionally, risky decision-making and IGA tendency are also expected to show a positive association. Furthermore, we anticipate that the internal connectivity of the LN, as well as its functional connectivity with other brain networks, will be positively associated with reward sensitivity, risk preference and IGA tendency, but negatively correlated with punishment sensitivity. The research framework is illustrated in Figure 1.

METHODS

Participants

University students were recruited through announcements on dedicated university-wide online recruitment platforms as well as posters. The study was introduced as an online survey and an 8-minute resting-state magnetic resonance imaging (MRI) scan. It ran from September 2019 to December 2020 (T1). After excluding participants with inadequate questionnaire responses or suboptimal scan data (identified through visual inspection for scan quality or excessive head motion, defined as a mean displacement of >2 mm or over 30% scrubbed timepoints), 1142 participants were included in the behavior-brain cross-sectional (BBC) dataset. From October 2021 to December 2022 (T2), a follow-up survey was conducted with a subset of BBC participants. Out of the 338 individuals re-contacted, 303 met the data quality criteria and were included in the behavior longitudinal (BL) dataset. The study was approved by the local ethics committee, and all participants provided written informed consent prior to their participation.

Behavior measures

Sensitivity to punishment and sensitivity to reward questionnaire (SPSRQ)

The SPSRQ [17] was administered to assess an individual's sensitivity to reward and punishment stimuli. This scale comprises two dimensions: reward sensitivity (RS), assessing motivation levels and approach towards rewards; and punishment sensitivity (PS), measuring anxiety and avoidance behaviors in response to punishment cues. The questionnaire comprises 48 items, with respondents indicating 'yes' or 'no' for each item. In this study, the questionnaire had a Cronbach's alpha of 0.704 for RS and 0.821 for PS in the BBC sample, and 0.760 for RS and 0.861 for PS in the BL sample. These scores suggest the acceptable reliability and quality stability of this scale across time points and samples.

Internet game addiction questionnaire

The questionnaire devised by Zhou and Yang [34] was used to assess an individual's levels of addiction symptoms in the context of internet gaming. It includes eight items using a five-point Likert scale (scored from 1 to 5), yielding a total maximum score of 40. Elevated scores reflect a stronger inclination towards IGA. In this study, the questionnaire had a Cronbach's alpha of 0.913 in the BBC sample and 0.928 in the BL sample. These scores suggest the acceptable reliability and quality stability of this scale across time points and samples.

Iowa gambling task (IGT)

The IGT [35] was developed to examine decision-making behavior under conditions of risk and uncertainty. In this task, participants are required to repeatedly select from four decks of cards, with each selection resulting in a distinct combination of rewards and losses. Specifically, the high-risk decks (A and B) provide larger immediate gains but are accompanied by greater long-term losses, whereas the low-risk decks (C and D) yield smaller short-term gains yet lead to more stable and favorable long-term outcomes. The IGT consists of 100 trials. After each trial, immediate feedback shows the amount of money won or lost. The IGT is commonly used to investigate the cognitive and neural mechanisms underlying risky decision-making [36].

Image acquisition

All participants in this study underwent a resting-state functional MRI (fMRI) scan lasting 8 minutes using a 3T PRISMA scanner (Siemens, Erlangen, Germany). Participants were asked to open their eyes and not think about anything during the fMRI scan. A gradient echo planar imaging sequence was used to obtain 240 functional volumes. The scanning parameters are as follows: repetition time (TR) = 2000 ms, echo time (TE) = 30 ms, field of view (FOV) = 224 × 224 mm^2, flip angle (FA) = 90°, slices = 62, thickness = 2 mm, slice gap = 0.3 mm and voxel size = 2 × 2 × 2 mm^3. In addition, the magnetization prepared rapid acquisition gradient echo (MPRAGE) sequence was used to obtain high-resolution T1 weighted structural images. The scanning parameters are as follows: TR = 2530 ms, TE = 2.98 ms, FOV = 224 × 256 mm^2, resolution matrix = 448 × 512, FA = 7°, slices = 192, thickness = 1.0 mm, inversion time = 1100 ms and voxel size = 0.5 × 0.5 × 1 mm^3.

MRI data preprocessing

Preprocessing of the fMRI data was conducted using the SPM12 and CONN 20.b toolboxes. The steps included temporal alignment, field-based deformation correction and motion correction. Following these corrections, spatial normalization was carried out to match high-resolution anatomical images of individuals with functional images. These images were then segmented into regions comprising gray matter, white matter, cerebrospinal fluid, etc. The segmented images were normalized to the Montreal Neurological Institute (MNI) space using the Dartel process workflow, and subsequently smoothed with a 6-mm full width at half maximum (FWHM) kernel. The de-noising process entailed regressing out head motion parameters using the Friston 24-parameter model [37], which includes the six motion parameters, their derivatives and squared terms. Scrubbing was applied based on framewise displacement (FD > 0.5 mm), with flagged volumes and adjacent time points modeled as nuisance regressors [38]. The further removal of individual physiological noise and head motion artifacts was done using the aCompCor method [39], which extracts the first five principal components from both white matter and cerebrospinal fluid signals. Subsequently, the data underwent linear detrending and band-pass filtering (0.008–0.09 Hz).

Statistical analysis

All behavioral data preprocessing and related analyses were conducted using R 4.3.3 (R Foundation for Statistical Computing, Vienna, Austria). Structural equation modeling (SEM) and panel cross-lagged models were constructed using Mplus 8.3 for the BBC and BL samples. The horizontal model analyzes concurrent associations using cross-sectional between-subject data at one time point. In contrast, the vertical model examines dynamic changes and lagged causal effects using longitudinal within-subject data across multiple time points. Model fit was assessed using the chi-square to degrees of freedom ratio (χ^2/d.f.), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR). A value of below 3 for the χ^2/d.f. ratio indicates an acceptable fit. CFI and TLI values above 0.90 indicate a good fit. RMSEA values below 0.05 indicate a close fit and SRMR values below 0.08 indicate a good fit. A combination of strong RMSEA (<0.05) and CFI (>0.95) values is particularly useful for assessing fit quality [40]. Age and sex were included as covariates in all models.

For the fMRI data, whole-brain functional connectivity matrixes were computed using GRETNA 2.0.0, based on the AAL90 template [41]. Then, this study divided the whole brain into seven functional networks based on the network partitioning method proposed by Yeo *et al.* [42]: visual network (VN), somatomotor network (SMN), dorsal attention network (DAN), ventral attention network (VAN), limbic network (LN), frontal parietal network (FPN) and default mode network (DMN). We used the AAL90 template to delineate brain regions and calculated the LN strength as well as the functional connectivity strength between the LN and the other six networks. Data analysis was conducted using MATLAB 2023a. Subsequently, the correlation between LN strength, the functional connectivity strength of the LN with the remaining six networks and behavioral variables was analyzed using R 4.3.3. To control for potential false positives arising from multiple comparisons, the false discovery rate (FDR) procedure was applied to adjust the *P*-values for all relevant analyses and modeling conducted in this study. Age and sex were included as control variables in the correlation analyses and the structural equation modeling. Finally, LN strength was integrated into structural equation modeling (SEM) and panel cross-lagged models to reveal the underlying neural mechanisms behind the behavior. Statistical significance was determined at a bilateral *P*-value threshold of $\alpha = 0.05$. The research questions and statistical analysis plans for this study were not preregistered in a publicly accessible repository prior to data analysis. Accordingly, the results presented herein should be interpreted as exploratory.

RESULTS

Behavioral results

Participant characteristics

In the BBC sample, 1142 participants (360 males and 782 females) were included, with a mean (SD) age of 18.75 (1.67) years. Their RS had a mean (SD) score of 12.90 (3.75), their PS had a mean (SD) score of 13.86 (4.87), their IGT net score had a mean (SD) value of −5.21 (20.76) and their IGA score had a mean (SD) value of 13.82 (6.04). In the BL sample, 303 participants (71 males and 232 females) were followed up, with a baseline mean (SD) age of 18.84 (1.72) years. At baseline, the participants' RS had a mean (SD) score of 12.61 (3.60), PS of 14.44 (4.61), IGT net score of −3.88 (19.62) and IGA score of 13.81 (6.19). At follow-up, the RS was 12.13 (4.09), PS was 14.07 (5.41), IGT net score was −1.93 (23.03) and IGA score was 15.76 (7.00). Additionally, comparisons between the BBC and the BL samples on behavioral measures revealed that the BL sample showed significantly lower RS ($t = -3.133$, $P = 0.002$), higher IGT net scores ($t = 2.383$, $P = 0.017$) and higher IGA scores ($t = 4.796$, $P < 0.001$) compared with the BBC sample, while there was no significant difference in PS ($t = 0.649$, $P = 0.516$).

Correlation analysis of behavioral variables

Correlations are shown in Figure 2. The diagonal density plots indicate that the behavioral variables were not normally distributed. Thus, Spearman correlation analyses were employed. In the BBC sample, RS was positively correlated with PS (rho = 0.125, $P < 0.001$) and negatively correlated with NS (rho = −0.181, $P = 0.022$), while PS was positively correlated with IGA tendency (rho = −0.068, $P < 0.001$). In the BL sample, RS at T1 was positively correlated with PS at T1 (rho = 0.164, $P = 0.004$), and with RS at T2 (rho = 0.604, $P < 0.001$), PS at T2 (rho = 0.224, $P < 0.001$) and IGA tendency at T2 (rho = 0.162, $P = 0.005$). PS at T1 was positively correlated with IGA tendency at T1 (rho = 0.134, $P = 0.02$), and with RS at T2 (rho = 0.195, $P < 0.001$), PS at T2 (rho = 0.672, $P < 0.001$) and IGA tendency at T2 (rho = 0.153, $P = 0.008$). NS at T1 was negatively correlated with RS at T2 (rho = −0.133, $P = 0.021$), but was positively correlated with NS at T2 (rho = 0.231, $P < 0.001$) and IGA tendency at T2 (rho = 0.153, $P = 0.008$). IGA tendency at T1 was positively correlated with PS at T2 and IGA tendency at T2 (rho = 0.122, $P = 0.034$; rho = 0.525, $P < 0.001$). Additionally, RS at T2 was positively correlated with PS at T2 (rho = 0.371, $P = 0.021$) and IGA tendency at T2 (rho = 0.121, $P = 0.036$). PS at T2 was negatively correlated with NS at T2 (rho = 0.118, $P = 0.041$), but was positively correlated with IGA tendency at T2 (rho = 0.190, $P < 0.034$).

Behavioral models from horizontal and vertical perspectives

To further analyze the relationships between behavioral variables, this study constructed horizontal and vertical behavioral models based on the results of correlation analyses, as shown in Figure 3. The horizontal behavioral model (Figure 3a) demonstrated a good fit with the following fit indices: χ^2/d.f. = 1.419, CFI = 0.988, TLI = 0.979, RMSEA = 0.019 and SRMR = 0.021. The results indicate that NS negatively predicted RS ($\beta = -0.060$, $P = 0.058$), RS positively predicted PS ($\beta = 0.147$, $P < 0.001$) and PS positively predicted IGA tendency

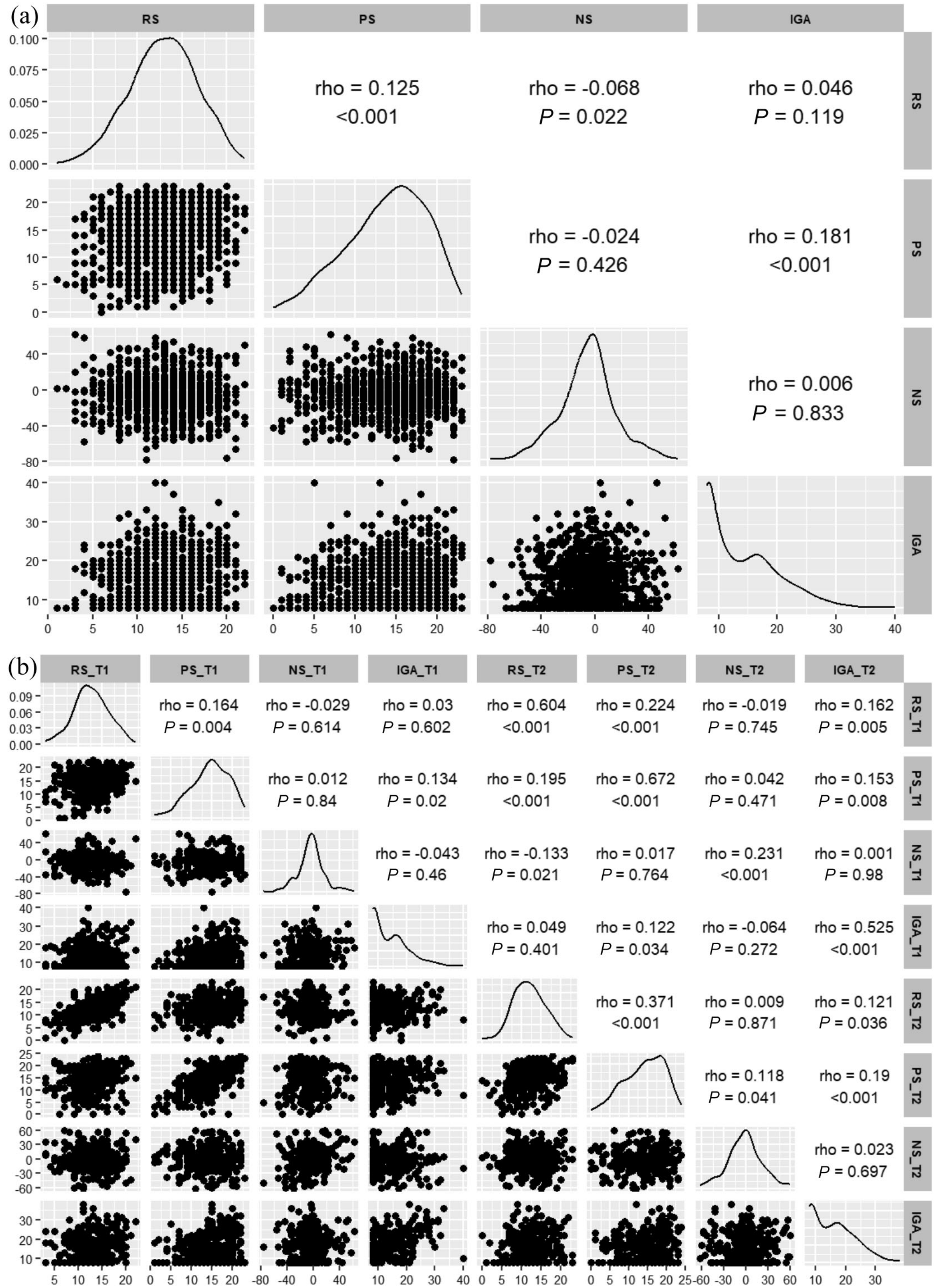

FIGURE 2 Distribution characteristics and correlation analysis of behavioral variables. Panels (a) and (b) illustrate the relationships and distribution patterns between behavioral variables in cross-sectional behavior and brain samples, as well as longitudinal behavior and brain samples. The rho values represent Spearman partial correlation coefficients calculated after controlling for age and sex. The diagonal elements display probability density plots, highlighting the distribution characteristics of each variable.

(β = 0.180, $P < 0.001$). The vertical behavioral model (Figure 3b) also demonstrated a good fit with the following indices: χ^2/d.f. = 1.638, CFI = 0.943, TLI = 0.907, RMSEA = 0.046 and SRMR = 0.038. The results show that NS at T1 negatively predicted RS at T2 (β = −0.123, $P = 0.031$), while RS at T2 positively predicted IGA tendency at T2 (β = 0.124, $P = 0.015$). The panel cross-lagged model for vertical behaviors (Figure 3c) also exhibited a good fit, with the following indices: χ^2/d.f. = 1.808, CFI = 0.981, TLI = 0.961, RMSEA = 0.052 and

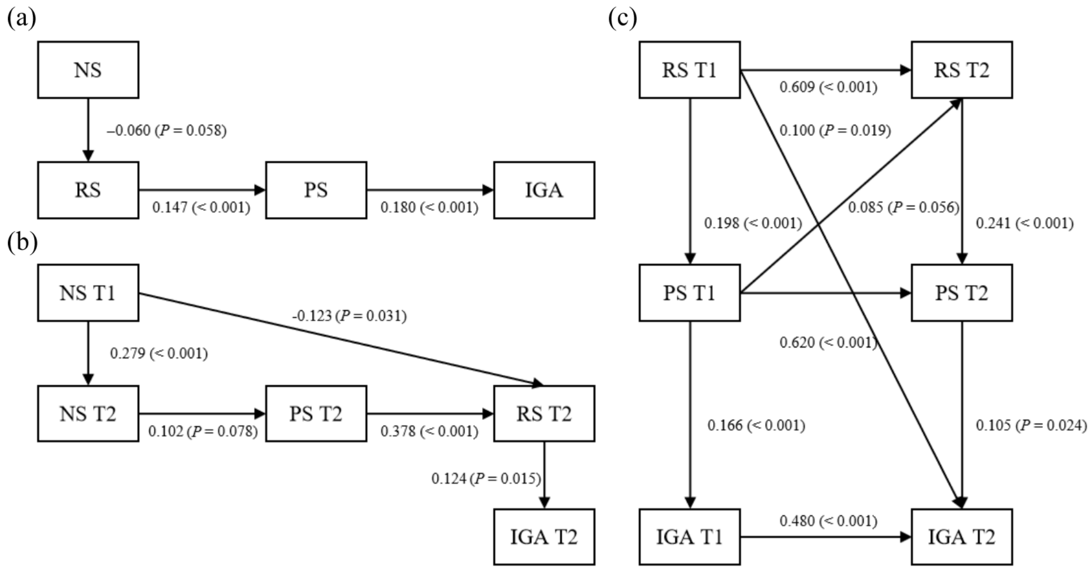

FIGURE 3 Structural equation models of the relationships between variables in horizontal and longitudinal behaviors. Panel (a) illustrates the significant and marginally significant relationships between variables in horizontal behaviors. Panels (b) and (c) both depict the significant and marginally significant relationships between variables in longitudinal behaviors. Specifically, panel (b) analyzes the influence path of the net score (NS) on the Iowa gambling task (T1) on internet gaming addiction (IGA) tendency (T2). Panel (c) presents a panel cross-lagged model involving reward sensitivity (RS), punishment sensitivity (PS) and IGA tendency across T1 and T2, which examines the causal relationships between variables at different time points, revealing dynamic interaction mechanisms among RS, PS and IGA tendency.

SRMR = 0.029. The results reveal that RS at both T1 and T2 positively predicted IGA tendency via PS (all $P < 0.05$), and the autoregressive effects of RS, PS and IGA tendency were all significant (all $P < 0.001$). Notably, RS at T1 directly and positively predicted IGA tendency at T2 ($\beta = 0.100$, $P = 0.019$), and PS at T1 positively predicted RS at T2 ($\beta = 0.085$, $P = 0.056$), which subsequently influenced PS and IGA tendency atT2.

Behavioral and neural results

Relationship predictions between the LN and behavioral outcomes

To elucidate the role of the LN in RS, PS and risky decision-making behavior, this study conducted a correlational analysis to examine the relationships between LN strength, the functional connectivity strength between the LN and six other major networks (DMN, DAN, FPN, SMN, VAN and VN), and their associations with RS, PS, NS and IGA tendency within the BBC sample. Following multiple comparison correction (FDR), LN strength was found to be significantly positively correlated with RS (Figure 4a, rho = 0.077, $P < 0.001$) and exhibited a marginally significant negative correlation with PS (Figure 4c, rho = −0.045, $P = 0.090$). Furthermore, the functional connectivity strength between the LN and the DMN, FPN, SMN, VAN and VN was positively associated with RS (Figure 4b), while the functional connectivity strength between the LN and the DMN, FPN, VAN and VN displayed marginally significant negative correlations with PS (Figure 4d). However, no significant associations were found between NS/IGA tendency and LN strength, nor between NS/IGA tendency and the functional connectivity strength between the LN and six other major networks. The detailed results are presented in Figure 4.

Brain–behavior modeling in BBC and BL samples

To further explore the potential mechanisms of the LN in the cross-sectional and longitudinal behavioral models, this study also constructed structural equation models. Based on the behavioral models and correlational analysis results of the LN, models with poor fit and variables (including the functional connectivity between the LN and the other six major networks) were excluded. In the BBC sample (Figure 5a), LN strength positively predicted RS ($\beta = 0.057$, $P = 0.055$) and negatively predicted PS ($\beta = -0.071$, $P = 0.015$). The model fit indices were χ^2/d.f. = 1.314, CFI = 0.990, TLI = 0.982, RMSEA = 0.017 and SRMR = 0.018. Further analysis revealed that in the BL sample (Figure 5b) the LN strength at T1 directly positively predicted RS at T1 ($\beta = 0.126$, $P = 0.027$), negatively predicted PS at T1 ($\beta = -0.104$, $P = 0.064$) and positively predicted RS at T2 ($\beta = 0.079$, $P = 0.080$). The model fit indices were χ^2/d.f. = 1.489, CFI = 0.986, TLI = 0.973, RMSEA = 0.040 and SRMR = 0.030. Detailed model results (path coefficients and P-values) are shown in Figure 5.

DISCUSSION

This study employed both cross-sectional and longitudinal designs to investigate relationships among RS, PS, risky decision-making and IGA

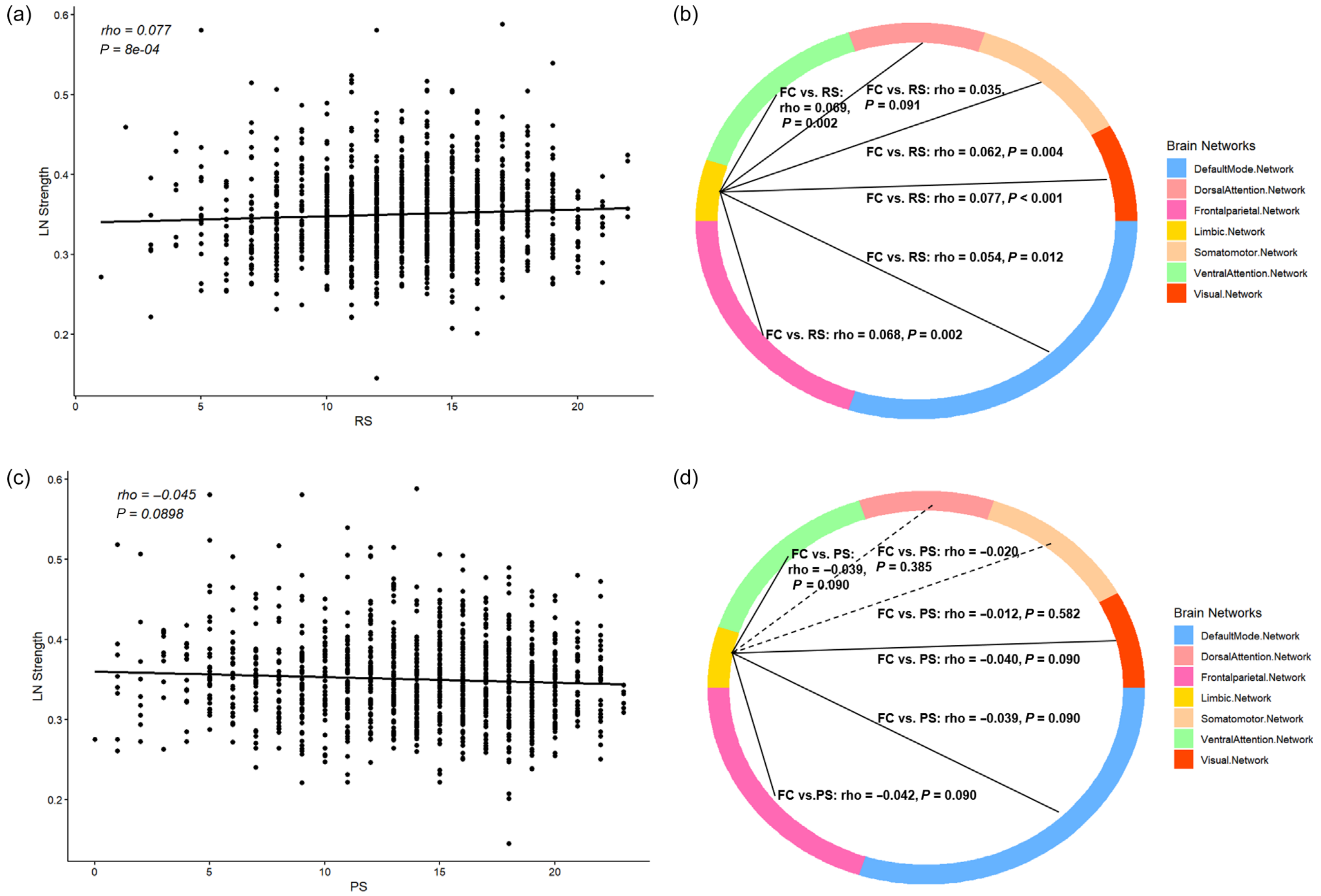

FIGURE 4 Correlation analysis of limbic network (LN) strength (and its functional connectivity with other networks) in relation to reward sensitivity (RS) and punishment sensitivity (PS) in the cross-sectional sample. Panels (a) and (c) illustrate the Spearman partial correlation results of LN strength with RS and PS, respectively. Panels (b) and (d) display the Spearman partial correlation results between the LN and the functional connectivity of six other major networks with RS and PS (FC vs RS/PS), respectively. In addition, solid black lines indicate functional connectivity between networks, while dashed lines represent non-significant correlations. All correlation analyses controlled for age and sex, and false discovery rate (FDR) correction was applied to adjust the *P*-values for multiple comparisons. FC, functional connectivity; rho, Spearman partial correlation coefficient.

tendency, while also exploring the neural underpinnings (especially the LN) of changes in RS and PS. Cross-sectional data reveal a significant positive correlation between RS and PS, while NS was negatively correlated with RS, and PS was positively correlated with IGA tendency. Longitudinal data further demonstrate the temporal stability of RS and PS across time points, as well as their predictive effects on IGA tendency. Neuroimaging analyses indicated that the internal connectivity strength of the LN and its functional connectivity with major networks, such as the DMN and the FPN, were significantly positively correlated with RS, while showing marginally significant negative correlations with PS. Additionally, cross-lagged panel models highlighted the potential mechanistic role of LN strength in behavioral traits, supporting its critical function in reward and punishment processing.

The behavioral results indicate that RS and PS play crucial roles in driving IGA tendency. The positive correlation between RS and PS suggests that individuals with high RS may also be more attuned to punishment signals. This dual sensitivity could lead them to excessively pursue gaming rewards while neglecting the potential negative consequences of their gaming behaviors. According to the dual-systems model, RS and PS may be co-activated, reflecting an approach–avoidance conflict that leads individuals to experience internal struggle between the attraction of rewards and the threat of punishment [43]. The escalating conflict between rewards and punishments may result in approach–avoidance conflict, which could provoke anxiety and yet still lead to risk-taking [44]. The finding that risky decision-making ability negatively predicts RS further indicates that deficiencies in risky decision-making may impair an individual's ability to evaluate the negative consequences of gaming behavior, thereby increasing the risk of IGA [45, 46]. Longitudinal data further reveal the predictive roles of RS and PS in driving IGA tendency across time points. Specifically, RS at T1 significantly positively predicts IGA tendency at T2, while PS at T1 indirectly influences IGA tendency at T2 by positively predicting RS at T2. This suggests that high RS may directly drive an individual's ongoing pursuit of gaming rewards, whereas high PS may indirectly exacerbate IGA tendency by enhancing RS. These findings underscore the long-term impacts of RS

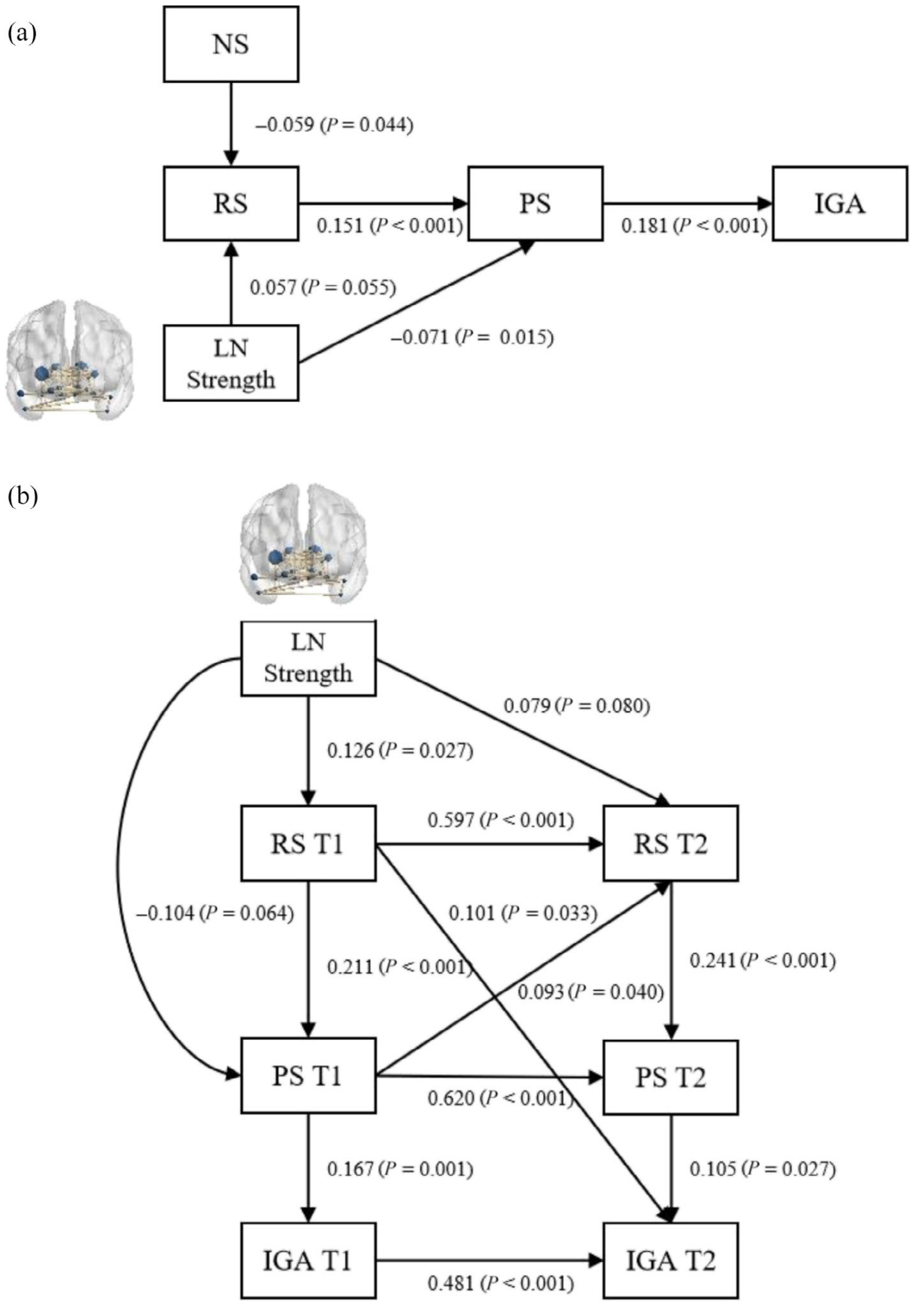

FIGURE 5 Structural equation model of LN strength and behavioral variables. Panel (a) illustrates the cross-sectional relationship between behavior and LN strength. Panel (b) illustrates the longitudinal relationships between behavioral and brain measures using a panel cross-lagged model. IGA, internet gaming addiction; LN, limbic network; NS, net score on the Iowa gambling task; PS, punishment sensitivity; RS, reward sensitivity; T1, timepoint 1; T2, timepoint 2.

and PS in the formation and maintenance of IGA tendency, as well as their dynamic interaction mechanisms. Although direct related literature is scarce, previous studies have touched upon these aspects [25, 47, 48]. This dynamic interaction mechanism provides a new perspective for understanding the multifactorial model underlying IGA.

Neuroimaging analyses indicate that the LN plays a crucial role in reward processing, and through this can elevate IGA tendency. Research has found a significant positive correlation between the internal connectivity strength of the LN and RS, likely reflecting the key role of LN structures such as the striatum and amygdala in processing reward signals [49]. Specifically, the level of activation in the LN, particularly involving the ventral striatum and orbitofrontal cortex, may affect an individual's expectations and perceptions of various rewards, thereby making them more inclined to pursue these rewards when faced with temptations [50]. This phenomenon is especially pronounced among adolescents and young adults, correlating with their neurodevelopmental stage and the heightened activity of their emotional and reward systems [51]. Furthermore, the functional connectivity between the LN and other networks, especially the DMN and FPN, correlates positively with RS, highlighting their joint role in reward processing [52, 53]. Additionally, structural equation modeling shows that LN strength positively predicts RS and negatively predicts PS, suggesting that LN internal connectivity may indirectly affect IGA risk by influencing both RS and PS. This highlights the key role of the LN in reward processing and the reward system [25, 54]. Therefore, interventions targeting LN activity and connectivity through, for instance, neurofeedback and non-invasive brain stimulation may help normalize reward processing circuits. Additionally, cognitive behavioral therapy can modulate an individual's RS and PS to mitigate maladaptive gaming behaviors. Early identification of heightened sensitivity traits could facilitate preventative strategies. Integrating neurobiological and behavioral approaches holds promise for enhancing treatment outcomes in IGA.

This study has some limitations that should be addressed and expanded upon in future research. First, the sample mainly included healthy young individuals. While this focus can expose the early onset of IGA mechanisms, we call for future research to involve clinical populations, such as patients diagnosed with IGA and different age groups, to increase generalizability and clinical relevance. Second, this study utilized resting-state fMRI, which captures overall brain connectivity but not neural activity during specific cognitive tasks. Future research can incorporate task-based fMRI to better elucidate the dynamic neural mechanisms of IGA. Third, in this study the panel data included only two time points, limiting the in-depth analysis of dynamic relationships and the ability to separate within-person changes from stable between-person differences. Future research should use more waves of data to apply methods like the random intercept cross-lagged panel model (RI-CLPM), enabling the clearer distinction between stable traits and dynamic changes, thereby enhancing causal inference. Fourth, the IGA tendency was measured using a domestic questionnaire targeting Chinese adolescents, suitable for this context but focused on subclinical behaviors rather than clinical diagnosis. Future studies should use internationally recognized scales like the Internet Gaming Disorder - 20 (IGD-20) test to enhance measurement accuracy and cross-cultural validity. Additionally, most correlation and path coefficients in this study are small, so the practical significance warrants cautious interpretation. Nonetheless, these subtle associations still provide valuable insights into the behavioral and neural mechanisms of IGA tendency in healthy university students. Future research should use larger, more diverse samples and improved methods to strengthen the results.

CONCLUSION

This study delves into the complex relationships among RS, PS, risky decision-making and IGA tendency, as well as the neural bases of these behavioral characteristics, with an emphasis on the LN. Behavioral results indicate that the interplay among RS, PS and risky decision-making can drive IGA progression. Neuroimaging analyses further highlight the critical functions of the LN in reward processing and emotional regulation, suggesting that its connectivity patterns may indirectly impact IGA tendency. By integrating behavioral and neuroimaging data, this study extends the nomological network of IGA tendency. It points to a novel brain–behavior mechanism for the development of IGA tendency. This extension is important because it unravels the key neural underpinnings of RS and PS, pointing to possible interventions that should be examined in future research.

AUTHOR CONTRIBUTIONS

Jingzhen He: Conceptualization (equal); formal analysis (lead); methodology (equal); writing—original draft (lead). **HaiChao Zhao:** Conceptualization (equal); methodology (equal). **Ofir Turel:** Methodology (equal); writing—original review and editing (supporting). **Shuyue Zhang:** Methodology (equal). **Xu Lei:** Conceptualization (equal). **Jiang Qiu:** Methodology (equal). **Tingyong Feng:** Conceptualization (equal); methodology (equal). **Hong Chen:** Methodology (equal). **Qinghua He:** Conceptualization (equal); data curation (lead); funding acquisition (lead); methodology (equal); writing—original review and editing (lead).

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DECLARATION OF INTERESTS

None to declare.

DATA AVAILABILITY STATEMENT

Researchers who require access may contact us via email, and we will provide the corresponding data and code based on the specific requests.

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