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FULL-LENGTH REPORT

Trait anxiety and corresponding neuromarkers predict internet addiction: A longitudinal study

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ABSTRACT

Background and Aims: The high prevalence of internet addiction (IA) has become a worldwide problem that profoundly affects people's mental health and executive function. Empirical studies have suggested trait anxiety (TA) as one of the most robust predictors of addictive behaviors. The present study investigated the neural and socio-psychological mechanisms underlying the association between TA and IA. *Methods:* Firstly, we tested the correlation between TA and IA. Then we investigated the longitudinal influence of TA on IA using a linear mixed effect (LME) model. Secondly, connectome-based predictive modeling (CPM) was employed to explore neuromarkers of TA, and we tested whether the identified neuromarkers of TA can predict IA. Lastly, stressful life events and default mode network (DMN) were considered as mediating variables to explore the relationship between TA and IA. *Findings:* A significant positive correlation between TA and IA was found and the high TA group demonstrated higher IA across time. CPM results revealed that the functional connectivity of cognitive control and emotion-regulation circuits and DMN were significantly correlated with TA. Furthermore, a significant association was found between the neuromarkers of TA and IA. Notably, the CPM results were all validated in an independent sample. The results of mediation demonstrated that stressful life events and correlated functional connectivity mediated the association between TA and IA. *Conclusions:* Findings of the present study facilitate a deeper understanding of the neural and socio-psychological mechanisms linking TA and IA and provide new directions for developing neural and psychological interventions.

KEYWORDS

IA, TA, functional connectivity, stressful life events, DMN, control circuit, emotion-regulation circuit

INTRODUCTION

The internet has reached more than 40% of the global population, and this phenomenon has been promoted with the development of mobile devices (Montag et al., 2018; Wolniewicz, Tiamiyu, Weeks, & Elhai, 2018). The development of the internet has played a positive role in education, leisure and information dissemination, although it has also been accompanied by the emergence of more widespread addiction disorders, such as IA and online gaming addiction (Aziz, Nordin, Abdulkadir, & Salih, 2021; Y. C. Pan, Chiu, & Lin, 2020), with an estimated prevalence of approximately 2% in the world's adult population (Kuss & Lopez-Fernandez, 2016; Poli, 2017; Wu et al., 2022). IA is a behavioral addiction characterized by compulsive, uncontrollable internet use that interferes with daily life (Poli, 2017). Previous studies have concluded that this disorder is associated with interpersonal problems (Chou et al., 2017), depression (Dieris-Hirche et al., 2017), anxiety (Arcelus et al., 2016), perceived stress (Canale et al., 2019), and problems with executive function such as suppression of cognitive, emotional, and behavioral (central executive) responses and that it also affects

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attention (Argyriou, Davison, & Lee, 2017; Nikolaidou, Fraser, & Hinvest, 2019). In the present study, we sought to characterize the relationship between TA and IA.

TA is a personality trait considered as a permanent psychological characteristic (Spielberger, 1966). It refers to a stable tendency to focus on and experience negative emotions in a variety of situations (Gidron, 2013). Previous studies have revealed a link between a higher level of TA and substance use disorders, such as alcohol, drug (Kushner, Krueger, Frye, & Peterson, 2008; Lai, Cleary, Sitharthan, Hunt, & dependence a, 2015; Litt, Cooney, & Morse, 2000). Similarly, recent studies have shown that TA is a strong personality factor for online gaming and social media addictions (Mehroof & Griffiths, 2010; Nikbin, Iranmanesh, & Foroughi, 2021). Thus, TA is widely considered to be a robust predictor of addictive behavior. However, these findings mostly indicate a positive relationship between TA and behavior disorders but have yet to establish the underlying mechanisms reliably (Kim et al., 2019; Y. Li, Li, Liu, & Wu, 2020; Yang, Zhou, Liu, & Fan, 2019; R. Zhang & Volkow, 2019).

Many previous studies have focused on the neural basis of anxiety. Generally, affective and cognitive control-related networks, such as the DMN, have been shown to be dysregulated in anxiety disorders (Janiri et al., 2020; Kolesar, Bilevicius, Wilson, & Kornelsen, 2019; McTeague et al., 2017). A meta-analysis concluded that task-related brain activity converges in regions associated with inhibitory control among anxiety disorders (Janiri et al., 2020). Additionally, the insular, prefrontal, and subcortical regions (particularly the hippocampus) as well as the anterior cingulate regions are the regions displaying significant neural phenotypes for anxiety disorders (Etkin, 2009; Janiri et al., 2020; Phillips, Drevets, Rauch, & Lane, 2003). Specifically, these regions significantly support the function of adaptive regulation (Kenwood, Kalin, & Barbas, 2022; Klumpp et al., 2017; Korotkova et al., 2018; Kouneiher, Charron, & Koechlin, 2009; Shackman et al., 2011; Teicher, Samson, Anderson, & Ohashi, 2016). Taken together, the evidence indicated that brain regions associated with TA are involved in the processes of executive control and emotional regulation. These processes have been emphasized to be impaired in studies on addictive behavior (Christensen et al., 2023; Marchica, Mills, Derevensky, & Montreuil, 2019). Accordingly, it would be valuable to explore the neural markers of TA and verify the predictive ability of these markers for IA.

Stressful life events have been proven to impair cognitive control (Wolff et al., 2021). Notably, some researchers have proposed a theory of compensatory internet use to explain the mechanism of IA (Kardefelt-Winther, 2014). This theory holds that negative life conditions will generate the motivation to use the internet to relieve negative emotions and emphasizes that negative life conditions are the root of the problem (Kardefelt-Winther, 2014). Accordingly, we are intrigued to speculate that high TA individuals are prone to perceive more negative impact introduced by adverse life experiences and thus further trigger more IA to cope with these stressful events. Moreover, stressful experiences modulate neuro-circuitry function heavily, which depends on processes that are engaged during resting-state, through active recollection of past experiences and anticipation of future events, all known to involve the DMN. A review of addictive behaviors revealed that aberrant patterns of brain functional connectivity in the DMN are associated with craving and relapse related to addictive behaviors, and that the resting functional connectivity of the anterior DMN, which is involved in impaired emotion regulation, was found to have decreased in addicted individuals (R. Zhang & Volkow, 2019). Thus, we further explored whether the functional connectivity of the DMN mediates the relationship between TA and IA.

Overall, despite extensive research investigating the neural basis of TA, few studies have explored the neural mechanisms by which TA predicts IA (Weinstein & Lejoyeux, 2010). Identifying neurobiological markers that can explain the mechanisms above-mentioned could contribute to improved approaches for predicting the emergence and development of addictive behaviors. Notably, most previous studies focusing the relationship between TA and IA employed a small sample size, and thus, the interpretations of the findings should be treated with caution. Moreover, the most previous studies focused on a cross-sectional design, which can hardly achieve the purpose of examining the direction of effects in a relationship between variables. Thus, we collected the resting-state functional MRI (fMRI) data for a longitudinal sample in this study.

Based on the aforementioned literature, the present study aimed to investigate the neural and socio-psychological mechanisms underlying the association between TA and IA. We first evaluated the predictive role of TA on IA and determined the difference of dynamic trajectory of addictive behavior across time for different severity of TA. In addition, we identified neuromarkers of TA and subsequently tested whether the discovered neuromarkers of TA can predict IA. Lastly, we paid particular attention to the role of stress life events and the functional connectivity of the DMN between TA and IA to reveal the socio-psychological mechanism of the effect of TA on IA. We hypothesized that high TA is a risk factor for addictive behaviors and that expression of neuromarkers of TA in regions related to the abilities of control and emotion regulation can predict IA as well. Moreover, we speculated that stress life events and the functional connectivity of the DMN might play key roles in the relationship between TA and IA.

METHODS

Participants

Participants recruited as part of two larger investigations were included in this study to be considered as two independent samples. The recruiting program and exclusion procedures for these larger investigations were described in detail elsewhere (Q. Chen et al., 2018; W. Liu et al., 2017). Participants with excessive head motion and who did not have behavioral data were excluded. The test sample consisted of 666 healthy undergraduates who completed the TA assessment. Of these, 446 and 483 also completed the IA and the stressful life events assessments, respectively. The validation sample included 127 students who completed all sessions, 538 participants who completed TA questionnaires and MRI scanning and 376 participants who completed IA questionnaires at time point 1. The average interval between the first scan and the second scan was 817.87 days.

In this study, TA was measured using the Spielberger State-TA Inventory (S-TAI) questionnaire (Spielberger, 1983) and the Adolescent Self-Rating Life Events Check-List (ASLEC) was used to evaluate the stressful life events (X. Liu, Liu, Yang, & Zhao, 1997). IA severity of participants measured by the Questionnaire of internet Addiction Tendency among the undergraduates (IUS) in the test sample and the Internet Addiction Test (IAT)in the validation sample respectively. Details of each test and the comparison of the IUS and IAT are provided in supplementary material Method S1 and S2.

All participants from the test and validation samples were right-handed, and none of them had a history of psychiatric or neurological illnesses and provided informed consent in writing prior to the experiment and were compensated with money at the end of the study.

fMRI data acquisition and analysis

Image acquisition and preprocessing. At the Southwest University Brain Imaging Center, 8 min of resting-state fMRI scanning was completed for all participants on a 3T Trio scanner (Siemens Medical Systems, Erlangen, Germany). The resting-state fMRI data were analyzed using the Data Processing Assistant for resting-state fMRI on SPM8 (Chao-Gan & Yu-Feng, 2010). The processing procedure included the following steps: removal of the first 10 volumes, correction of slice timing and head motion, spatial normalization, nuisance signal regression, data scrubbing, spatial smoothing, and band-pass filtering. The detailed scanning parameters are provided in the supplementary material (see Method S3).

Functional connectivity. Whole-brain functional connectivity was analyzed on the Graph Theoretical Network Analysis (GRETNA) platform for each participant (Wang et al., 2015). Power, Schlaggar, Lessov-Schlaggar, and Petersen (2013) defined a 264 putative functional area template that was used to identify nodes in the whole-brain network. The time courses for each region of interest (ROI) were extracted, and the Pearson correlation coefficients between each pair of ROIs were calculated to generate a 264×264 correlation matrix for each participant. We constructed a brain network consisting of the 264 brain regions connected by 34,716 functional connectivity links. Additionally, Power's 264-region atlas divided all 264 nodes into 13 functional networks, and the DMN was chosen to enter into the follow-up mediation analysis. Detailed information regarding how the within-network connectivity of the DMN was calculated is provided in the supplementary material (Method S4).

CPM-based prediction

CPM is a data-driven protocol for developing predictive models of brain–behavior relationships from connectivity data using cross-validation. The final result is a generalizable model that uses brain connectivity data to predict behavioral indicators for individual participants (Shen et al., 2017). In this study, CPM was implemented with an example MATLAB code that allowed us to identify neuromarkers of TA and test whether the neuromarkers could predict IA. Subjects with missing information for sex and age were excluded, and finally, 572 subjects (195 males, aged 16–26 years) were included in the analysis of CPM. We briefly summarize the CPM processing here (Fig. 1b).

Firstly, a vector of behavioral value (here, TA) was correlated with each edge (i.e., Pearson correlation coefficient between each pair of ROIs) in the functional connectivity matrix of each participant. Similar to the original paper, a threshold (here, thresh = 0.001) was applied to the matrix to retain only connections that were significantly correlated with TA scores. Thus, edges correlated with TA scores were defined as the TA network. Note that we used a leave-one-out approach to identify the sets of edges that make up TA network, in each case generated by repeating the edge identification process while leaving one participant out of the dataset. The sum of the strength of connections within the TA network was then calculated for each participant, which provides a quantitative summary of the overall strength of functional connectivity each participant has in the relevant connections that have been identified to either effectively predict the TA scores.

Secondly, fed these summed network strengths into the predictive models with TA scores assuming linear relationships. A leave-one-out approach was used in this step.

After each iteration of these regression models are completed, the resulting models are used to generate predicted TA scores for the left-out participant. Summing the network strengths of the left-out participant and entered these strengths into the regression models, and the regression models output predicted TA scores.

Thirdly, aim to determine the prediction performance, which was accessed by correlating predicted TA scores and observed TA scores. Significant correlation suggests that the CPM was successful in its prediction. Next, we randomly shuffled TA scores 1,000 times and ran the above prediction procedure, which resulted in a null distribution of the Pearson correlation coefficient between the predicted and observed scores. The number of the null r values was greater than or equal to the observed r value plus one and then divided by 1,001 providing an estimated p value.

Thus, we trained a predictive model of TA using the CPM and then identified the neuromarkers of TA. Then we wanted to further explore whether the neuromarkers of TA could predict IA. Specifically, we conducted a correlation analysis between the predicted scores of TA generated by the predictive model and the observed scores of IA in test sample. Matching the completion of S-TAI and IUS, a total of 416 subjects were included in this analysis. Notably, to examine whether this effect is driven by the relationship between TA and IA, we statistically controlled TA score as covariate.

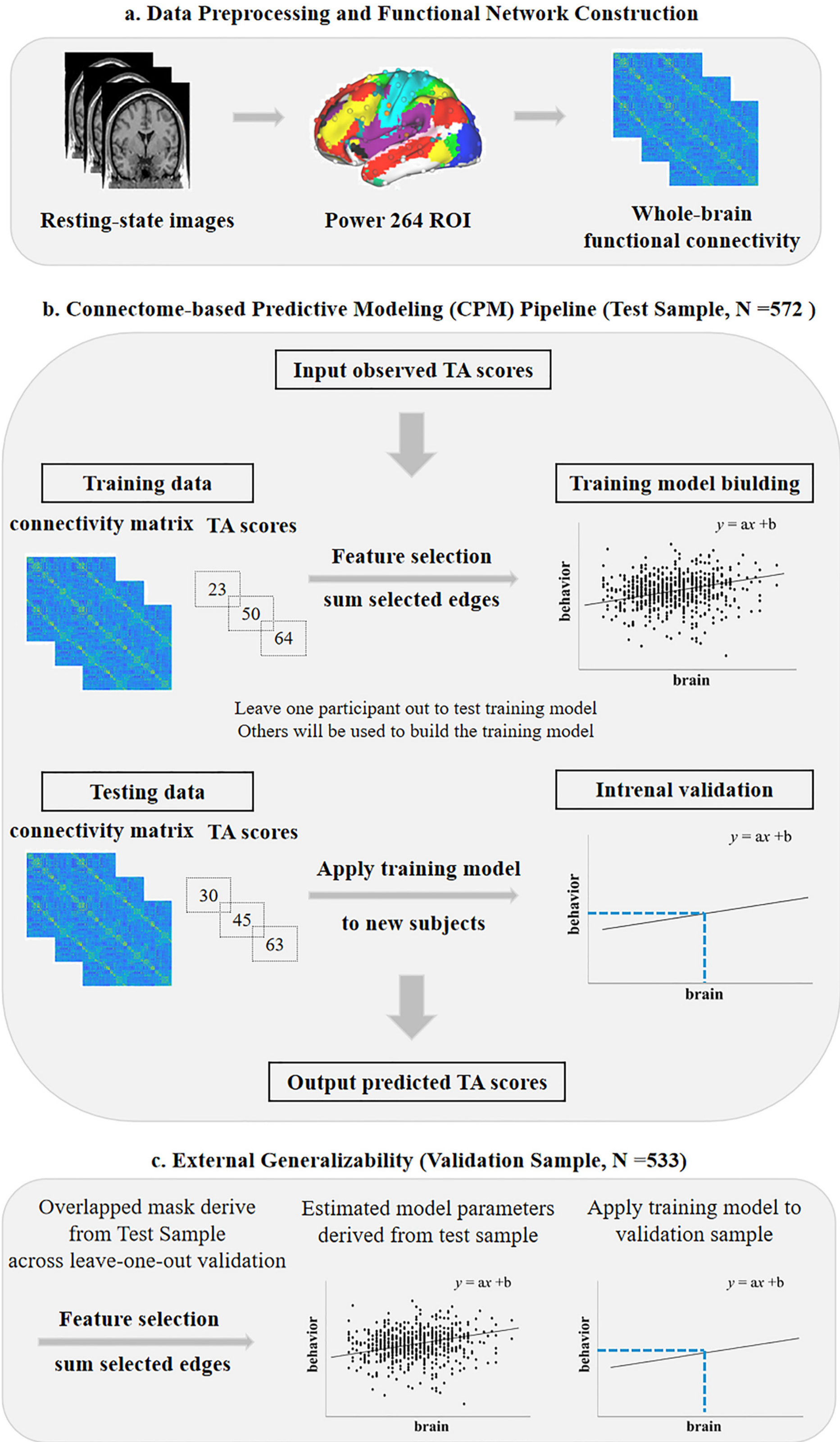

Fig. 1. Flowchart for prediction of individual TA scores using whole-brain functional connectivity

Finally, to test the generalization of the predictive model, we applied it to an independent validation sample. We performed external validation of the neuromarkers of TA identified in the test sample by testing whether the neuromarkers could predict TA significantly in an independent validation sample (Shen et al., 2017). The detailed information of the external validation method is provided in the supplementary material Method S5. Similarly, we analyzed the correlation of the observed IA with the predicted TA in the validation sample to estimate the validity of these predictions.

Statistical analysis

Demographic and correlation analysis. We used SPSS 26.0 software for all analyses of outliers, descriptive statistics, *t*-test and correlations. The stressful life events scores of 39 participants were detected as outliers and excluded from the sample. We used *t*-test to examine whether there were gender differences in TA and IA scores. The relationships between all behavior variables and the within-network connectivity of the DMN were analyzed in the test sample. To control for the influence of confounding factors, we employed partial correlation analysis, gender and age were controlled.

Linear mixed-effect (LME) model. In the validation sample, we used a LME with the 'lme4' package in R (version 4.2.1) to examine the changing trajectory of individuals' IA across two time points. In addition, we determined whether the TA level could be used to identify groups at high or low risk of IA. Specifically, the mean of TA scores was used here as a grouping basis. Then, the LME was used to estimate the group difference (low-TA group vs. high-TA group) in the change trajectory of IA over the two time points. Group, time, and the time × group interaction was included in the model.

Mediation analysis. To examine whether the stressful life events could explain the relationship between TA and IA, a mediation analysis was conducted for 362 participants in the test sample by applying the indirect macro designed for SPSS (Preacher & Hayes, 2008). In this algorithm, 5,000 bootstrapped samples were drawn, and bias corrected 95% bootstrap confidence intervals (CI) were reported. CI that does not include zero indicate a significant indirect effect of the independent variable on the dependent variable through the mediators. Additionally, we explored whether the within-network connectivity of the DMN could explain the association between TA and IA, and the same mediating analyses was performed for 446 participants in the test sample.

Ethics

Ethical approval of this study was granted by the Ethics Committee of Southwest University, and all procedures involved were in accordance with the sixth revision of the Declaration of Helsinki.

RESULTS

Participant characteristics and correlations among variables

Table 1 shows the distribution range, mean and standard deviation (SD) values for the IA, TA, and stressful life events scores. Results of the *t*-test indicated that the IA scores of males were significantly higher than females (see Fig. 2a). Additionally, our results revealed that the IA was positively correlated with the TA ($r = 0.33$, $p < 0.001$; see Fig. 2b). Figure 3a and b show separately that the stressful life events were significantly positively correlated with TA ($r = 0.12$, $p < 0.05$) and IA ($r = 18$, $p < 0.001$). Similarly, the negative correlations between the within-network connectivity of the DMN and TA, IA were shown in Fig. 3c and d respectively.

Group difference in the change trajectory of IA in the validation sample

It is clearly showed in Fig. 4 that many participants seem to have high IA scores at baseline. As shown in Table 2 and Fig. 4, the LME model revealed significant time × group interaction. Specifically, a lower decrease in IA was seen in the high-TA group across the two time points, compared with the low-TA group. However, the high-TA group did not show significantly higher levels of IA than the low-TA group.

CPM results

We defined the TA network as the edges that appeared in the TA network, and the TA network had 47 edges (see Table S1). The results of other thresholds of CPM were presented in the supplementary material Figure S1.

Table 1. Basic characteristics of participants in the test sample and validation sample

Variable	n	Range	Mean	SD
Test sample				
Age, years		16–26	19.57	1.56
TA (S-TAI score)	666	23–64	39.89	7.89
IA (IUS score)	446	48–164	101.01	19.46
Stressful life events (ASLEC score)	444	3–83	40.56	14.79
Validation sample				
Age, years		17–27	19.89	2.26
TA1 (S-TAI score T1)	551	13–79	39.89	8.53
TA2 (S-TAI score T2)	207	20–67	40.16	9.06
IA1 (IAT score T1)	401	0–79	40.23	12.64
IA2 (IAT score T2)	129	0–68	31.86	16.91

Abbreviations: IUS score, score on the Questionnaire of internet addiction tendency among undergraduates; S-TAI score, last 20 items of Spielberger State-TA Inventory representing the level of trait anxiety; ASLEC score, Adolescent Self-Rating Life Events Check-List score; IAT score, Internet Addiction test score; T1, time 1; T2, time 2.

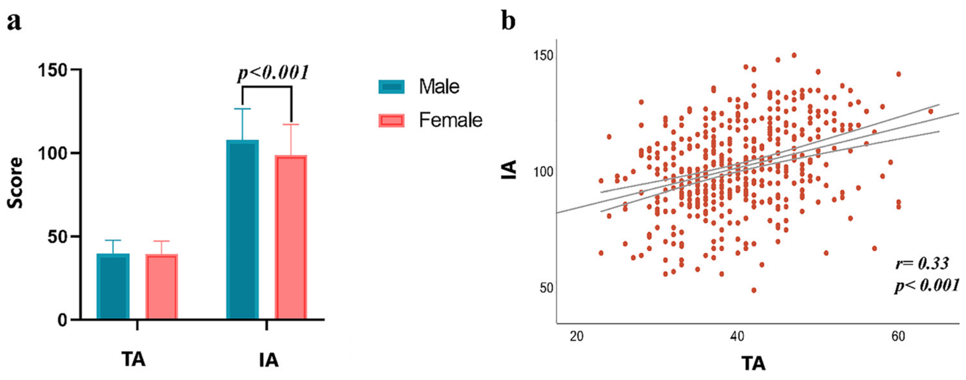

Fig. 2. Shows the results of *t*-test and partial correlation analysis for TA and IA scores. a) Results of *t*-test analysis indicated that the IA scores of males were significantly higher than those of females. b) Scatter plots showing a positive correlation between TA and IA scores

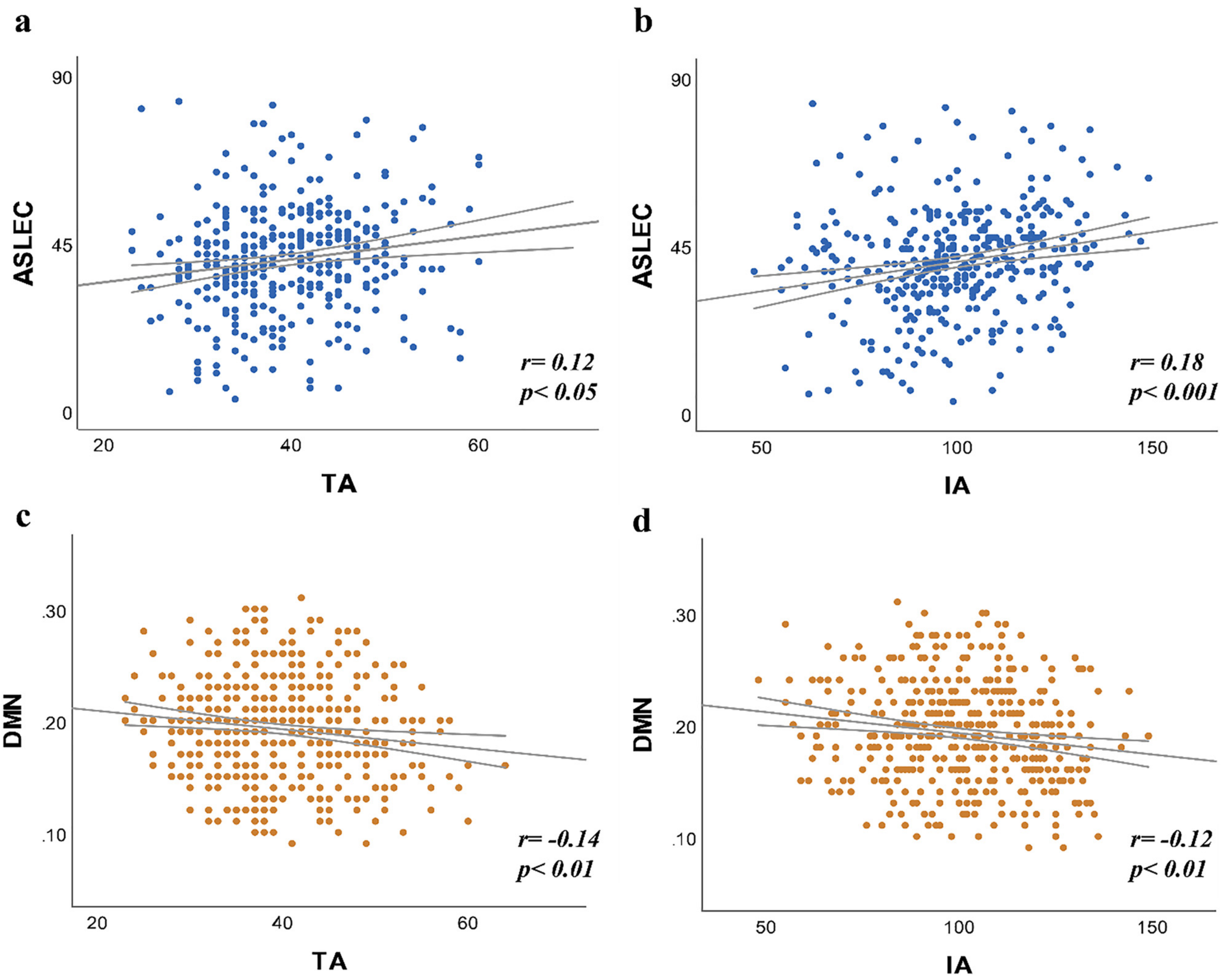

Fig. 3. Scatter plots shows the results of partial correlation analysis among the variables. a) and b) showing that the stressful life events scores are positively correlated with the TA and IA scores respectively. c and d showing that the within-network connectivity of the DMN are positively correlated with the TA and IA scores respectively

We then calculated the TA network strength for each participant. The results indicated that all sets of edges in the TA network significantly correlated with observed TA scores, as evidenced by positive correlations between the model predicted TA scores and actual observed TA scores (TA network: $r = 0.19$, $p < 0.001$), which suggested that the TA network all effectively predicted individual differences in TA scores. The scatter plot for the model is shown in

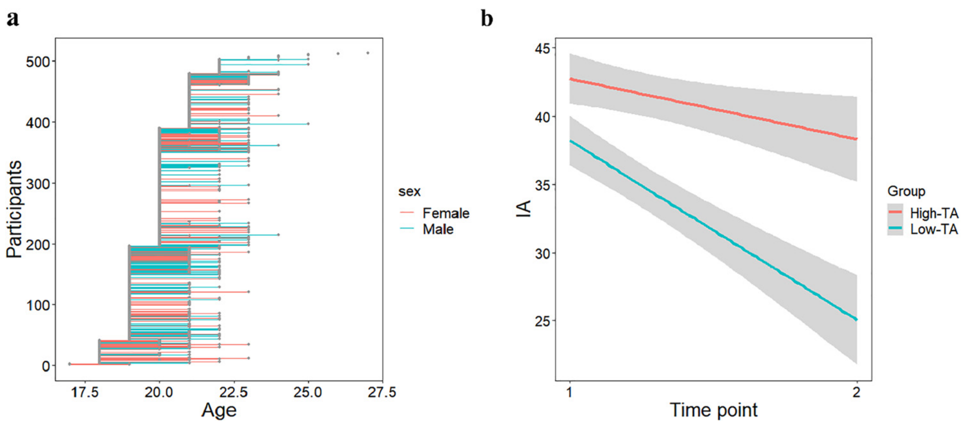

Fig. 4. (a) Scatter plot for the predictive model. Each dot denotes one participant at each scan. Each line connects the repeated scans for the same individual. The orange line represents the results for female participants, and the green line represents the results for male participants. (b) Change trajectories for internet addiction. The orange line represents the results for the high-TA group, and the green line represents the results for the low-TA group

Table 2. LME model estimates for time, group, and time × group effects on IA

Parameters	Estimate	Standard error	*t*-value	*p*-value
Time	−13.54	1.68	−8.08	<0.01
Group (low vs. high)	−3.94	3.05	−1.29	0.19
Time × group	8.47	2.32	3.66	<0.01

Fig. 5a. We then identified the neuroanatomy of the TA network. Figure 6a shows the visualization of all the edges of the TA network, and Fig. 6b shows the perspectives of all relevant nodes found in the TA network. Specifically, the predicted TA connection was mainly distributed in the DMN.

Additionally, we input the mask of the TA network into GRETNA to calculate the degree center number of all nodes in the mask. Table 3 shows the top 10 nodes with the highest contribution values that were most well-represented in the TA network. The regions with the largest number of these connections were the left parahippocampal gyrus (PhG), right cuneus, right precuneus, and left middle cingulate gyrus (MCG).

Finally, we tested the neuromarkers of TA could predict IA successfully. The results indicated that the combination of TA-associated features predicted IA significantly ($r = 0.11$, $p < 0.05$). The scatter plots for the best predicting models are shown in Fig. 5b.

External validation

An independent validation sample was used to test the generalizability of the predictive model. Significant correlation between the observed TA scores in the validation sample and the predicted TA scores generated from the regression model using parameters from the test sample would provide strong evidence of the generalizability. The results indicated a significant association between the TA scores in the validation sample and the neuromarkers identified in the test sample ($r = 0.01$, $p < 0.05$, Fig. 5c). Additionally, we found that the neuromarkers of TA could predict the IA scores in the validation sample ($r = 0.13$, $p < 0.01$, Fig. 5d).

Mediating results

As shown in Fig. 7a, the first mediation analysis indicated that ASLEC mediated the relationship between IA and TA [$\beta = 0.03$, 95% confidence interval (CI) [0.008,0.058], $p < 0.05$]. Standardized coefficients are present in the path diagram, which represent the covariant relationship between two variables. In addition, the second mediation analysis indicated that the within-network connectivity of the DMN mediated the association between IA level and TA ($\beta = 0.02$, 95% CI [0.005, 0.037], $p < 0.05$, see Fig. 7b).

DISCUSSION

The present study aimed to explore the underlying neural and socio-psychological mechanisms of the effect of TA on IA. Firstly, we obtained results that TA is positively correlated with IA. Secondly, LME modeling suggested the different change trajectories of IA in individuals with different levels of anxiety. Specifically, the high-TA group had a higher risk of IA. Thirdly, our study determined neuromarkers of TA from their unique whole-brain functional connectivity profile by CPM, and the results showed that TA-related connectomes predicted IA relatively well. In addition, our results demonstrated the successful generalizability of the CPM in an independent validation sample. Lastly, we estimated the mediating role of stressful life events and the within-network connectivity of the DMN in the relationship between TA and IA.

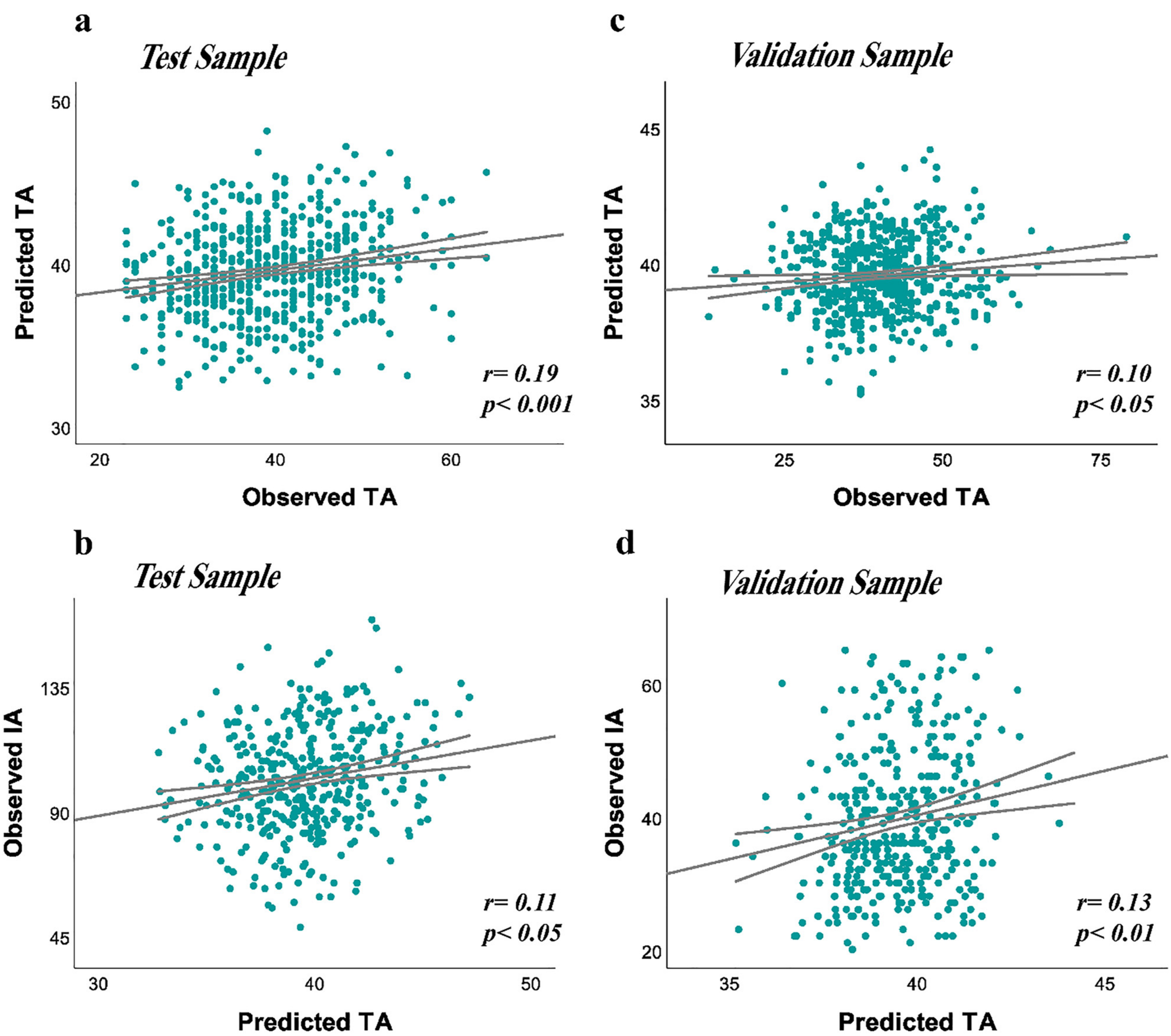

Fig. 5. Scatter plots showing the predicted and observed scores from the best predictive combination of edges in the following CPM models; a and c) correlations between the predicted TA value and actual TA value in the test sample and validation sample; and b and d) neuromarkers of TA predicting IA in the test sample and validation sample

Predictive role of TA for IA

Our study revealed that TA could predict IA in college students significantly. This finding is consistent with previous studies in which participants with high TA were more inclined to experience IA. We examined the different change trends in a LME model, and the results showed that participants with high TA exhibited high IA scores at baseline and less decrease in IA across the time. Indeed, previous studies indicated that on average self-control increases during adolescence, which in turn contributes to the prevention or intervention in internet gaming disorder as well (Xiang, Gan, Jin, Zhang, & Zhu, 2022; Zondervan-Zwijnenburg et al., 2020). Similar results suggested that greater self-control of adolescents is associated with negative network coupling between the limbic and right fronto-parietal resting state networks (Rubin et al., 2016). However, it has been proven that less involvement of the brain circuitry that supports top-down attentional control predicts more problematic drinking among college students (Cohen-Gilbert et al., 2022). Thus, subjects showed higher levels of IA at a younger baseline time point. Additionally, more mature participants use a wider variety of emotion regulation strategies compared to younger participants (Puente-Martínez, Prizmic-Larsen, Larsen, Ubillos-Landa, & Páez-Rovira, 2021). In summary, individuals experience maturity of self/attention control and emotional regulation abilities. Therefore, the participants reported lower IA at the second time point. However, these abilities were impaired in high TA individuals, who showed smaller decreases in addictive behavior over a longer period.

Emotion regulation circuit

Among the top 10 nodes we observed, the PhG had the highest centrality index. The functional connectivity

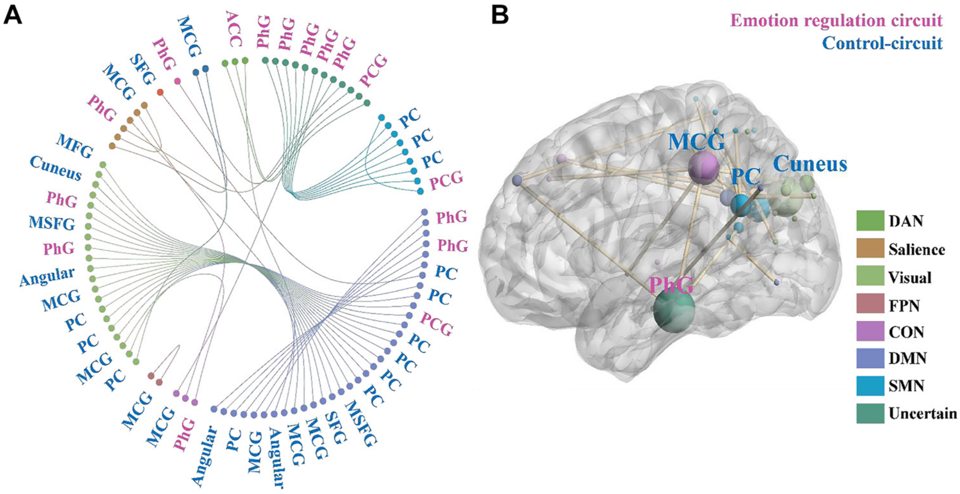

Fig. 6. Functional connections predicting individual TA. (a) The functional connections in TA networks, plotted as the number of connections within each lobe. PhG = parahippocampa gyrus; PCG = post cingulate gyrus; PC = precuneus; MSFG = medial superior frontal gyrus; SFG = superior frontal gyrus; MCG = middle cingulate gyrus; MFG = middle frontal gyrus; ACC = anterior cingulate cortex; (b) The brain network patterns in TA networks. DAN = dorsal attention network; FPN = fronto-parietal task control network; CON = cingulo-opercular task control network; DMN = default mode network; SMN = sensory/somatomotor hand network
Note: The nodes in the a and b are colored according to the different brain networks they belong to, as shown in the legend at the bottom right. In addition, the legend at the top right explains the rule for setting the font color of the labels in this figure, which are different for nodes belonging to emotion regulation circuit and control-circuit.

Table 3. Nodes in the TA network with the most connections that contributed to predicting TA

Node number	Node name	Network	X	Y	Z
6	ParaHippocampal_L	Uncertain	−21.38	−22.22	−19.97
159	Cuneus_R	Visual	15.18	−76.68	31.00
94	Cingulum_Mid_L	Default mode	−2.2	−36.68	43.85
93	Precuneus_R	Default mode	15.12	−63.09	25.98
88	Precuneus_L	Default mode	−6.84	−54.9	27.05
92	Cingulum_Post_R	Default mode	7.94	−48.37	30.57
156	Occipital_Sup_R	Visual	15.27	−87.09	36.89
95	Precuneus_R	Default mode	10.77	−53.83	17.09
97	Frontal_Sup_R	Default mode	23.33	33.07	47.68
102	Frontal_Sup_Medial_R	Default mode	12.73	54.87	38.19

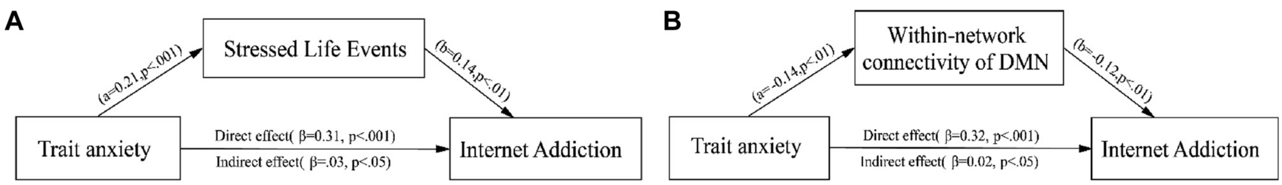

Fig. 7. (a) Mediating effects of stressful life events on the relationship between TA and IA on test sample. (b) Mediating effects of the within-network connectivity of DMN on the relationship between TA and IA on test sample

between the postcentral gyrus and PhG was found frequently in our results. A study of voxel-based morphometric analysis to determine the relationship between brain regions and high negative emotions indicated that altered activation of the PhG and precuneus regions in high TA individuals can have a detrimental effect on their emotion regulation ability (L. Zhang et al., 2022). Similarly, depression patients with increased posterior cingulate cortex–PhG connectivity were shown to experience a sadder mood and more rumination in daily life (Zamoscik, Huffziger, Ebner-Priemer, Kuehner, & Kirsch, 2014). These results may provide neurophysiological evidence for the pathway via which TA can predict IA based on emotion regulation impairment.

Control-circuit

The neuromarkers of TA involved the precuneus, frontal gyrus and MCG. Previous studies underscored the key role of the precuneus regions in facilitating vigilance (Castellanos et al., 2008; R. Chen et al., 2022; B. Li, Zhang, et al., 2020; Nagahama et al., 1999). Clinical studies have suggested that the attention deficit in attention deficit hyperactivity disorder (ADHD) is correlated with activation of the precuneus. Specifically, individuals with ADHD had lower connectivity in regions of the default-mode (precuneus) and dorsal attention (superior parietal cortex) networks (Christakou et al., 2013; Tomasi & Volkow, 2012). Empirical studies have found similar results indicating important roles of the cuneus, precuneus and right frontal gyrus in attention regulation (R. Chen et al., 2022; Mahayana, Tcheang, Chen, Juan, & Muggleton, 2014; Song et al., 2019). The frontal gyrus has been shown to be a key region of dorsal and ventral attention networks and for the reorientation of attention from exogenous to endogenous attentional control (Japee, Holiday, Satyshur, Mukai, & Ungerleider, 2015; B. Li, Zhang, et al., 2020; Song et al., 2019). In the same line of thinking, we speculate that the decrease of functional connections involving the precuneus, cuneus and frontal gyrus regions was associated with deficient attention, and thus, might contribute to the loss of attention control, which represents a key symptom across addictive disorders.

Additionally, the MCG is implicated in inhibitory control (Kana, Keller, Minshew, & Just, 2007). The insula and MCG have been shown to impair the supervisory attentional control system (R. Zhang, Geng, & Lee, 2017). A previous study in heavy smokers discovered deficiencies in some brain regions including the MCG and precuneus, which are highly relevant to addiction to chronic smoking (Ye et al., 2020). We propose that the neural mechanism through which TA affects IA is associated with the MCG as found in the negative TA network, which might indicate that the inhibitory control ability of individuals with high TA is affected, thereby contributing to IA.

Mediating effects of stressful life events and the DMN

The present study revealed a close relationship between TA and IA, but our findings cannot prove that TA will lead to IA. In order to explore the underlying socio-psychological mechanisms for the influence of TA on IA, we introduced stressful life events as a mediating variable between TA and IA. The results of our mediating effect analysis showed that TA could significantly predict IA behavior through stressful life events. Specifically, when individuals with high-TA suffer stressful life events, internet use offer an easy way for negative emotion regulation induced by these events. Thus, as a way to compensate stress regulation, individuals will participate in more problematic internet use.

Consistent with the study by Rebello et al., our results showed that exposure to stressful life events is related to the potential neural embodiment in the DMN (Rebello, Moura, Pinaya, Rohde, & Sato, 2018). The DMN is widely recognized as the neural substrate of self-referential processes. It has the capacity to integrate salient external or internal stimuli with current emotional personal experiences and perceptions. This process is of paramount importance for resilience in the face of adversity. As for the effect of stressful life events in the relationship between TA and IA, one possible neural basis is that reduced within-network connectivity of the DMN might relate to decreased resilience, which affects the response to adverse experiences.

Similarly, CPM results emphasized the functional connectivity of the DMN in the neuropathology of TA. Consistent with previous studies, our results indicate that high TA subjects showed significantly reduced functional connectivity in the DMN, which might underlie the emotional regulation (Imperatori et al., 2019; J. Pan et al., 2018). Aberrant activation of functional connectivity in the DMN also has been observed in substance addiction and is related to craving and relapse (R. Zhang & Volkow, 2019). In addition, our mediation analysis emphasized the role of the DMN in the relationship between TA and IA. Accordingly, we speculate that connectivity of the DMN is reduced in individuals with high TA, which might lead to affect dysregulation. Eventually, individual with high TA will experience difficulties in coping with negative emotions and are more likely to develop addictive behaviors.

LIMITATIONS AND CONCLUSION

The present study has still several limitations. Firstly, the participants were all university students. Future research should include additional types of participants (e.g., primary and secondary school adolescents). Secondly, because the data in this study were collected at individual time points, additional approaches, such as the empirical sampling method, should be adopted in future research for improved ecological validity. Thirdly, the number of subjects available for analysis decreased at time point 2 due to academic advancement, which should be avoided in subsequent researches on other samples. Furthermore, the participants of this study were mostly females, and we found that males had more severe IA than females. Therefore, it is necessary for future studies to include more male subjects. Lastly, exploration of the dynamic mechanism between negative emotions and IA among individuals with TA is another valuable direction for future studies.

Despite these limitations, our findings suggest that TA is a robust risk factor of IA. Moreover, we demonstrated that neuromarkers of TA can predict IA and that the control-circuits and emotion-regulation circuits can explain the further occurrence of IA. This information may facilitate a deeper understanding of the specific mechanism by which TA influences IA. Lastly, we examined the mediating effects of stressful life events and the within-network connectivity of the DMN in the relationship between TA and IA. Overall, our study provides a promising direction for psychological intervention and psychological health education, which is promoting the ability of adolescents to cope with stressful life events effectively and related psychological ability training. Because problematic internet use is an increasingly prevalent problem today, future policy should consider possible IA rather than the existing IA.

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SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2023.00086.

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