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Connectome-based predictive modelling of problematic gaming in youth from the ABCD study

JENNIFER J. PARK[1**], CHERYL M. LACADIE[2], DUSTIN SCHEINOST[2], LI YAN MCCURDY[1,2], MARC N. POTENZA[1,3,4,5,6,7†*] and YIHONG ZHAO[8†]

[1] Department of Psychiatry, Yale University School of Medicine, New Haven, CT, USA

[2] Department of Radiology and Biomedical Imaging, Yale University School of Medicine, New Haven, CT, USA

[3] Child Study Center, Yale University School of Medicine, New Haven, CT, USA

[4] Department of Neuroscience, Yale University School of Medicine, New Haven, CT, USA

[5] Connecticut Council on Problem Gambling, Wethersfield, CT, USA

[6] Connecticut Mental Health Center, New Haven, CT, USA

[7] Wu Tsai Institute, Yale University, New Haven, CT, USA

[8] Columbia University School of Nursing, New York, NY, USA

FULL-LENGTH REPORT

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ABSTRACT

Background: Despite the rapid growth in gaming consumption and associated harms in adolescents, data-driven research to identify brain networks underlying problematic gaming remains limited. This study aimed to identify neural networks predictive of problematic-gaming severity in youth using connectome-based predictive modelling (CPM), a machine-learning approach that employs whole-brain functional connectivity data. *Methods:* From the Adolescent Brain Cognitive Development study at the two-year follow-up, 1,036 participants (M_{age} = 12.0, 60.7% male) were studied. CPM with 10-fold cross-validation was applied to problematic-gaming scores and functional magnetic resonance imaging (fMRI) data collected during the performance of a reward-processing task. To determine generalizability, additional CPM analyses were performed using other task-based (e.g., those relevant to response inhibition, emotion regulation, and working memory) and resting-state fMRI data. *Results:* CPM successfully predicted problematic-gaming scores ($r = 0.12$, $p = 0.002$). Predictive networks involved several connections within and between canonical networks implicated in visual processing (visual area 2 and visual association networks), cognitive control and executive functioning (frontoparietal and medial frontal networks), and relevance and motor response (salience and sensorimotor networks). CPM predicted problematic-gaming scores across all analyzed brain states and found shared predictive canonical networks, indicating generalizability. Applying the final reward-processing model to other task-based and resting-state fMRI data also successfully predicted problematic-gaming severity. *Conclusions:* The identified large-scale networks predictive of problematic-gaming severity in adolescents may serve as promising targets for personalized and novel interventions. Before using these results to guide clinical advances, future research should use external samples to evaluate replicability of the identified network.

KEYWORDS

addictive behaviors, video games, internet addiction, compulsive behaviors, functional magnetic resonance imaging, youth

†Shared senior authorship.

*Corresponding author.
E-mail: marc.potenza@yale.edu

**Corresponding author.
E-mail: jennifer.j.park@yale.edu

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INTRODUCTION

In the 11th revision of the International Classification of Diseases (ICD-11), gaming disorder (GD) is defined as a pattern of persistent or recurrent gaming behavior characterized by impaired control over gaming, increasing prioritization of gaming over other interests and daily activities, and continuation or escalation of gaming despite negative consequences (World Health Organisation, 2019). The prevalence of GD appears to be the highest in children and adolescents (6.6%) compared to young adults (3.4%) and adults (1.9%) (Kim et al., 2022). However, the advancement of data-driven research to identify neural networks predictive of problematic gaming in adolescents has not met the rapid growth in gaming consumption and harm within this population.

Previous neuroimaging studies of problematic gaming have reported functional alterations in brain regions implicated in cognitive control, emotion regulation, reward processing, sensorimotor integration, and visual processing (Kuss, Pontes, & Griffiths, 2018; Mestre-Bach & Potenza, 2023; Weinstein & Lejoyeux, 2020). A meta-analysis reported that adolescents with internet gaming disorder (IGD) exhibited large-scale network alterations, with decreased resting-state functional connectivity within the default mode network (DMN) and increased connectivity between the DMN and ventral attention, ventral attention and sensorimotor, and limbic and frontoparietal networks, compared to adolescents without IGD (Yan, Li, Yu, & Zhao, 2021). Despite the identification of multiple networks associated with IGD, several barriers to identifying clinically viable neuromarkers in youth persist in the literature. Functional connectivity analyses typically employ seed-based approaches limited to pre-defined brain regions of interest (ROIs), which prevent the understanding of whole-brain functional connectivity (Shen et al., 2017; Whelan & Garavan, 2014). Traditional correlation or regression approaches used in most neuroimaging studies of individual differences in behavior tend to overfit data, thereby diminishing the ability to generalize to novel data. To address these issues, machine-learning approaches (e.g., multi-voxel pattern analysis or support vector machine analysis) have been applied to fMRI data to identify networks predictive of IGD in adults (Dong et al., 2020; Song et al., 2021; L. Wang et al., 2023; Wang, Dong, Du, Zhang, & Dong, 2020; Wang et al., 2022; Wen et al., 2021). However, none of these studies included child/adolescent participants. Some of these studies were also limited by small and gender-biased samples or did not examine brain-wide connectivity.

Connectome-based predictive modelling (CPM) is a machine-learning method that uses whole-brain functional-connectivity data to generate brain-behavior models (Finn et al., 2015; Shen et al., 2017). To protect against overfitting, CPM implements built-in cross-validation by testing the model using held-out samples, which increases rigor and generalizability of findings. CPM is data-driven, which eliminates the need for *a priori* selection of brain regions or networks and allows one-to-one mapping back to brain anatomy. In other words, this approach not only has the potential to test the predictive value of brain-behavior relationships in problematic gaming, but also to identify complex networks subserving these behaviors (i.e., neural fingerprints) (Finn et al., 2015; Shen et al., 2017). Furthermore, CPM has the potential to contribute to clinical practice by identifying neural targets for treatment, which has the potential to assign patients to treatments based on neuromarkers (Bzdok & Meyer-Lindenberg, 2018). The introduction of personalized and novel treatment approaches for problematic gaming, such as transcranial direct current stimulation of personalized ROIs, may expand the currently limited and relatively homogeneous treatment options for youth, which are predominantly psychotherapeutic and not always tailored to individuals (King et al., 2017; Park et al., 2022, 2025; Sauvaget et al., 2015; Zajac, Ginley, & Chang, 2020).

The demonstrated success of CPM in predicting a range of substance use disorders and behavioral addictions, along with associated factors such as craving and abstinence (Antons et al., 2023; Feng et al., 2024; Garrison et al., 2023; Lichenstein, Scheinost, Potenza, Carroll, & Yip, 2021; Yang et al., 2023; Yip, Scheinost, Potenza, & Carroll, 2019; Zhou et al., 2022), suggests CPM could likewise be a promising tool for predicting severity of problematic gaming. To date, only one study of problematic gaming has employed CPM to predict craving for gaming in adults with IGD (Zhou et al., 2022). This study identified connections between networks implicated in executive control, cognitive control, and reward responsiveness. Studies have yet to use CPM to predict severity of problematic gaming at earlier developmental stages despite the potentially unique influences on brain development and behavior during development (Kolb & Gibb, 2011). Expanding CPM research to include youth may contribute to the development of more appropriate and effective interventions for young individuals experiencing problems with gaming.

In this study, CPM was used to identify neural networks predictive of problematic-gaming severity in youth aged around 11–13 years. The term “problematic-gaming severity” is used here instead of GD or IGD to emphasize the use of CPM to predict symptom severity rather than a clinical diagnosis. CPM was applied to monetary incentive delay task-based (MIDT) fMRI data acquired by the Adolescent Brain Cognitive Development (ABCD) study at the two-year follow-up. MIDT data were used for the main CPM analysis for two reasons: (i) CPM using task-based data, as opposed to resting-state data, often improves the prediction of individual measures and better reveals brain-behavior relationships (Greene, Gao, Scheinost, & Constable, 2018), and (ii) altered reward sensitivities, including the anticipation, processing, and response to rewards and losses, have been observed in individuals with problematic gaming (Dong, Li, Wang, & Potenza, 2017; Skok & Waszkiewicz, 2024; Wu et al., 2020; Yao, Zhang, Fang, Liu, & Potenza, 2022; Zhou et al., 2021). Additionally, the present study sought to examine the generalizability of the identified predictive network across multiple brain states by conducting independent CPM analyses using stop signal task (SST), emotional n-back task (EN-back), and resting-state fMRI data. Generalizability was further examined by applying the final MIDT model to the SST, EN-back, and resting-state fMRI data.

MATERIALS AND METHODS

Participants

This study analyzed the two-year follow-up data from the 5.1 data release of the ABCD study. The ABCD study is an ongoing longitudinal project with 11,878 children aged 9–10 years enrolled at baseline, with behavioral and neuroimaging data collected from 21 research sites across the United States (Karcher & Barch, 2021). Detailed information on recruitment and data collection procedures has been published elsewhere (Karcher & Barch, 2021; Luciana et al., 2018) and is provided on the ABCD study website: https://abcdstudy.org/. For the purpose of the present study, only the two-year follow-up cross-sectional data from the ABCD study were used, when participants were aged around 11–13 years. In the present study, participants were excluded from analyses based on the following criteria: (i) no self-reported engagement with single-player or online multi-player video games, (ii) no valid fMRI data, or (iii) missing data on Video Game Addiction Questionnaire (VGAQ) scores and basic demographic variables.

Measures

Based on the Bergen Facebook Addiction Scale, the VGAQ is a 6-item measure of problematic-gaming severity that assesses preoccupation with gaming (i.e., spending a lot of time thinking about gaming), tolerance (i.e., feeling a need to increase game play), gaming to forget about problems, unsuccessful attempts to reduce gaming, withdrawal symptoms when unable to game (e.g., becoming stressed or upset), and negative consequences to functioning at school and work due to gaming (Andreassen, Torsheim, Brunborg, & Pallesen, 2012; Bagot et al., 2022). The VGAQ appears to align more closely with the DSM-5 IGD criteria than with the ICD-11 GD criteria, but does not include IGD-specific criteria on (i) loss of interests in previous hobbies due to, and with the exception of, gaming, (ii) continuation of gaming despite knowing the presence of psychosocial problems, and (iii) deception of others (e.g., family members) regarding the amount of gaming engagement (American Psychiatric Association, 2013). Participants who self-reported any gaming time on single-player or online multiplayer video games were prompted to complete the VGAQ. The measure was rated on a 6-point Likert scale (ranging from 1 = never to 6 = very often), rendering a total score between 6 and 36, with higher scores indicating greater problematic-gaming severity. In the present study, a total summary score was used due to the absence of a recommended cut-off point, which has previously been recommended for scales that demonstrate strong reliability (Sullivan & Artino Jr, 2013; Warmbrod, 2014). The VGAQ has demonstrated good internal consistency reliability (McDonald's $\omega = 0.90$) (Bagot et al., 2022).

Neuroimaging data acquisition and preprocessing

The ABCD study acquired fMRI data during performance of a MIDT, which measured reward processing. The ABCD Data Analysis, Informatics, and Resource Center performed the fMRI preprocessing. Additional details regarding neuroimaging and preprocessing can be found in the Supplementary Material. Tables S1–S3 also provide results on behavioral performance for MIDT and other tasks (i.e., SST and EN-back) collected by the ABCD study.

Functional connectivity

As previously described (Finn et al., 2015; Lichenstein et al., 2021; Rosenberg et al., 2016; Yip et al., 2019), whole-brain functional-connectivity analyses were conducted using BioImage Suite. Network nodes were defined using the Shen 268-node brain atlas, which provides whole-brain coverage, including the cortex, subcortex, and cerebellum (Shen, Tokoglu, Papademetris, & Constable, 2013) (see details in the Supplementary Material). The mean time courses for each of the 268 nodes were calculated, representing the average time courses of voxels within each node. Node-by-node pairwise Pearson's correlations were computed and transformed using Fisher's z-transformation to generate symmetric 268×268 functional connectivity matrices (i.e., "connectomes") for each participant and state. Within a matrix, edges indicated the strength of connection between two nodes (Shen et al., 2017).

Connectome-based predictive modelling

CPM was conducted to create neural predictive models for problematic-gaming severity. CPM was undertaken using a validated MATLAB script (Shen et al., 2017), which took connectivity matrices and VGAQ scores as inputs. Model performance was evaluated using 10-fold cross-validation, which involved randomly dividing the participants into ten subsets or "folds" and training a CPM model on all but one of the folds (i.e., 9 folds in the training set) to predict VGAQ scores in the excluded fold (i.e., 1 fold in the test set) (see Fig. 1). One iteration of 10-fold cross-validation repeated this process for each fold until all participants had a predicted VGAQ value. 100 iterations of 10-fold cross-validation were completed to ensure model results were not biased by the random assignment of the 10 folds.

To construct each CPM model, all edges in the connectivity matrices of the training set were correlated with VGAQ scores using Pearson's correlation or partial correlation when controlling for the following covariates: age, sex, race/ethnicity, parental marital status, parental education, family income, and mean frame-wise displacement. Edges with a statistically significant correlation to VGAQ scores were identified to yield positive and negative predictive networks, characterized by increased VGAQ scores being associated with increased and decreased edge weights (i.e., connectivity), respectively. For each individual, edges in these networks were summed to obtain single-subject summary values. A linear model was then fit between the single-subject summary values and VGAQ scores. Lastly, single-subject summary values were calculated for the connectivity matrices of individuals in the test set, and the linear model was used to generate predictions of VGAQ scores. Pearson's

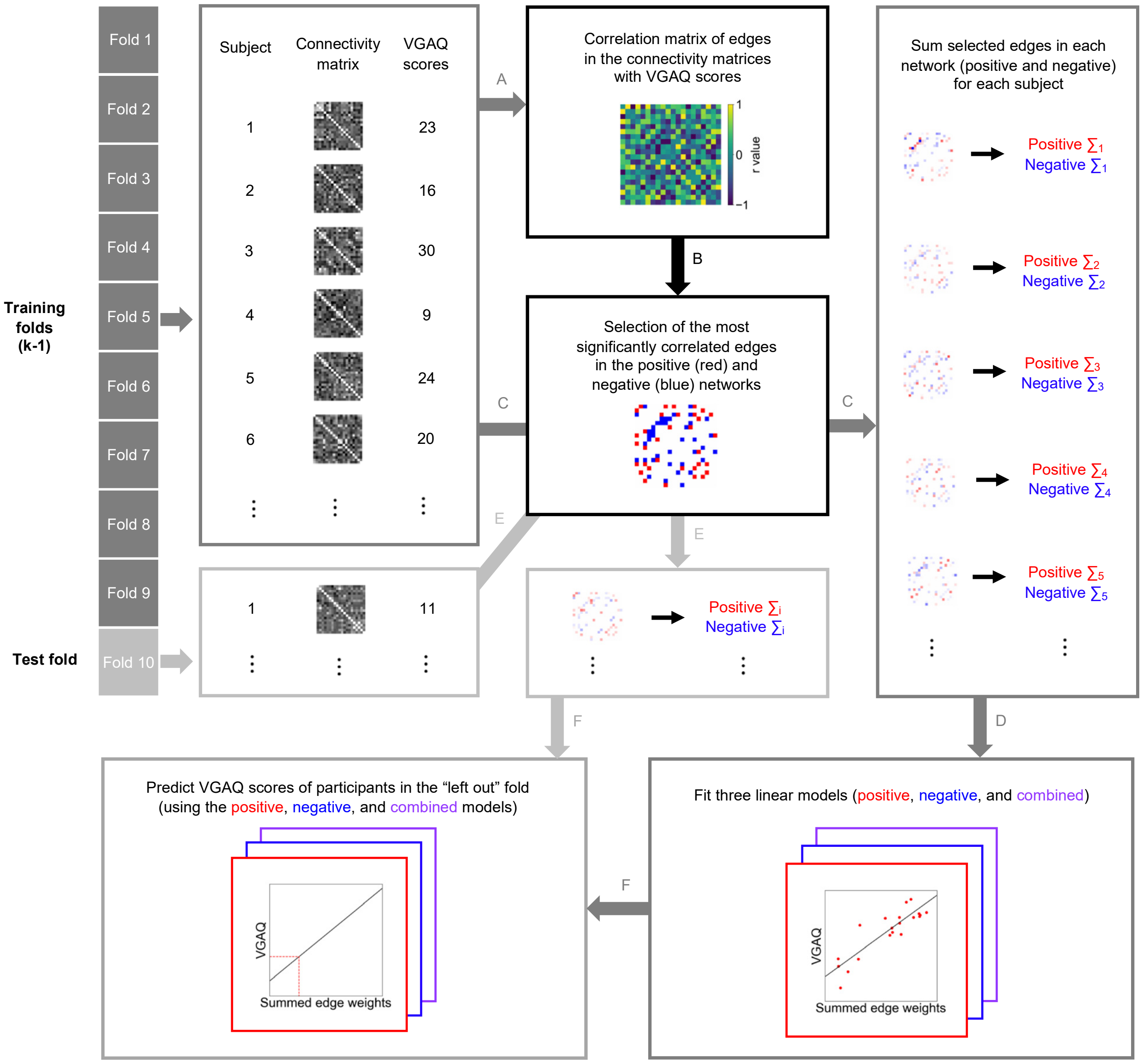

Fig. 1. One iteration of 10-fold cross-validation for connectome-based predictive modelling (CPM). Connectivity matrices and VGAQ scores were used as inputs to CPM. **A)** All edges in the connectivity matrices of the training set (i.e., all but one fold) were correlated with VGAQ scores using Pearson's correlation or partial correlation. **B)** From the correlation matrix, positively and negatively correlated edges that were statistically significant were selected to form the positive (red) and negative (blue) networks, respectively. **C)** Single-subject summary values were calculated for each subject in the training set by summing the edge weights in the positive and negative networks. **D)** Three linear models (positive, negative, combined) were fit between single-subject summary values and the VGAQ scores. **E)** Single-subject summary values were calculated for the left-out fold (i.e., testing set) using the positive and negative networks derived from the training set. **F)** The summary values of individuals in the left-out fold were inputted into the linear models to predict VGAQ scores

r correlation and partial correlation (when controlling for the aforementioned covariates) between the predicted and observed VGAQ scores were used to assess model performance. Permutation testing with 1,000 iterations was used to assess statistical significance. Information on how the resulting network anatomy was characterized has been provided in the Supplementary Material.

Given the potential impact of depression, anxiety, impulsivity, and crystallized intelligence, we conducted additional independent CPM analyses using these factors as covariates. Further details on the additional covariates can be found in the Supplementary Material.

Generalizability across brain states

To examine the generalizability of the identified predictive network from the CPM analysis using MIDT data, independent CPM analyses were repeated using SST, EN-back task, and resting-state fMRI data from ABCD study participants at the two-year follow-up. Further details on the brain states and additional CPM analyses can be found in the Supplementary Material.

To further assess generalizability, models from each k-fold iteration of CPM using MIDT fMRI data were combined (edges that appeared 50% of the time were included) to form the final consensus model. The final consensus MIDT model was then applied to the SST fMRI data using the same linear regression method. The performance of the model using the new data was evaluated by the correlation between predicted VGAQ scores and actual VGAQ scores. Permutation testing with 1,000 iterations was used to assess statistical significance. These methods were repeated for the EN-back and resting-state fMRI data.

Ethics

IRB approval and informed consent from a parent/guardian were obtained at ABCD sites. Adolescents capable of assent confirmed their willingness to participate in the ABCD study. The present study analyzed de-identified data and was exempted by the Yale IRB and the Yale Human Investigation Committee.

RESULTS

Participants

The final sample for the CPM analysis using MIDT data included 1,036 participants who were around 12 years old on average (*SD* = 0.63), as indicated in Table 1. Participants were predominantly male (*n* = 629, 60.7%) and White (*n* = 644, 62.2%), with an average VGAQ score of 11.7 (*SD* = 5.8, range = 6–36). There were statistically significant differences between the included and excluded groups across all variables except for family income and parental marital status. Compared to the excluded group, the included group was slightly younger, consisted of more male and White participants, reported lower VGAQ scores (see Table S4 in the Supplementary Material), and had more participants from families with higher levels of parental education.

Table 1. Demographic characteristics of ABCD participants included in and excluded from CPM analysis using MIDT fMRI data (*N* = 10,973)

	Included in the analysis (*N* = 1,036)	Excluded from the analysis (*N* = 9,937)	*p* value
Age (years)			
Mean (*SD*)	11.95 (0.63)	12.03 (0.67)	<0.001
Median [Min, Max]	12.00 [10.75, 13.33]	12.00 [10.58, 14.00]	
Missing	0 (0%)	1 (0.0%)	
Sex			
Male	629 (60.7%)	5,127 (51.6%)	<0.001
Female	407 (39.3%)	4,810 (48.4%)	
Race/ethnicity			
White	644 (62.2%)	5,217 (52.5%)	<0.001
Black	85 (8.2%)	1,476 (14.9%)	
Hispanic	203 (19.6%)	1961 (19.7%)	
Asian	16 (1.5%)	215 (2.2%)	
Other	88 (8.5%)	1,067 (10.7%)	
Missing	0 (0%)	1 (0.0%)	
Family income			
≥200k	168 (16.2%)	1,275 (12.8%)	0.208
100–200k	338 (32.6%)	3,053 (30.7%)	
50–100k	288 (27.8%)	2,400 (24.2%)	
<50k	242 (23.4%)	2,245 (22.6%)	
Missing	0 (0%)	964 (9.7%)	
Parental education			
Postgraduate degree	348 (33.6%)	3,285 (33.1%)	<0.001
Bachelor's degree	265 (25.6%)	2055 (20.7%)	
Some college	105 (10.1%)	910 (9.2%)	
HS diploma/GED	66 (6.4%)	944 (9.5%)	
< HS diploma	35 (3.4%)	453 (4.6%)	
Missing	217 (20.9%)	2,290 (23.0%)	
Parental marital status			
Married	736 (71.0%)	6,707 (67.5%)	0.175
Not married	300 (29.0%)	3,230 (32.5%)	
Missing	0 (0%)	139 (1.4%)	
VGAQ score			
Mean (*SD*)	11.65 (5.76)	12.58 (6.42)	0.001
Median [Min, Max]	10.00 [6.00, 36.00]	11.00 [6.00, 36.00]	
Missing	0 (0%)	2,923 (29.4%)	

SD = standard deviation; Min = minimum; Max = maximum; *k* = 1,000; HS = high school; GED = Graduate Equivalency Diploma.

Prediction of problematic-gaming severity

CPM applied to MIDT fMRI data successfully predicted problematic-gaming severity (combined positive and negative networks: $r = 0.12$, $p = 0.002$ via permutation testing; positive network only: $r = 0.12$, $p < 0.001$; negative network only: $r = 0.11$, $p < 0.001$). This model utilized all of the covariates mentioned in the methods.

The Supplementary Material includes results on model performance when controlling for specific individual covariates (i.e., age, sex, race/ethnicity, parental marital status, parental education, family income, and mean frame-wise displacement). Results on model performance when controlling for the aforementioned covariates as well as depression, anxiety, impulsivity, and crystallized intelligence (which similarly successfully predicted problematic-gaming severity) can also be found in the Supplementary Material.

Network anatomy

A summary of positive and negative problematic-gaming severity networks based on connectivity between macroscale brain regions is presented in Fig. 2. Network anatomies were complex for both networks, with connections between several macroscale brain regions (Fig. 2A and B). There were 396 positive edges and 446 negative edges (842 total), representing 2.35% of all possible edges. The highest-degree nodes (i.e., nodes with the most connections) for the positive network included a left occipital node (left peristriate area, Brodmann area 19, MNI: −43, −70, −14) with connections to temporal, limbic, insular, prefrontal, parietal, subcortical, bilateral brainstem, and cerebellar nodes. In the negative network, the highest-degree nodes included a right prefrontal node (right Broca's area, Brodmann area 44, MNI: 55, 10, 22) with connections to insular, parietal, motor strip, temporal, other prefrontal, and limbic nodes. Additional details have been provided in Table S5 in the Supplementary Material.

Overlap of canonical brain networks

For the positive and negative networks, connectivity derived from the number of connections within and between canonical brain networks is presented in Fig. 3. The comparison of networks (Fig. 3C) indicated that the positive network included relatively more connections between the sensorimotor and visual area 2, sensorimotor and visual association, and medial frontal and visual association networks. In the negative network, considering the comparison of networks, there were more connections between the frontoparietal and sensorimotor, medial frontal and frontoparietal, and sensorimotor and salience networks.

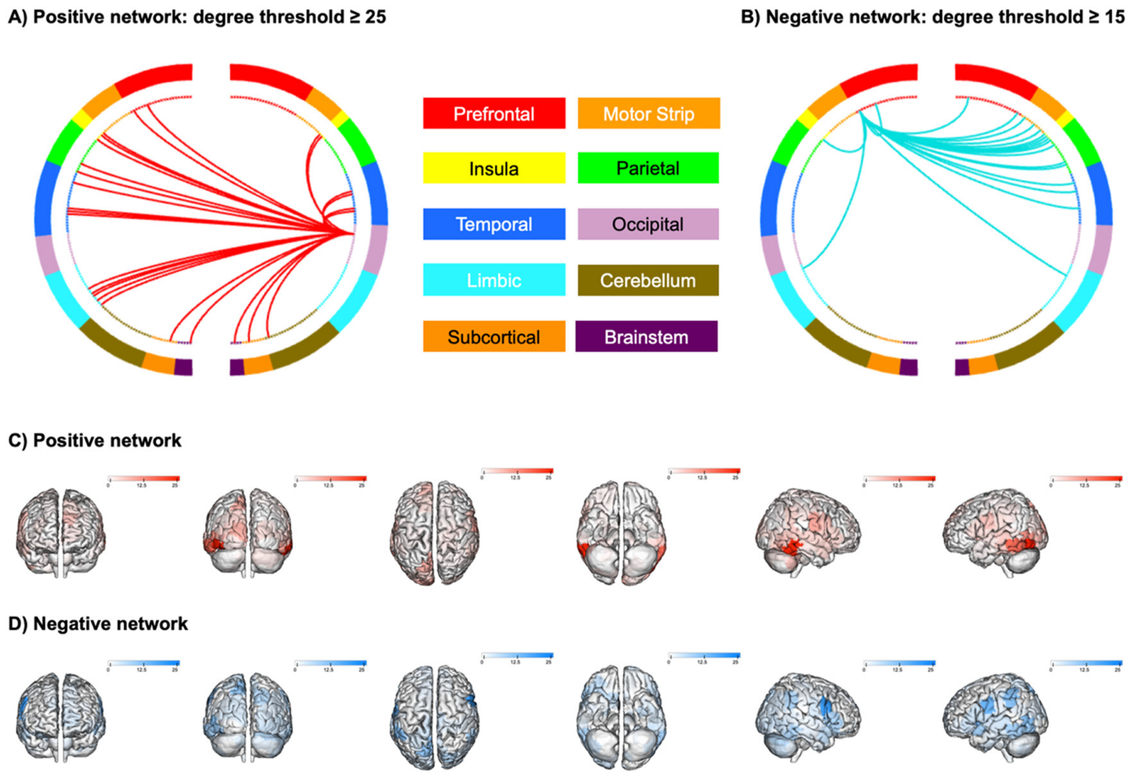

Fig. 2. Positive and negative problematic gaming networks. **A–B)** 268 nodes are organized to reflect macroscale brain regions in approximate anatomical order from the top (anterior) to the bottom (posterior) of the circle plots. Longer-range connections are indicated by longer lines. The left side of the circle plot represents the right hemisphere, while the right side represents the left hemisphere. **C–D)** Visualization of the node degree, which is the sum of predictive edges for a node. Higher degree nodes, which have more edges contributing to the CPM models, are indicated by darker colors

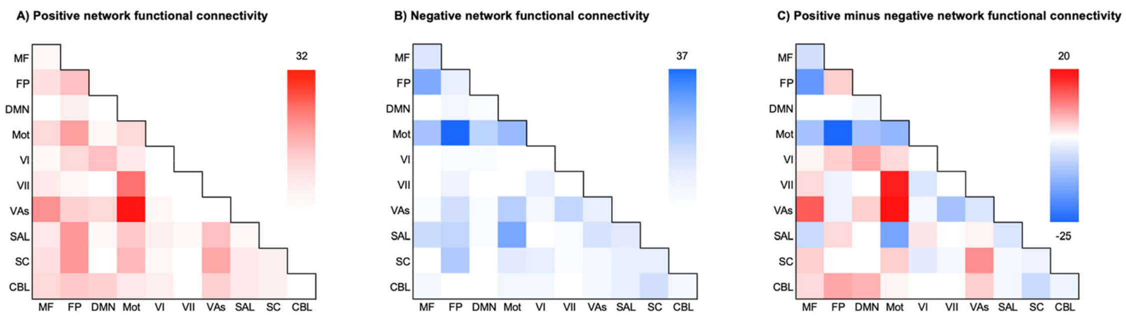

Fig. 3. Problematic gaming networks summarized by overlap with canonical neural networks. A summary of within- and between-network connectivity for the positive network, negative network, and the positive minus negative network is provided. **A–B)** The total number of edges connecting nodes within and between each network are represented as cells in matrix A and matrix B, with more edges being represented by darker cells. **C)** Cells show the positive minus negative network (i.e., the number of positive edges minus the number of negative edges connecting nodes within and between each network). Though positive and negative networks do not contain overlapping edges, matrix C is a visual representation of findings that align with recommendations by Shen et al. (2017) that cells may represent differences. Red represents more edges in the positive network, and blue indicates more edges in the negative network. *MF, medial frontal; FP, frontoparietal; DMN, default mode network; Mot, sensorimotor; VI, visual area 1; VII, visual area 2; VAs, visual association; SAL, salience; SC, subcortical; CBL, cerebellum*

Generalizability of the problematic-gaming severity network across brain states

The demographic characteristics of participants in the CPM analyses using SST, EN-back, and resting-state fMRI data are provided in Table S6 of the Supplementary Material. CPM analyses using other task-based fMRI data predicted problematic-gaming severity when controlling for all covariates (combined positive and negative networks for SST: $r = 0.15$, $p = 0.001$ via permutation testing; positive network only: $r = 0.12$, $p = 0.001$; negative network only: $r = 0.18$, $p < 0.001$; combined positive and negative networks for EN-back: $r = 0.17$, $p = 0.001$ via permutation testing; positive network only: $r = 0.13$, $p < 0.001$; negative network only: $r = 0.15$, $p < 0.001$). Similarly, the CPM model applied to resting-state fMRI data predicted problematic-gaming severity when all covariates were controlled for (combined positive and negative networks: $r = 0.09$, $p = 0.009$ via permutation testing; positive network only: $r = 0.08$, $p = 0.003$; negative network only: $r = 0.08$, $p = 0.007$). The Supplementary Material also includes results on model performance across brain states when controlling for additional covariates (i.e., depression, anxiety, impulsivity, and crystallized intelligence).

Similar to the model that used MIDT data, there were relatively more connections within the sensorimotor network and between sensorimotor, visual association, salience, cerebellar, medial frontal, and frontoparietal networks in the models using SST, EN-back task, and resting-state data, considering the positive and negative networks (see Figure S1 in the Supplementary Material). Additionally, the model using resting-state data notably had more connections involving the DMN in the negative network than the models using task-based data.

Additionally, applying the final consensus MIDT model to the SST, EN-back, and resting-state fMRI data successfully predicted problematic-gaming severity (SST: $r = 0.24$, $p = 0.001$ via permutation testing; EN-back: $r = 0.21$, $p = 0.001$ via permutation testing; resting-state: $r = 0.11$, $p = 0.001$ via permutation testing).

DISCUSSION

Given that evidence-based psychiatry is moving towards tailored and individualized patient care, individual-level predictions may facilitate early detection and personalized treatment for problematic gaming (Bzdok & Meyer-Lindenberg, 2018). This is the first CPM study to predict problematic-gaming severity in youth and identify underlying networks based on whole-brain functional connectivity during a MIDT. Shared predictive canonical networks were identified when CPM was applied to SST, EN-back, and resting-state fMRI data, indicating generalizability across multiple brain states. The model using resting-state data identified more connections involving the DMN, aligning with findings from previous resting-state functional connectivity studies on GD in youth (Yan et al., 2021). Consistent with previous CPM work (Greene et al., 2018), models using task-based rather than resting-state data appeared numerically more robust in predicting VGAQ scores. CPM analyses using SST and EN-back data were slightly (numerically) more robustly predictive than CPM using MIDT data, despite having smaller sample sizes (i.e., around 67% of the sample size for MIDT). Additionally, applying the final consensus MIDT model to SST, EN-back, and resting-state fMRI data successfully predicted problematic-gaming severity.

Problematic-gaming severity networks in our youth sample included connections between and within multiple well-established neural networks, consistent with other applications of the connectome-based approach in studies with adult samples (Finn et al., 2015; Yip et al., 2019;

Zhou et al., 2022). We created a theoretical network model of problematic-gaming severity to summarize the dominant connections derived from a comparison of the positive and negative networks to enhance the interpretability of findings (Yip, Kiluk, & Scheinost, 2020). As indicated in Fig. 4, the model proposes that severity of problematic gaming is associated with (i) a visual processing system, including visual area 2 and visual association networks, (ii) a cognitive control and executive functioning system, including frontoparietal and medial frontal networks, and (iii) a relevance and motor response system, including salience and sensorimotor networks. The model further proposes that decreased connectivity of networks within these systems is predictive of increased problematic-gaming severity, such as decreased connectivity between the medial frontal and frontoparietal networks. Decreased connectivity between the cognitive control and executive function system and the relevance and motor response system may also predict increased problematic-gaming severity. Furthermore, increased connectivity between the visual processing system and the two remaining systems may be positively predictive of problematic-gaming severity.

The predictive networks may represent promising targets to guide the development of personalized and novel treatment for problematic gaming in adolescents, including neuromodulation (Antons, Müller, Liebherr, & Brand, 2020). These networks and nodes may inform clinical practice by assigning patients to treatments based on neuromarkers (Bzdok & Meyer-Lindenberg, 2018), which is an approach that remains understudied in the context of problematic gaming, where existing treatment options in the literature for youth are limited and rarely personalized (Park et al., 2025). Additionally, highly connected nodes (like the right prefrontal node in the negative network, with connections to insular, parietal, motor strip, temporal, other prefrontal, and limbic nodes) may also represent potential intervention targets, including for non-invasive neuromodulation. However, before directly translating the CPM results into clinical practice, future research should work towards replicating the findings using a second independent sample and further refining the predictive model (Yip et al., 2019).

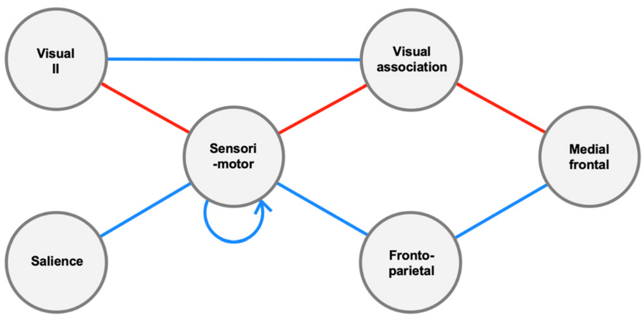

Fig. 4. Theoretical network model predictive of problematic gaming. This network model was derived from a comparison of the positive (red) and negative (blue) networks identified with CPM using task-based fMRI data. Problematic-gaming severity was positively predicted by increased connectivity between sensorimotor and visual area 2, sensorimotor and visual association area, and visual association area and medial frontal networks. Problematic-gaming severity was also positively predicted by decreased connectivity within the sensorimotor network as well as between the sensorimotor and salience, sensorimotor and frontoparietal, frontoparietal and medial frontal, and visual area 2 and visual association area networks

Elaborating on the theoretical model, the sensorimotor network (as part of the relevance and motor response system) is central to our model of problematic-gaming severity among youth and various CPM-related theoretical models of substance use disorders and addictive behaviors among adults, such as internet addiction (IA) (Antons et al., 2024; Feng et al., 2024). The sensorimotor network has previously been implicated in problem severity, craving, and automatized and compulsive reactions toward drug-related stimuli in adults with substance use disorders, such as cocaine, alcohol, and opioid use disorders (Hanlon, Wesley, Roth, Miller, & Porrino, 2010; Nikolaou, Critchley, & Duka, 2013; Porrino, Lyons, Smith, Daunais, & Nader, 2004; Yalachkov, Kaiser, & Naumer, 2010; Zeng, Su, Jiang, Chen, & Ye, 2015). These relationships may extend to youth with problematic gaming, with studies reporting enhanced engagement of sensorimotor networks in individuals with IGD compared to those without (Dong, Huang, & Du, 2012; Hong et al., 2015; Lee, Park, et al., 2021; Park et al., 2017; Wang et al., 2016, 2018; Zheng et al., 2019). Consistent with the I-PACE (Interaction of Person, Affect, Cognition and Execution) model of behavioral addictions, gaming behaviors may shift toward more compulsive, habitual, and seemingly automatic patterns of engagement (Brand et al., 2016, 2019, 2025), which parallel the functional role of the sensorimotor network among individuals with substance use disorders.

Participants included in the CPM analyses were about 12 years old on average, which precedes the average age of individuals with GD by around 6 (Stevens, Dorstyn, Delfabbro, & King, 2021) to 8 years (Kim et al., 2022). Research should examine whether the sensorimotor network remains a dominant component in the problematic-gaming model as individuals age and undergo significant maturation of the brain. In a previous study of IA symptomology in adults (mean age = 20, SD = 7.1), CPM applied to resting-state fMRI data similarly found that the sensorimotor network was important in the IA symptomology model (Feng et al., 2024). However, additional research may be insightful given that compared to the positive network identified in the present study, CPM applied to cue-craving task fMRI data in adults with IGD (mean age = 21, SD = 2.2) found relatively fewer connections between the sensorimotor network and other large-scale networks in the positive network (connections between large-scale networks in the negative network were not presented in that study) (Zhou et al., 2022). Instead, the adult-only CPM study of IGD reported relatively more connections within the default mode network and between the default mode and subcortical networks. This may reflect a developmental shift from more sensorimotor-driven patterns of engagement during early adolescence to greater involvement of higher-order networks (e.g., default mode and subcortical networks) as regulatory, motivational, and self-referential processes mature (Grayson & Fair, 2017). Future research may also test adult-specific IGD and IA models from previous CPM studies (Feng et al., 2024; Zhou et al., 2022) on the current youth dataset to examine replicability and model validation.

Unlike some CPM-related theoretical models of substance use disorders (e.g., outcomes related to cocaine (Yip et al., 2019) and opioid (Lichenstein et al., 2021) use), the problematic-gaming severity model includes a distinct visual processing system with increased connections to the sensorimotor network, as shown in our theoretical model. This may reflect a heightened reliance on visual-motor coordination, where youth with problematic gaming may more quickly react or respond to visual gaming cues (e.g., flashing lights, enemy movements, power-ups) in a compulsive, seemingly automatic manner (Brand et al., 2016, 2019, 2025). Such coordination may be particularly pronounced in youth who play popular action games, including multiplayer online battle arena and first-person shooter games (Homer, Hayward, Frye, & Plass, 2012), which have been suggested to be among the most addictive game genres (Kuss, Louws, & Wiers, 2012; Lemmens & Hendriks, 2016). Action games are unpredictable and typically require rapid detection of stimuli, top-down attention, and decision-making for motor responses (e.g., aiming, navigation, and shooting), often at a greater intensity than, for example, puzzle games (Bediou et al., 2018; Gong et al., 2015; Gozli, Bavelier, & Pratt, 2014; Moënne-Loccoz et al., 2023). Future data-driven studies should investigate the influence of game genres on the prediction of problematic-gaming severity in youth, as action games may alter sensorimotor network connectivity (Gong et al., 2015) to a greater extent than other genres like social simulation games (Mundorf, Siebert, Desmond, & Peterburs, 2023). Given increased preferences for action games among males compared to females (Lange, Wühr, & Schwarz, 2021), gender-related differences of neuromarkers of problematic gaming in adolescents according to game genres warrant further investigation.

The left peristriate area in the occipital lobe was identified as the node with the most connections in the positive network. The left peristriate area is involved in the visual association network in the proposed theoretical model and overlaps with parts of the middle occipital gyrus (MOG) implicated in the complex processing of visual information, which is characteristic of in-game visual demands (Renier et al., 2010). Several studies have reported increased activation of MOG in individuals with problematic gaming compared to those without (Kim, Han, Lee, Kim, & Renshaw, 2012; Leménager et al., 2014; Ma et al., 2019; Yao et al., 2017; Zhang et al., 2016). For example, one study reported specific associations between MOG and diminished body self-awareness in individuals experiencing problematic engagement with massively multiplayer online role-playing games (MMORPGs) (Leménager et al., 2014). This form of altered visual processing may reflect greater identification with virtual avatars than with the real self, consistent with the emerging evidence on social appearance anxiety in younger individuals with IGD (Yilmaz, Sulak, Griffiths, & Yilmaz, 2023) and virtual avatars often manifesting as representations of the ideal self (Szolin, Kuss, Nuyens, & Griffiths, 2022). Furthermore, the MOG has been observed to have increased resting-state functional connectivity with the dorsal putamen implicated in motor control (Lee, Namkoong, Lee, & Jung, 2021) and decreased connectivity with the dorsolateral prefrontal cortex (DLPFC) implicated in the strengthening of the sensorimotor network (Ge et al., 2017; Skok & Waszkiewicz, 2024) in individuals with IGD.

In the present study, several connections were identified between the left peristriate area and temporal nodes associated with language comprehension and social cognition. This finding suggests that the comprehension and application of strategies discussed by other individuals during a gaming session may enhance immersion, visual processing, and social relatedness, thereby reinforcing problematic gaming as a means to obtain social and cognitive rewards (Ma et al., 2019; Paulus, Ohmann, Von Gontard, & Popow, 2018). Typically, games with potentially high addictive potential, such as MMORPGs, often lack auditory storylines but call for communication among individuals in-game or through external online platforms, such as Discord (Hsu, Wen, & Wu, 2009; K. Wang, Tai, & Hu, 2023). As one advances in an MMORPG, the need for coordination with others often increases.

Similar to findings in this study, previous research has indicated greater engagement of the temporo-occipital functional network in response to gaming-specific stimuli compared with general internet surfing in individuals with IGD (Ma et al., 2019). The temporo-occipital network has also been linked to IA more broadly. For example, Ma et al. (2019) reported a positive correlation between this network and IA severity and Feng et al. (2024) demonstrated that this network was predictive of IA symptoms using CPM with resting-state fMRI data. Thus, the current evidence base appears to suggest a shared neuromarker across internet-enabled addictive behaviors, which could potentially indicate common predisposing factors underlying such behaviors. Given the potentially shared neural mechanisms, it might be that some interventions that are effective for problematic gaming are also effective for other internet-enabled addictive behaviors, such as problematic use of social media. That said, other factors, including genetics, early childhood experiences, psychopathology, and environmental aspects (Brand et al., 2019), should be considered when translating interventions across multiple behavioral addictions, as these factors may also influence problem development and maintenance.

In the negative network, the most predictive node was identified as the right Broca's area located in the prefrontal cortex, which is part of the frontoparietal network in the proposed theoretical model. Unlike its left homolog, the right Broca's area is arguably understudied (Magan & Yadav, 2021). However, functional neuroimaging studies have previously demonstrated that the right pars opercularis, a region included in the right Broca's area, plays an important role in implementing top-down controlled response inhibition (Forstmann, van den Wildenberg, & Ridderinkhof, 2008). Impaired response inhibition has been observed in individuals with IGD using a variety of tasks, including Stroop, go/no-go, and task-switching tasks (Dong, Lin, Hu, Xie, & Du, 2015). Supporting findings from this study, a meta-analysis of fMRI studies found differences in the activation of several areas of the prefrontal cortex in individuals with IGD (Meng, Deng, Wang, Guo, & Li, 2015), which have been considered in the context of response inhibition (Argyriou, Davison, & Lee, 2017).

Several connections between the right Broca's area and bilateral insular nodes were observed in the negative network, potentially implying that deficits in neural mechanisms for cognitive control and emotion regulation may contribute to the compulsive nature of problematic gaming and changes in reward sensitivity (Vaccaro & Potenza, 2019). Decreased functional connectivity between these two regions suggest that the right Broca's area may contribute importantly to impaired control over gaming, which warrants further investigation given limited gaming-related studies of this brain region. This study presents a novel finding that extends previous theory-driven neuroimaging studies using ROIs that have found decreased functional connectivity between several regions in the prefrontal cortex (e.g., DLPFC and the supplementary motor area) and the bilateral insula in individuals with IGD (Chen et al., 2016; Ge et al., 2017; Han et al., 2018; Jin et al., 2016; Mestre-Bach & Potenza, 2023). As machine-learning research for problematic gaming is in early stages compared to that for substance use disorders (Chhetri, Goyal, & Mittal, 2023; Mak, Lee, & Park, 2019), both whole-brain data-driven approaches and theory-driven neuroimaging studies should be considered to continue advancements in individual-level predictions (Antons et al., 2024; Yip et al., 2020).

Limitations

The present study has limitations. First, though the study demonstrated the generalizability of the problematic-gaming-severity network across multiple brain states, an external replication sample was not used. Future studies should incorporate a second independent sample to further examine the replicability and generalizability of the predictive model. Second, the functional significance of the identified networks in relation to other forms of psychopathology associated with problematic gaming in adolescents remains to be tested, as similarly described by Yip et al. (2019) and Ibrahim et al. (2022). The present study did not entirely rule out the potential influence of other clinical variables (e.g., the concurrent use of substances) on connectivity, but notably remained robust when multiple covariates were included. Third, the CPM analyses used scores on the VGAQ, which is a relatively infrequently used measure. That being said, no single assessment tool has been found to be superior in measuring GD or the spectrum of problematic-gaming behaviors (King et al., 2020; Park, King, Wilkinson-Meyers, & Rodda, 2023). When a gold standard for assessing problematic gaming is established, it could be used to validate and extend the current study findings.

Conclusion

In this study, CPM successfully identified neural networks predictive of problematic-gaming severity in youth. The left peristriate area in the positive network and the right Broca's area in the negative network were identified as nodes with the most connections. Additionally, canonical networks that predicted problematic gaming included visual area 2, visual association, frontoparietal, medial frontal, salience, and sensorimotor networks. CPM was able to successfully predict problematic-gaming-severity scores across multiple brain states and identified similar relationships among canonical networks, indicating generalizability across brain states. Overall, the findings highlight that individual differences in connectivity across networks associated with visual processing, cognitive control, executive function, salience, and motor response can predict problematic-gaming severity in youth. These networks and constituent regions may reflect neuromarkers that serve as promising targets for informing the development of personalized interventions for youth with problematic gaming. Future CPM research should incorporate an external sample to investigate the replicability of the identified problematic-gaming-severity network.

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Authors' contribution: JJP: methodology, visualization, writing – original draft, writing - review & editing. CL: methodology, formal analysis, visualization, writing - review & editing. DS: methodology, writing - review & editing. LYM: methodology, writing - review & editing. MNP: conceptualization, methodology, writing - review & editing, funding acquisition, supervision. YZ: conceptualization, methodology, formal analysis, writing - review & editing, funding acquisition.

Data and code availability: Data analyzed in this study can be found in the ABCD data repository, which are available in the National Institute of Mental Health Data Archive (https://nda.nih.gov/). The CPM code is available at the following website: https://github.com/YaleMRRC/CPM.

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SUPPLEMENTARY MATERIAL

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