Addictive Behaviors 143 (2023) 107683

Contents lists available at ScienceDirect

Addictive Behaviors

journal homepage: www.elsevier.com/locate/addictbeh

Decision-making and frontoparietal resting-state functional connectivity among impulsive-compulsive diagnoses. Insights from a Bayesian approach

J.J. León [a,b], P. Fernández-Martin [a,b], A. González-Rodríguez [a,b], R. Rodríguez-Herrera [a,b], J. García-Pinteño [a,b], C. Pérez-Fernández [a,b], A. Sánchez-Kuhn [a,b], L. Amaya-Pascasio [c], M. Soto-Ontoso [d], P. Martínez-Sánchez [c], F. Sánchez-Santed [a,b], P. Flores [a,b,*]

[a] Department of Psychology, Faculty of Psychology, University of Almeria, Carretera de Sacramento S/N, 04120, La Cañada de San Urbano, Almeria, Spain
[b] Health Research Centre (CEINSA), University of Almeria, Carretera de Sacramento S/N, 04120, La Cañada de San Urbano, Almeria, Spain
[c] Department of Neurology and Stroke Centre. Torrecárdenas University Hospital, Spain
[d] Mental Health Departament. Torrecárdenas University Hospital, Spain

ARTICLE INFO

Keywords:
Decision-making
IGT
fNIRS
Resting-state functional connectivity
Bayesian general linear model

ABSTRACT

The Iowa Gambling Task (IGT) is one of the most widely used paradigms for assessing decision-making. An impairment in this process may be linked to several psychopathological disorders, such as obsessive–compulsive disorder (OCD), substance abuse disorder (SUD) or attention-deficit/hyperactivity disorder (ADHD), which could make it a good candidate for being consider a transdiagnostic domain. Resting-state functional connectivity (rsFC) has been proposed as a promising biomarker of decision-making. In this study, we aimed to identify idiosyncratic decision-making profiles among healthy people and impulsive-compulsive spectrum patients during the IGT, and to investigate the role of frontoparietal network (FPN) rsFC as a possible biomarker of different decision-making patterns. Using functional near-infrared spectroscopy (fNIRS), rsFC of 114 adults (34 controls; 25 OCD; 41 SUD; 14 ADHD) was obtained. Then, they completed the IGT. Hybrid clustering methods based on individual deck choices yielded three decision-makers subgroups. Cluster 1 ($n = 27$) showed a long-term advantageous strategy. Cluster 2 ($n = 25$) presented a maladaptive decision-making strategy. Cluster 3 ($n = 62$) did not develop a preference for any deck during the task. Interestingly, the proportion of participants in each cluster was not different between diagnostic groups. A Bayesian general linear model showed no credible differences in the IGT performance between diagnostic groups nor credible evidence to support the role of FPN rsFC as a biomarker of decision-making under the IGT context. This study highlights the importance of exploring in depth the behavioral and neurophysiological variables that may drive decision-making in clinical and healthy populations.

1. Introduction

Transdiagnostic approaches to psychopathology, such as the Research Domain Criteria (RDoC), are emerging as a new framework for researchers and clinicians with the long-term goal of clarifying the etiopathogenesis and clinical manifestation of psychiatric symptoms using broad biologically and clinically relevant dimensions (Cuthbert, 2020). Actions involving decision-making processes are crucial for daily and social life functioning and constitute one of these proposed dimensions to explain behavioral variability across individuals.

The Iowa Gambling Task (IGT) (Bechara et al., 1994) is one of the most widely used paradigms to assess contingency-based decision-making processes under uncertain situations. Participants have to learn about the reward/punishment contingencies of four different decks and make choices based on that experience to maximize long-term profits. Although healthy people are supposed to optimize their gains by establishing a long-term advantageous choice strategy (Bechara et al., 1994; Steingroever et al., 2013), it is also argued that their choices are

* Corresponding author.
E-mail addresses: jld774@ual.es (J.J. León), pfm246@ual.es (P. Fernández-Martin), agr609@ual.es (A. González-Rodríguez), mrh586@ual.es (R. Rodríguez-Herrera), jgp381@ual.es (J. García-Pinteño), cpf603@ual.es (C. Pérez-Fernández), ask940@ual.es (A. Sánchez-Kuhn), laura.amaya.pascasio.sspa@juntadeandalucia.es (L. Amaya-Pascasio), Miguel.Soto.ontoso.sspa@juntadeandalucia.es (M. Soto-Ontoso), patrinda@ual.es (P. Martínez-Sánchez), fsanchez@ual.es (F. Sánchez-Santed), pflores@ual.es (P. Flores).

https://doi.org/10.1016/j.addbeh.2023.107683
Received 14 October 2022; Received in revised form 20 February 2023; Accepted 24 February 2023
Available online 11 March 2023
0306-4603/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

driven by the frequency of the punishment instead of by long-term benefits (Horstmann et al., 2012; Kumar et al., 2019; Steingroever et al., 2013). Patients with a diagnosis of an impulsive-compulsive spectrum disorder, such as Obsessive-Compulsive Disorder (OCD) (Cavedini et al., 2006), Attention-Deficit/Hyperactivity Disorder (ADHD) (Malloy-Diniz et al., 2007), or Substance Use Disorder (SUD) (Bartzokis et al., 2000; Bechara & Martin, 2004) seem to underperform healthy matched adults on this task in terms of a lower net score, which is the number of long-term disadvantageous choices minus the number of long-term advantageous choices. However, some inconsistent results have also been reported, showing no differences when comparing the net score obtained by ADHD (Agay et al., 2010; Ernst et al., 2003; Groen et al., 2013; Norman et al., 2018), OCD (Lawrence et al., 2006; Norman et al., 2018) and alcohol dependent patients (Delibaş et al., 2018; Zorlu et al., 2014) to healthy controls. As each deck in the IGT presents particular reward/loss contingencies, paying attention only to the net score might lead to the loss of valuable information about each participant's task strategy. Instead, analyzing deck choice behavior along the task may provide a more accurate characterization of each individual decision-making strategy, which could shed some light on the abovementioned mixed findings (Horstmann et al., 2012; Ma et al., 2015; Steingroever et al., 2013; Toplak et al., 2005).

In line with RDoC initiatives, understanding brain resting-state functional connectivity (rsFC) as a transdiagnostic target may be helpful to identify specific neurobiological patterns associated (or not) with specific cognitive profiles (Siugzdaite et al., 2020). The frontoparietal network (FPN) seems to be implicated in coordinating and adapting behavior in a goal-driven manner (Marek & Dosenbach, 2018), and seems to comprise a wide-spread network including frontal and parietal main cores: the dorsolateral prefrontal cortex (DLPFC), orbital gyrus, medial prefrontal cortex, frontopolar areas and posterior parietal regions (Markett et al., 2014; Stern et al., 2012).

Frontoparietal network has shown to present an aberrant rsFC in some impulsive-compulsive spectrum disorder patients compared to healthy controls. Vaghi et al. (2017) showed a reduced connectivity between the striatum and frontoparietal regions in OCD patients. In this line, recent *meta*-analysis and reviews have revealed an hypoconnectivity between caudate and FPN regions such as DLPFC and dorsomedial (dmPFC) prefrontal cortex and a general hypoconnectivity within the FPN (Gürsel et al., 2018; Liu et al., 2022). Regarding SUD patients, increased connectivity within orbitofrontal cortex has been reported in heroin users (Ieong & Yuan, 2017). Additionally, a recent *meta*-analysis has reported a reduced rsFC within the FPN in different SUDs (Taebi et al., 2022). Concerning ADHD, aberrant connectivity in the FPN has been also shown, althought the directionality of the relationship between the strength of the rsFC and ADHD symptomatology remains unclear (Bush, 2011; Lin et al., 2015; Mostert et al., 2016; Silk et al., 2008).

In these terms, from a psychological perspective, rsFC could be a predictor of behavioral patterns, which could make rsFC a promising biomarker for decision-making.The predictive role of different rsFC networks, including FPN, has been studied in decision-making paradigms such as the Delay Discounting Task (Hobkirk et al., 2019; Li et al., 2013) and the Balloon Analogue Risk Task (Wei et al., 2016). While these experimental works showed a negative relationship between the strength of the rsFC within and between different networks and impulsivity during decision-making tasks, other research has revealed a positive relationship and different interactions between the strength of the rsFC in the executive control network (or FPN) and other networks and ADHD symptomatology (Gao et al., 2019; Mostert et al., 2016). Also, a general dysconnectivity between different hubs of different networks, including FPN, has been proposed as a characteristic of OCD pathophysiology (Liu et al., 2022).

Although the rsFC of the FPN is supposed to be critical in controlling and adapting behavior in a goal-directed manner during both, resting- and task-induced sates (Marek & Dosenbach, 2018), its relationship with IGT performance remains, to the best of our knowledge, unclear.

Taking into account all the above exposed, in this study, we aimed (i) to identify potential particular decision-making profiles in impulsive-compulsive spectrum patients and healthy controls based on their deck choice behavior during the IGT through the application of an exploratory clustering approach and (ii) to investigate the role of rsFC between different regions of the FPN as a possible biomarker of each potential idiosyncratic choice behavior. We hypothesized that (i) decision-making profiles will mainly depend on the frequency of punishment instead of on the long-term profit associated with each deck, (ii) decision-making profiles in healthy adults and impulse-compulsive spectrum patients will cut across diagnostic labels, and (iii) identified decision-making profiles will show different and specific predictive rsFC patterns. Specific directions of these effects are difficult to predict due to the abovementioned inconsistences in the literature, so our approach regarding these issues will be mainly exploratory.

2. Method

2.1. Participants

A total of 114 adults participated in this study. All participants gave verbal and written informed consent. The study was approved by the local Ethics Committee of the University of Almeria and the Torrecardenas University Hospital and was conducted following the Declaration of Helsinki. Demographic and clinical features are detailed in Table 1.

41 inpatients with SUD were recruited from a recovery and relapse-prevention center. A clinical psychologist introduced them to the study and checked the eligibility criteria. They must have been abstinent for at least 15 days. If so, they underwent a clinical interview and completed rating scales, including the Spanish version of the Beck Depression Inventory-II (Sanz et al., 2003) and the State-Trait Anxiety Inventory (Buela-Casal et al., 2015). 33 SUD patients had a diagnosis of poly-substance abuse while 8 SUD patients had been addicted to one substance ($n = 4$ alcohol; $n = 3$ cocaine; $n = 1$ cannabis). All SUD participants were men because of the internal rules of the center. 30 SUD patients were on pharmacological treatment.

OCD ($n = 25$) and ADHD ($n = 14$) participants were recruited from the mental health unit of the Torrecardenas University Hospital. An experienced psychiatrist introduced them the project and assessed eligibility criteria by phone. They must have a clinical diagnosis of OCD/ADHD according to DSM-5 criteria (American Psychiatric Association, 2013). Healthy controls (HC; $n = 34$) were recruited by word of mouth from the community. They must have no history of neurological or psychiatric diseases. After eligibility assessment, OCD, ADHD, and HC participants were administered a clinical interview and several questionnaires to confirm the diagnosis, in the case of patients, and to rule out exclusion criteria in healthy participants at the University of Almeria. They completed the Spanish version of the ADHD Rating Scale-5 (Richarte et al., 2017), the Obsessive Compulsive Inventory-Revised (Fullana et al., 2005), and the Adult Self-Report Scale (Achenbach & Rescorla, 2003). ADHD patients met criteria for Combined ($n = 5$), Inattentive ($n = 6$), Hyperactive ($n = 1$) and non-specified ($n = 2$) presentations. 18 OCD and 13 ADHD patients were undertaking medication. 6 OCD and 9 ADHD patients had a wash-out period of at least 24.

2.2. Materials

2.2.1. Iowa Gambling task

We used a computerized version of the IGT (Bechara et al., 1994). The task comprised 100 trials. In each trial, four decks of cards (A, B, C, and D) appeared on the screen. Participants had to press the keys 1, 2, 3, or 4, respectively, to pick one. After each choice, a feedback display showing the outcomes received was presented for 2000 ms. During the whole task, Decks A and B entailed a long-term loss (disadvantageous

Table 1
Demographics and clinical measures of the sample.

	HC ($n = 34$)	OCD ($n = 25$)	SUD[b] ($n = 41$)	ADHD[b] ($n = 14$)	Comparisons[e]
Demographics					
% Women	58.82	40	0	21.42	$p < .05$
Age[a, d]	35.21 ± 11.36	38.28 ± 11.91	44.12 ± 8.67	34.36 ± 13.26	$p > .05$
Annual income[a]	22,117.65 ± 11,996.3	13,464 ± 12,373.32	6,091.625 ± 5309.576	19,276.92 ± 19,543.89	HC > OCD = SUD = ADHD
Years of formal education[c]	16.794 ± 3.675	15.44 ± 4.673	8.735 ± 4.406	14.929 ± 3.245	SUD < HC = OCD = ADHD
% comorbidities					
Depressive disorder	–	16	19.51	7.14	
Anxiety disorder	–	20	7.32	7.14	
Bipolar disorder	–	0.00	2.44	0.00	
Personality disorder	–	16	2.44	14.29	
Tics disorder	–	4	0.00	7.14	
Learning disorder	–	0.00	0.00	28.57	
Eating disorder	–	12	0.00	0.00	
ADHD	–	4	0.00	0.00	
OCD	–	0.00	0.00	7.14	
SUD	–	4	0.00	7.14	
ICD	–	0.00	0.00	7.14	
PTSD	–	4	0.00	0.00	
% Prescribed medication	–	72	73.17	92.86	
Stimulants	–	0.00	0.00	42.86	
Antihypertensive	–	0.00	2.44	0.00	
Antipsychotic	–	50	14.63	0.00	
Antidepressant	–	77	31.71	14.28	
Anxiolytic	–	50	51.22	14.28	
Antiepileptic	–	0.00	2.44	7.14	
Opioid	–	0.00	21.95	0.00	
Clinical measures[a]					
ADHD-RS-V	11.24 ± 6.44	18.58 ± 10.24	–	**31.07 ± 7.74**	ADHD > OCD > HC
OCI-R	17.25 ± 11.76	**39.91 ± 13.49**	–	**23.93 ± 13.22**	OCD > ADHD = HC
ASR DSM OCD	55.12 ± 6.81	**72.52 ± 8.70**	–	64.86 ± 8.88	OCD > ADHD > HC
ASR DSM ADHD	56.68 ± 7.18	64 ± 11.09	–	**70 ± 10.86**	ADHD = OCD > HC
BDI-II	–	–	**18.60 ± 9.25**	–	
STAI-State	–	–	22.69 ± 11.65	–	
STAI-Trait	–	–	25.77 ± 10.89	–	

Note. SUD participants did not complete ADHD-RS-5, OCI-R and ASR questionnaires, while ADHD, OCD and HC participants did not complete BDI-II and STAI questionnaires because clinical groups belonged to two different funded research projects. Scores in the clinical range are boldfaced.
ICD = Impulse Control Disorder; PTSD = Post-traumatic stress disorder; ADHD-RS-V = ADHD Rating Scale-5; OCI-R = Obsessive-Compulsive Inventory-Revised; ASR DSM OCD = Adult Self-Report OCD DSM-Oriented Scale; ASR DSM ADHD = Adult Self-Report ADHD DSM-Oriented Scale; BDI-II = Beck Depression Inventory-II; STAI = State-Trait Anxiety Inventory.
aMean ± SD is represented. bInformation on prescribed medication and comorbid disorders from 4 SUD participants is missing. We could not collect annual income from nine of the SUD participants and from one of the ADHD participants. cYears of formal education from seven of the SUD participants is missing. dAge from six of the SUD participants is missing. eStatistical comparissons were performed using a Welch-James ANOVA. Fisher Exact Test was used to compare sex proportion between groups.

decks) while decks C and D supposed a long-term benefit (advantageous decks). Decks could also be classified according to the frequency and magnitude of losses. Therefore, any choice of Deck A (high frequency-low magnitude losses) would result in a gain of 100 points, but participants could also receive a loss of 150/200/250/300/350 points in a 1:2 ratio. Deck B (low frequency-high magnitude losses) also offered 100 points but they could lose 1250 points in a 1:10 ratio. Deck C (high frequency-low magnitude losses) was rewarded with 50 points but penalized with losses of 25/50/75 points in a 1:2 ratio. Lastly, Deck D (low frequency-high magnitude losses) also offered 50 points when chosen, but participants could lose 250 points in a 1:10 ratio. The dependent variable in this study was the number of choices of each deck in each of the five blocks of the task, each block consisting of 20 trials.

All participants began with an amount of 2000 points and were instructed to maximize their benefits by picking cards from the different decks. They were not informed about the number of trials. Task instructions are detailed in Supplementary Material 1.

2.2.2. rsFC data acquisition

We recorded the relative changes in the concentration of oxy- (HbO_2) and deoxy- (HbR) hemoglobin in cortical areas of the FPN during 10 min of resting state. We used two portable continuous-wave functional near-infrared spectroscopy (fNIRS) systems in tandem mode (NIRSport device, NIRx Medical Technologies LLC, Berlin, Germany). fNIRS data were acquired using the NIRStar Software version 15.0 (NIRx Medical Technologies LLC, Berlin, Germany) at a sampling rate of 3.41 Hz.

We employed a custom probe array of 32 optodes (16 light sources and 16 detectors at two wavelengths, 760 nm and 850 nm) according to the International 10–10 system of electrode layout with an inter-optode distance of approximately 30 mm. This source-detector configuration resulted in 54 fNIRS measurement channels. In this study, we selected 18 channels that cover up six regions of interest (ROIs) from the FPN: dorsolateral prefrontal cortex (DLPFC), orbitofrontal cortex (OFC) and posterior parietal cortex (pPC), each of them in the right and left hemisphere. The remaining channels were used for a larger research project.

AtlasViewer software was employed to evaluate the probe sensitivity. Fig. 1 depicts the spatial sensitivity profile obtained for each used measurement channel on the cortical surface after performing a Monte Carlo photon migration simulation with 10^7 photons.

2.2.3. rsFC data pre-processing

fNIRS signals were pre-processed and analyzed using a customized MATLAB-based script from the open-source package NIRS Brain AnalyzIR toolbox (Santosa et al., 2018). We downsampled the raw intensity signal to 1 Hz and then converted it into changes in optical density. We

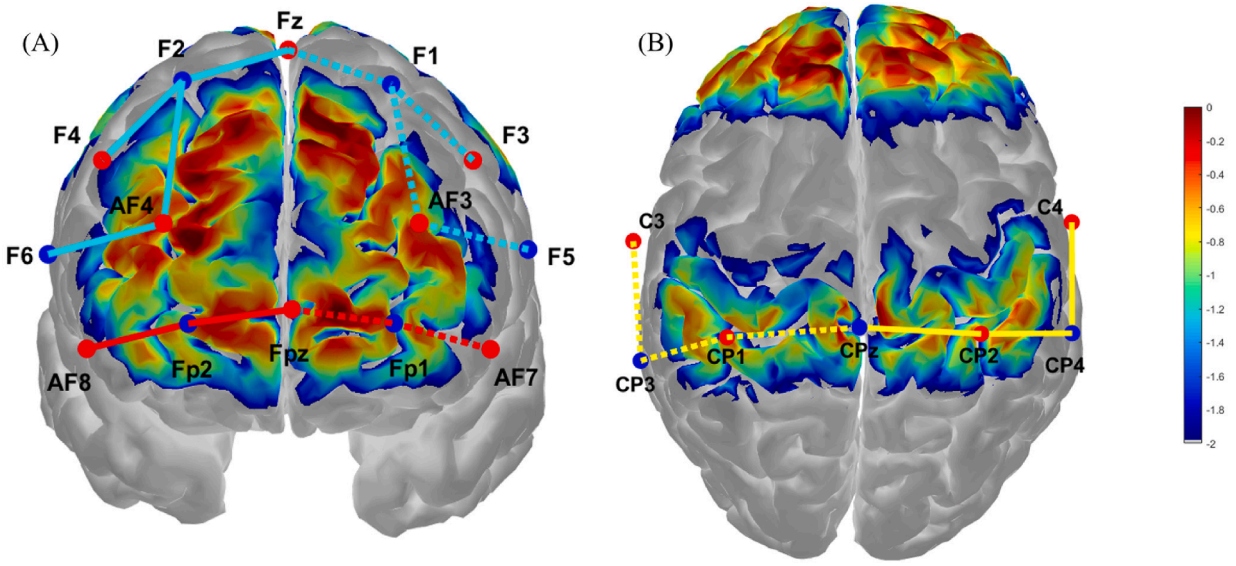

Fig. 1. Graphical visualization of the spatial sensitivity profile in $\log_{10}(mm^{-1})$. Red and blue dots represent the position of sources and detectors. Solid and dotted lines represent right and left hemisphere. Red, light blue and yellow lines cover up, respectively, the defined ROIs: orbitofrontal, dorsolateral and posterior parietal cortex. (A) Coronal plane. (B) Horizontal plane.

applied the modified Beer-Lambert Law to obtain the relative changes in the concentration of HbO_2 and HbR. We select HbO_2 signals to compute the analyses since it is the most correlated measure with the blood oxygen level-dependent (Duan et al., 2012). Pre-whitening and pre-weighting methods were applied to ensure the correction of confounding signals such as systemic physiological noise and motion artifacts. The combination of both filtering methods has been suggested to be a reliable approach to better control type-I errors (Barker et al., 2013; Huppert, 2016; Santosa et al., 2017).

rsFC was computed at the time domain through a whole-brain correlation approach. Functional connectivity was then understood as the strength of the temporal correlation of the hemodynamic activity of each pairwise comparison. We conducted Pearson correlation analyses between the time series of every pair of ROIs to obtain the functional connectivity between the measured areas.

2.3. Procedure

First, we collected rsFC data for 10 min. Participants were instructed to be seated, relaxed, and as quiet as possible, keeping their eyes open and looking at a blank wall. The experimental room was well-acclimated and soundproofed. At least one researcher was always monitoring the recording. fNIRS data from 8 participants were discarded due to technical issues during the recording.

Afterward, we removed the fNIRS cap and participants completed the IGT, which lasted approximately 10 min. After they read the instructions, participants were asked to explain the task before starting to make sure they understood it correctly. Once they finished, we explicitly asked them (60.42% of the participants were asked) whether they thought there was an optimal strategy to maximize their profits and, if so, which decks they had to pick.

2.4. Statistical analysis

2.4.1. Clustering procedure

We used hybrid hierarchical K-means clustering analyses to identify specific behavioral profiles associated with the IGT. This method combines hierarchical (Ward's linkage method on Euclidean distance) and non-hierarchical (K-means) methods to deal with the randomness of initial centroids selection (Hair et al., 2019). This algorithm was performed over the whole sample on the standardized number of choices of each deck in each 20-trial block of the IGT. We selected the optimal number of clusters based on dendrogram visualization and the gap statistic method (Tibshirani et al., 2001). Proportion tests were then performed to check if the number of cases in each cluster concerning to the total sample for each diagnostic group and sex was different from the expected. All analyses were run in R software (R Core Team, 2021).

2.4.2. Bayesian data analysis

We were interested in the number of choices of each deck in each block, as well as in the effect that rsFC, traditional diagnostic labels, and cluster membership, may exert on these choices. As several comparisons were going to be made, we decided to employ Bayesian data analysis, which allows us to explore a single posterior distribution from multiple perspectives granting a higher control over Type I errors (Kruschke, 2015). For making these estimations, we designed a General Linear Model (GLM) that considers, for each deck, block, and group, an estimated number of choices that may also be affected by the standardized rsFC between each of the ROIs of each individual. Additionally, Bayesian mean comparisons were used to explore whether there were differences in rsFC between diagnostic groups or cluster membership between the ROIs. For each of these purposes, two different models were run, with the only difference between them being the variable used as "Group", which could be diagnostic group or cluster membership. The full details of these models are specified in Supplementary Material available at https://osf.io/5hj48/.

After the models were run, statistical decisions were made employing the 95% Highest Density Intervals (HDIs) as well as Regions Of Practical Equivalence (ROPEs), which determine a range around specific values of interest, such as zero when we estimate the difference between means or the value of regression coefficients. When the HDI completely excludes the ROPE, we will conclude that the values inside the ROPE are not credible (Kruschke, 2011). Regarding the number of choices, we will only consider as relevant those effects that suggest at least a change of one in the number of decks chosen per block, so we will establish a ROPE of (-1,1) for mean comparisons and a ROPE of (-0.5, 0.5) on the standardized regression coefficients of the rsFC between our ROIs, which would suppose a difference of at least one choice when this measure varies by two standard deviations (SDs). On the other hand, when we explore differences in rsFC between our ROIs in the different groups, we will consider as relevant all the differences in which the 95% HDIs exclude the value 0. As this measure is given as the correlation between

two areas and since our approach here is exploratory, we have no a priori knowledge of which amount of change would suppose a relevant difference.

All analyses were performed using the RStan package (Stan Development Team, 2022). For each analysis, we extracted 12,000 samples using Markov Chain Monte Carlo (MCMC) sampling, each of the 4 chains having 2000 warmup samples and saving 3000 samples. Traceplots for all chains and parameters, as well as the Gelman-Rubin test (Gelman & Rubin, 1992) showed an appropriate convergence with all $\widehat{R}$ values below 1.05.

3. Results

3.1. Clustering analyses

A three-cluster structure was the optimal solution to characterize all participants' deck choice behavior according to the Gap statistic method. Graphical exploration of the dendrogram also supported this clustering solution (Fig. 2).

The first cluster ($n = 27$; $M_{age} = 37.72$, $SD_{age} = 9.71$) exhibited a preference for Deck D. The second cluster ($n = 25$; $M_{age} = 43.37$, $SD_{age} = 10.41$) exhibited a preference for Deck B. The third cluster ($n = 62$; $M_{age} = 37.81$, $SD_{age} = 12.14$) did not develop a preference for any deck. Thus, we labeled these profiles as "D-Learners", "B-Exploiters" and "Scattering", respectively. Proportion tests suggested there were no differences in the number of individuals belonging to each cluster

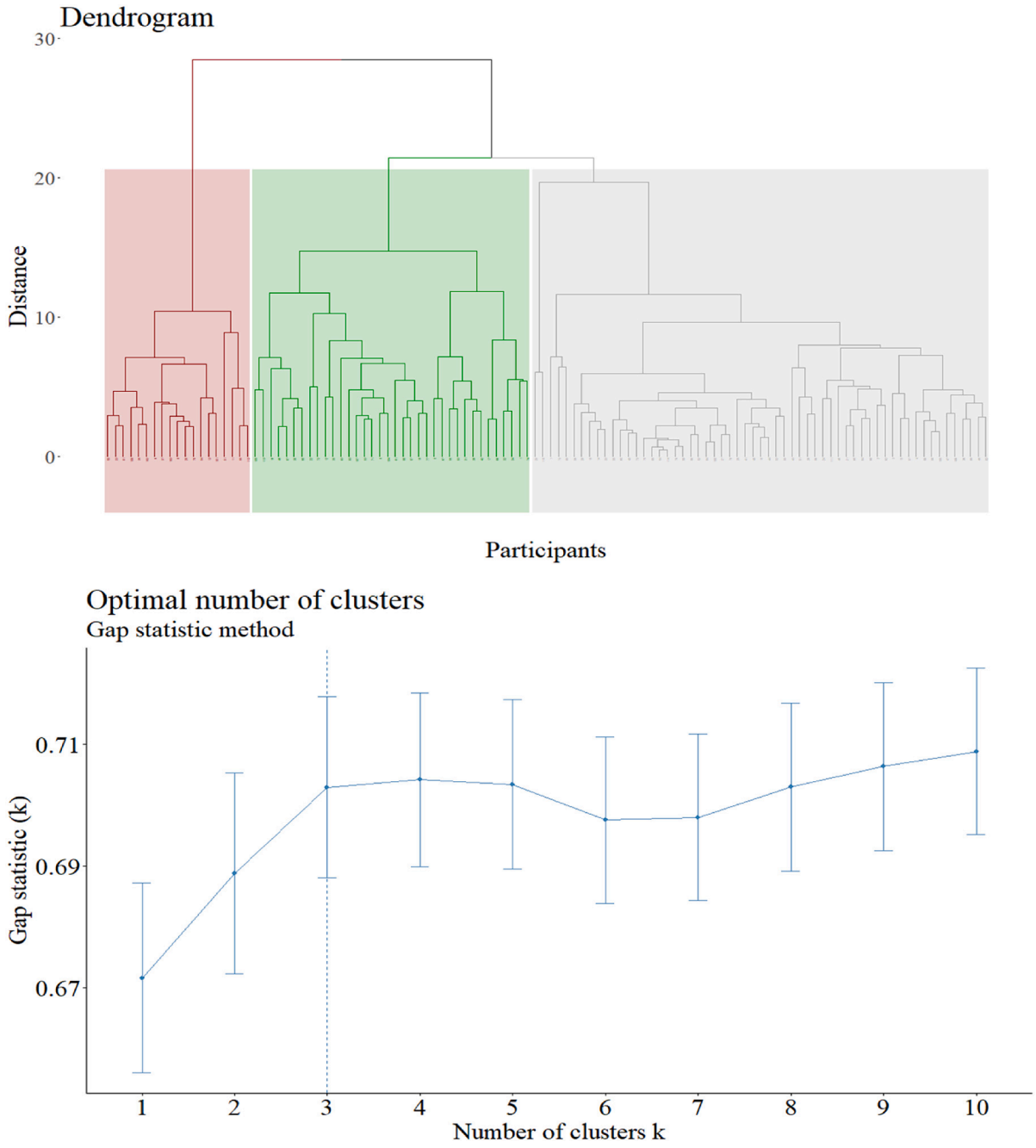

Fig. 2. Graphical representation of the best clustering solution.

depending on their diagnostic group or sex when compared to the expected proportion of cases within each cluster (see Table 2, Table 3, and Fig. 3).

3.2. Deck preference

To ease the comprehension of the results, only credible differences will be commented on. Statistics regarding the differences in means are exposed in Supplementary Material 1 (tables S1 to S8).

3.2.1. Diagnostic group

Participants did not show any credible differences regarding deck choice behavior in the IGT as a function of their diagnostic group (see Fig. 4).

3.2.2. Cluster membership

"D-Learners"(Cluster 1) showed a preference for Deck D from the beginning of the task when compared with the other clusters, which was maintained until the last block of the task. Starting on Block 3, this cluster showed a higher preference for Deck D than for the other decks. "B-Exploiters" (Cluster 2) revealed a preference for Deck B starting in the first block and also maintained until the last block of the task. These participants showed a higher preference for this deck from the first block of the task onward. Lastly, "Scattering" (Cluster 3) was distinguished by showing no credible differences between any of the chosen decks in any of the blocks, suggesting they had no preferred strategy and responded randomly. This information is graphically depicted in Fig. 5.

3.3. Resting-state functional connectivity differences

Bayesian mean comparisons revealed no credible differences in the rsFC between any of the ROIs neither comparing Clusters nor diagnostic groups. Data regarding these values are exposed in Fig. 6 and Fig. 7, respectively, and in Supplementary material.

3.4. Resting-state functional connectivity as a predictor of deck choice behavior

Analyses showed no credible relationship between the rsFC between any of the ROIs and deck choice behavior in any stage of the task, neither at the whole sample level nor in any diagnostic group or cluster (see Supplementary materials 2 and 3).

4. Discussion

In this study, we employed hybrid clustering analyses to identify specific decision-making profiles among a sample of healthy adults and OCD, ADHD and SUD patients during the IGT. We also applied a bayesian GLM to explore the role of rsFC between cortical areas of the FPN as a biomarker of deck choice behavior in the IGT.

Our first hypothesis is partially supported since two of the clusters show a notable preference for decks associated with infrequent losses. Concretely, cluster analyses revealed three different subpopulations. Importantly, all clusters presented no differences regarding sex distribution, annual income or years of formal education, which has been proposed as critical variables for the IGT performance (Evans et al., 2004; Ursache & Raver, 2015; van den Bos et al., 2013). The first cluster, "D-Learners", developed a long-term advantageous decision-making strategy, characterized by a preference for advantageous choices that carried low-frequency but high-magnitude losses. The second cluster, "B-Exploiters", was characterized by the exploitation, since the early stages of the task, of the disadvantageous deck that also offers low-frequency but high-magnitude losses, which could be understood as a long-term maladaptive strategy. Lastly, a fully scattering-based strategy profile was shown by the third cluster. These latter participants did not develop a preference for any deck at any stage of the task.

Theoretically, developing a long-term advantageous strategy during the IGT requires, in the first place, exploring the different choices to learn the contingency rules of each deck. After this, behavior may be adapted in a goal-directed manner, exploiting the most profitable choice. "D-Learners" seem to show this exploration–exploitation strategy since at the beginning of the task they had a similar number of choices of each deck, and from the third block onwards, they show a high preference for Deck D.

On the other hand, presenting a non-profitable behavior in the IGT may be due to different reasons. Scarce early exploration could generate a lack of information about the possible decisions and their outcomes, which inevitably leads to a biased representation of the alternatives presented in the task. In our case, in pursuit of early exploitation, "B-Exploiters" revealed a notable preference for Deck B since the beginning of the task. Another explanation of this behavior could be a negligent evaluation, driven by a high outcome sensitivity and a low loss aversion, of the expected utility of this deck considering the frequency and magnitude of gains and losses, which may be in accordance with models that aim to explain the way people evaluate decisions under risk (Kahneman & Tversky, 1979). This profile is also consistent with the so-called prominent Deck B phenomenon (Lin et al., 2007; Toplak et al., 2005) by which non-defective decision-makers would also tend to choose this deck over the rest. It has been used to claim a reformulation of the basic assumptions of the IGT (Lin et al., 2007).

Contrarily, showing excessive exploration may also be undesirable in this paradigm, since the maximization of profits requires the exploitation of specific choices over the rest. The "Scattering" cluster does not present a preference for any deck in any stage of the task, which may suggest they do have not a clear representation of the different outcomes carried out by each deck, which may make them evaluate all choices similarly. Another possibility is that participants could have learned a fictitious *do-not-exploit-a-deck* rule, which is consistent with a sequential exploration pattern (Ligneul, 2019), and would reflect an incorrect evaluation of the ratios and magnitudes of the gains and losses of each deck. In this sense, when asked, many participants (43.07% of asked participants) declared that the optimal strategy was to switch when a loss appears, or even when no penalties were given.

The existence of such differential response styles also highlights the importance of studying decision-making processes at the individual level, especially when the IGT is employed, because it is a complex task that encompasses a wide variety of possible strategies to be followed (Verdejo-Garcia et al., 2022). Importantly, even our healthy individuals reflect this same variability of preferences, so we think more caution should be taken when drawing inferences from findings when assuming that either (i) healthy people will adapt a long-term advantageous behavior or (ii) that maladaptive patterns detected in clinical populations are due to the key features of the clinical diagnoses.

Regarding our second hypothesis, we predicted that these profiles would cut across diagnostic labels, which has also been supported by data. We observed that maladaptive decision-making in the IGT is not a core feature of patients with a diagnosis of ADHD, OCD and SUD.

Table 2
Participants' proportional distribution in each cluster according to each diagnostic label.

Cluster	HC (n = 34)	OCD (n = 25)	SUD (n = 41)	ADHD (n = 14)
D-Learners	$n = 9$	$n = 10$	$n = 6$	$n = 2$
($n = 27$)	$\chi^2 = 0.03$	$\chi^2 = 2.84$	$\chi^2 = 1.39$	$\chi^2 = 0.26$
	$p = .09$	$p = .09$	$p = .24$	$p = .61$
B-Exploiters	$n = 5$	$n = 6$	$n = 9$	$n = 5$
($n = 25$)	$\chi^2 = 0.66$	$\chi^2 = 0.000$	$\chi^2 = 0.000$	$\chi^2 = 0.85$
	$p = .42$	$p = .99$	$p = .99$	$p = .36$
Scattering	$n = 20$	$n = 9$	$n = 26$	$n = 7$
($n = 62$)	$\chi^2 = 0.12$	$\chi^2 = 2.71$	$\chi^2 = 1.02$	$\chi^2 = 0.004$
	$p = .73$	$p = .10$	$p = .32$	$p = .95$

Table 3
Demographic information (sex distribution, annual income and years of formal education) of each cluster.

Cluster	Number of women	Annual income[a]	Years of formal education[b]
D-Learners ***(n = 27)***	8 $\chi^2 = 0.00$ $p = .999$	14,300.46 ± 11,150.65	15.58 ± 5.62
B-Exploiters ***(n = 25)***	8 $\chi^2 = 0.012$ $p = .911$	11,352.38 ± 9,830.70	11.65 ± 5.20
Scattering ***(n = 62)***	17 $\chi^2 = 0.024$ $p = .876$	16,209.12 ± 15,249.68	13.62 ± 5.02

Note. [a]We could not collect annual income from nine of the SUD participants and from one of the ADHD participants. [b]Years of formal education from seven of the SUD participants is missing.
Welch-James ANOVA revealed no main effect of cluster in annual income ($T_{WJ(2,\ 42{,}78)} = 1.043$, $p = .378$) nor in years of formal education ($T_{WJ(2,\ 39.79)} = 2.532$, $p = .084$).

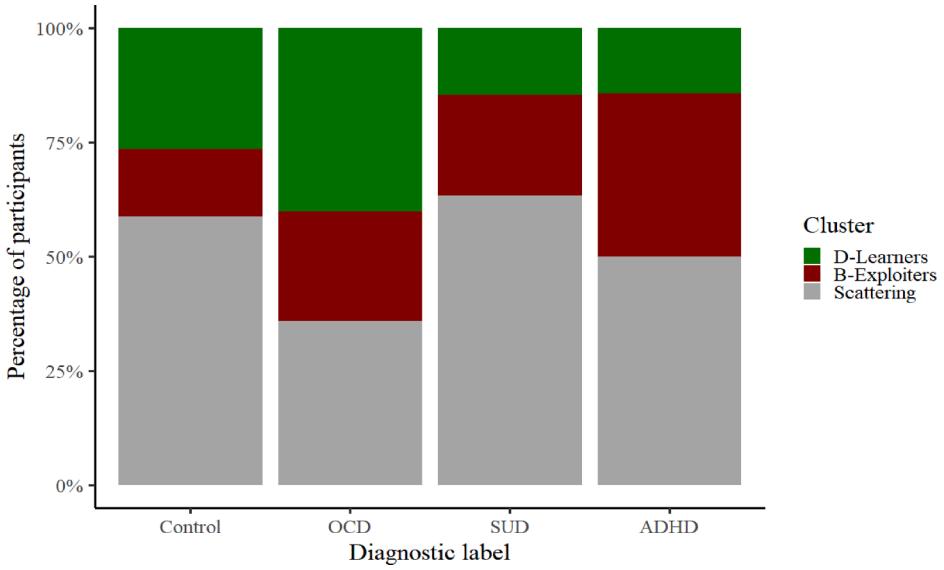

Fig. 3. Graphical representation of the percentage of participants in each cluster based on their diagnostic label.

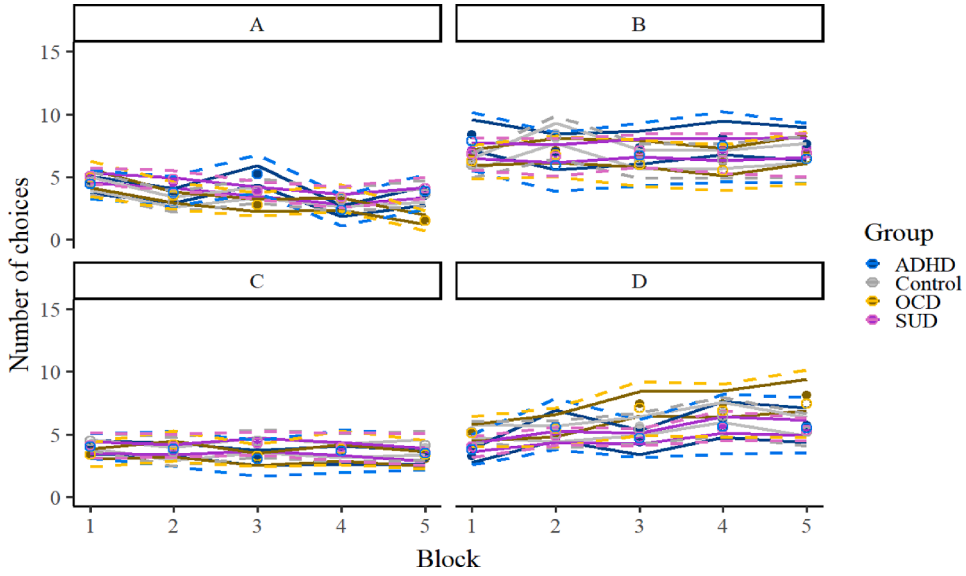

Fig. 4. Real (solid points) and predicted (blank points) number of choices of each deck as a function of diagnostic group and block, respectively representing the true means and the mean of the posteriors. The solid and dashed lines represent the standard error of the mean (SEM) and the 95% HDIs.

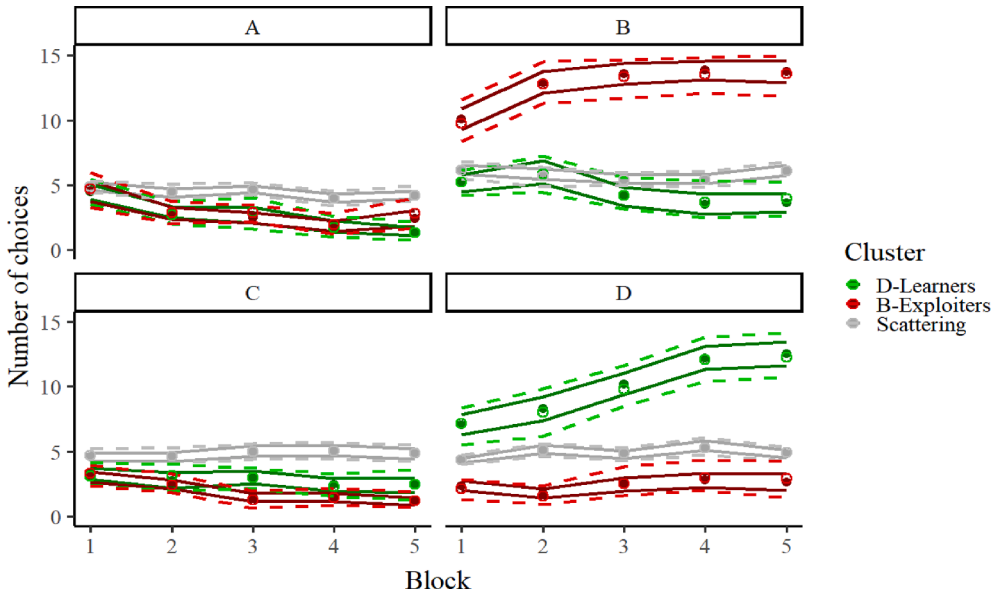

Fig. 5. Real (solid points) and predicted (blank points) number of choices of each deck as a function of clusters and blocks, respectively representing the true means and the mean of the posteriors. The solid and dashed lines represent the standard error of the mean (SEM) and the 95% HDIs.

Instead, participants from each diagnostic group, as well as healthy participants, showed not a different probability of being included in each of the abovementioned clusters. When we explored the number of choices of each deck in each of the blocks we did not find any credible differences between diagnostic groups and healthy participants either. So, according to our data, variability in deck choice behavior during the IGT seems to be similarly distributed among individuals with and without diagnoses. These findings are in line with studies reporting no differences in IGT performance between ADHD and OCD and healthy people (Groen et al., 2013; Norman et al., 2018). However, it has been widely reported that SUD patients underperform healthy controls in the IGT (Bartzokis et al., 2000; Bechara & Martin, 2004; Kovács et al., 2017; Verdejo-García et al., 2007), which is inconsistent with our results.

These studies usually report the net score as a measure of decision-making, which may lead to the loss of valuable information. We suggest that deck preferences develop as individuals experience the contingencies associated with each deck and that this process will be mediated by individual differences in factors such as loss aversion, risk aversion, reward sensitivity or error processing, which are not possible to address paying attention only to the net score. Global outcomes such as the net score hide the genuine behavioral pattern of the participants and may contribute to contradictory results in the literature. Instead, focusing on how each individual develops a certain deck preference during the task may provide insightful information about the underlying mechanisms of decision-making that may drive the formation of an optimal or suboptimal choice strategy. In this sense, following Steingroever et al. (2013), healthy participants would prefer decks offering infrequent losses instead of those which offer a long-term profit, which is also supported by Kumar et al. (2019), and would present an idiosyncratic choice behavior. We consider that our results are in line with this research, and to some extent, extends it to impulsive-compulsive spectrum diagnosed patients' behavior.

Regarding clinical implications, our results may shed light on disentangling symptoms heterogeneity and guiding novel conceptualizations of psychiatric dimensions. Here we show that not all individuals belonging to clinical groups commonly attributed with a defective decision-making process manifest this deficit, and if they do, they do not manifest it in the same way. Understanding these individual differences may be important to identify relevant psychological traits across the spectrum of psychopathology, and, therefore, to design effective and personalized interventions. Future research could try to further investigate on this issue since the replication of the obtained decision-making profiles may suggest a need for a paradigm shift in the way performance in the IGT is conceptualized.

Concerning our third and last hypothesis, rsFC between ROIs has not shown any relationship with the behavior of the participants at any level. In contrast to other research (Hobkirk et al., 2019; Li et al., 2013; Wei et al., 2016), we found no evidence to support rsFC as a biomarker of decision-making processes in the IGT, as has been suggested by the absence of credible differences in connectivity patterns between different clusters, as well as by the lack of influence of the rsFC between ROIs on the number of choices of any deck in any block. A possible explanation for this result would be in line with the hypothesis of the FPN as a flexible cognitive control node. Following this, the FPN would be functionally connected to other specialized networks, such as salience or default mode network, which have been not assessed in the present study, and it would be specially implicated in rapidly adapting the connectivity across widespread brain regions according to task demands (Cole et al., 2013; Zanto & Gazzaley, 2013). Following this hypothesis, further research could investigate the between-networks functional connectivity (instead of only within-network functional connectivity) and its potential role in uncertain decision-making. Another explanation could be derived by the imbalance between the DMN and the FPN in resting- and task induced states. While the DMN connectivity usually decreases under challenging tasks, so it could be a reflect of spontaneous brain activity during resting-state (Raichle, 2015; Smallwood et al., 2021), FPN seem to be recruited in contexts where executive functioning is needed (Niendam et al., 2012). In relation to this, functional changes in FPN connectivity from rest to IGT context have been reported. However, no relationship between those changes and IGT performance was found (Bolt et al., 2016).

We found no credible differences in rsFC between FPN nodes between our clinical groups when compared to healthy controls either, unlike previous studies, which have found abnormal connectivity between nodes of this network in OCD (Gürsel et al., 2018; Stern et al., 2012), SUD (Taebi et al., 2022) and ADHD (Mostert et al., 2016) patients when compared to healthy controls. In this sense, it is relatively well-established that rsFC presents high variability across individuals. rsFC is sensitive to many potential confounding variables such as pharmacological treatment, early-stress, personality and behavioral traits and even different genotypes (Gordon et al., 2015; Marek & Dosenbach, 2018; Vaidya & Gordon, 2013). Despite rsFC seems to be a reliable

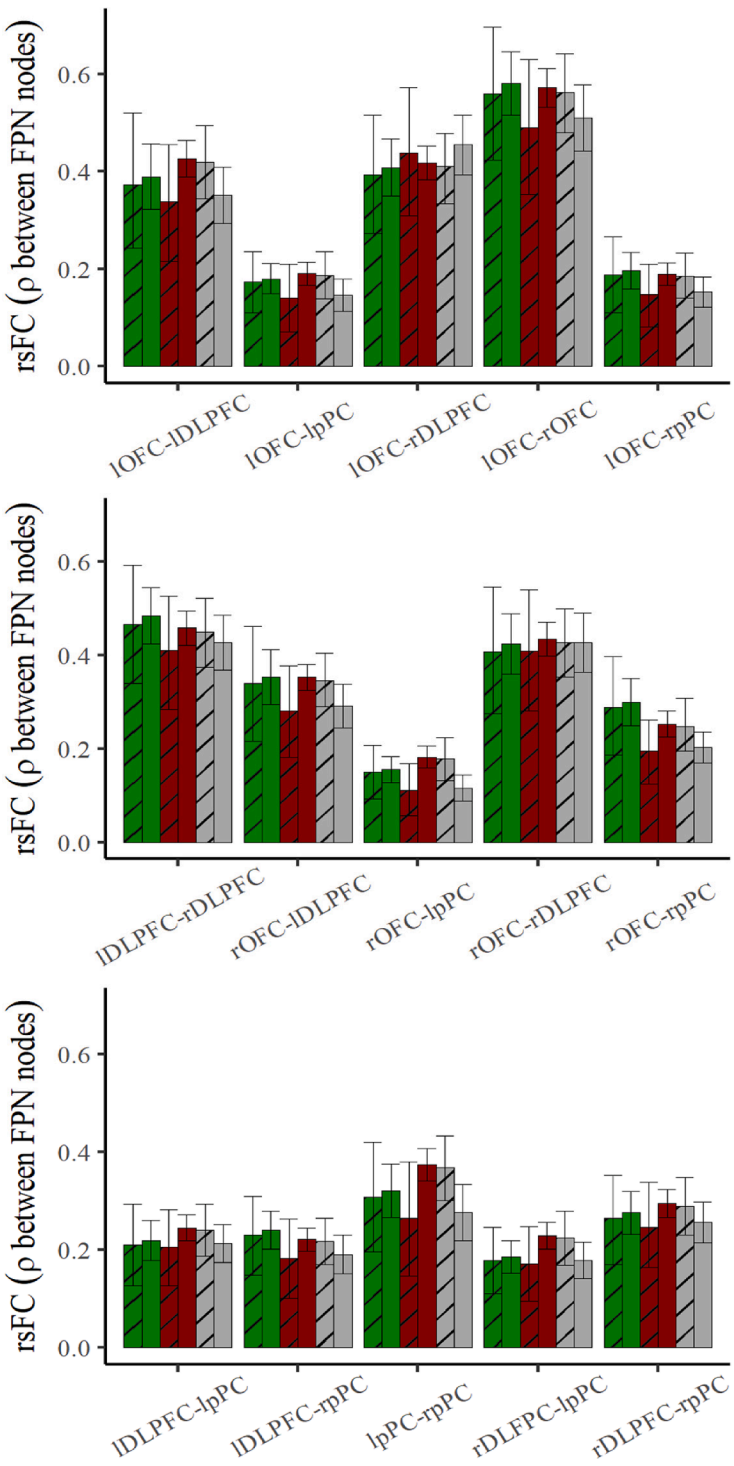

Fig. 6. Real (solid bars) and predicted (stripped bars) rsFC values between each ROI as a function of clusters, representing the true means and the mean of the posteriors. The vertical bars represent the standard error of the mean (SEM) or the 95% HDIs.*Note.* Abbreviations correspond to left orbitofrontal cortex (lOFC), right orbitofrontal cortex (rOFC), left dorsolateral prefrontal cortex (lDLPFC), right dorsolateral prefrontal cortex (rDLPFC), left posterior parietal cortex (lpPC) and right posterior parietal cortex (rpPC).

measure of the architecture of brain networks (van den Heuvel et al., 2009), and emerging literature in transdiagnostic samples has shown that rsFC can predict rumination (Feurer et al., 2021), amotivation severity (Park et al., 2017), reward responsivity deficits (Sharma et al., 2017) and executive cognition (Wei et al., 2022), we consider that further research is needed to clarify its role in such an important daily life process as decision-making. Additionally, the variability across employed methodologies in different studies, as well as the interpretation of results may hinder the clarity of inferences about the brain-behavior relationship. Taken together, the study of the type of existent relationship between brain resting-state connectivity and behavior would greatly benefit from research carried out on a large enough sample size and from methodological and conceptual homogenisation (Marek et al., 2022; Marek & Dosenbach, 2018).

Some limitations of this study should be noted. First, most patients were on medication without a wash-out period, so we could not control its influence on IGT performance and rsFC recording. Second, the absence of a real monetary reward in a gambling paradigm as the IGT might have a negative impact on participants' motivation (Bowman & Turnbull, 2003). Third, IGT performance seems to recruit subcortical brain areas (Li et al., 2010), but, as a limitation of the fNIRS technique, they could not be measured in this study. Fourth, other variables such as

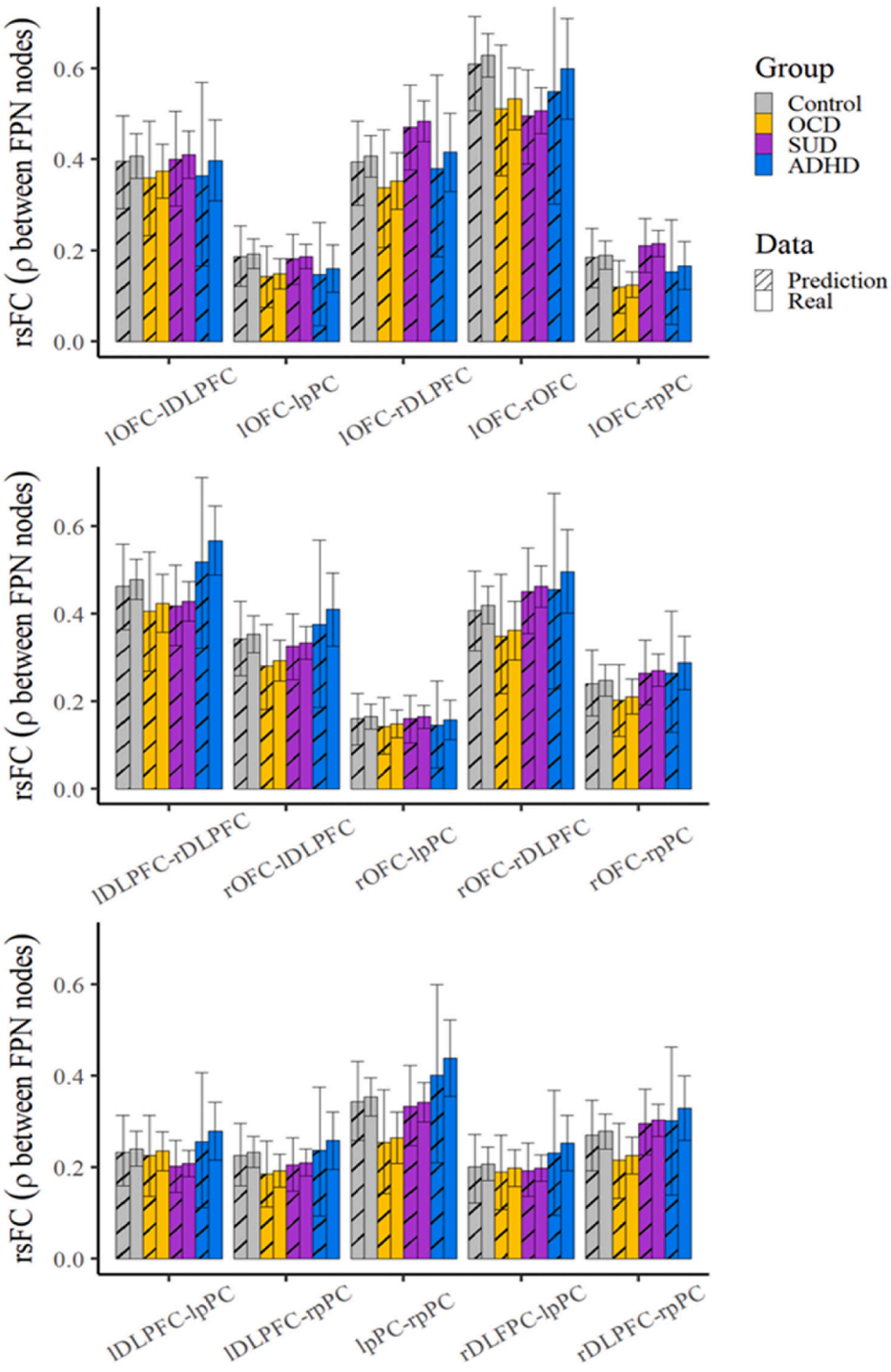

Fig. 7. Real (solid bars) and predicted (stripped bars) rsFC values between each ROI as a function of diagnostic group, representing the true means and the mean of the posteriors. The vertical bars represent the standard error of the mean (SEM) or the 95% HDIs.*Note.* Abbreviations correspond to left orbitofrontal cortex (lOFC), right orbitofrontal cortex (rOFC), left dorsolateral prefrontal cortex (lDLPFC), right dorsolateral prefrontal cortex (rDLPFC), left posterior parietal cortex (lpPC) and right posterior parietal cortex (rpPC).

risk aversion or reward sensitivity, which may be at the basis of individual differences driving the development of different decision-making strategies (Capa & Bouquet, 2018; Penolazzi et al., 2012; Tom et al., 2007), have not been directly assessed in the present study. In this sense, further research could focus directly on these variables, applying an event-related design, to investigate the individual differences in neural reward/punishment processing driving deck choice preferences during the IGT. Finally, some authors have suggested that larger sample sizes could be required to extract more reliable conclusions from brain and behavior studies (Marek et al., 2022; Turner et al., 2018), so it could also be desirable to increase sample size to diminish the standard error of the employed measurements.

5. Conclusion

We found three different response styles during the IGT that cut across diagnostic categories, so impulsive-compulsive spectrum patients and healthy controls seem to share some underlying mechanisms driving their decision-making strategy during the task. This could suggest that decision-making, at least under the IGT context, is not a core feature of our diagnostic labeled patients. But it also could mean that the IGT is not such an appropriate paradigm to detect the alleged decision-making deficits that are assumed in those populations. In this sense, IGT construct validity has been questioned by some researchers (Barnhart & Buelow, 2021; Buelow & Suhr, 2009).

Moreover, we found no evidence to support the role of frontoparietal rsFC as a biomarker of defective or adaptive decision-making processes regarding any diagnostic group or any behavioral cluster. Further research is needed in this sense in order to clarify the core features of decision-making under uncertainty of healthy people and impulsive-compulsive spectrum disorder patients and its neurofunctional basis.

Funding

This work was supported by the Ministry of Science and Innovation of the Spanish government [Grant number PID2019-108423RB-I00] and by the Regional Government of Andalusia [Grant numbers P18-RT-1886; P20_00308]. J. J. L., P.F.M and R.R.H were supported by the FPU Fellowship Program of the Spanish Ministry of Education [Grant numbers FPU 17/03100; FPU18/01509; FPU20/01770].

Availability of data and materials

The complete dataset used during the present study and the code employed for the cluster analysis, as well as the figures and the Supplementary material is available at public repository: https://osf.io/5hj48/.

CRediT authorship contribution statement

J.J. León: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – review & editing. **P. Fernández-Martin:** Conceptualization, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – review & editing. **A. González-Rodríguez:** Data curation, Formal analysis, Methodology, Software, Writing – review & editing. **R. Rodríguez-Herrera:** Investigation. **J. García-Pinteño:** Investigation. **C. Pérez-Fernández:** Investigation, Writing – review & editing. **A. Sánchez-Kuhn:** Investigation, Project administration. **M. Soto-Ontoso:** Resources. **P. Martínez-Sánchez:** Resources. **F. Sánchez-Santed:** Funding acquisition, Writing – review & editing. **P. Flores:** Conceptualization, Funding acquisition, Supervision, Project administration, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Achenbach, T. M., & Rescorla, L. A. (2003). *Manual for the ASEBA Adult Forms & Profiles*. Burlington, VT: University of Vermont, Research Center for Children, Youth, & Families.

Agay, N., Yechiam, E., Carmel, Z., & Levkovitz, Y. (2010). Non-specific effects of methylphenidate (Ritalin) on cognitive ability and decision-making of ADHD and healthy adults. *Psychopharmacology, 210*(4). https://doi.org/10.1007/s00213-010-1853-4

American Psychiatric Association, (2013). Diagnostic and statistical manual of mental disorders (5th ed.). doi:10.1176/appi.books.9780890425596.

Barker, J. W., Aarabi, A., & Huppert, T. J. (2013). Autoregressive model based algorithm for correcting motion and serially correlated errors in fNIRS. *Biomedical Optics Express, 4*(8), 1366. https://doi.org/10.1364/boe.4.001366

Barnhart, W. R., & Buelow, M. T. (2021). The Performance of College Students on the Iowa Gambling Task: Differences Between Scoring Approaches. *Assessment, 29*(6), 1190–1203. https://doi.org/10.1177/10731911211004741

Bartzokis, G., Lu, P. H., Beckson, M., Rapoport, R., Grant, S., Wiseman, E. J., & London, E. D. (2000). Abstinence from cocaine reduces high-risk responses on a gambling task. *Neuropsychopharmacology, 22*(1), 102–103. https://doi.org/10.1016/S0893-133X(99)00077-9

Bechara, A., Damasio, A. R., Damasio, H., & Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition, 50*(1–3), 7–15. https://doi.org/10.1016/0010-0277(94)90018-3

Bechara, A., & Martin, E. M. (2004). Impaired Decision Making Related to Working Memory Deficits in Individuals with Substance Addictions. *Neuropsychology, 18*(1), 152–162. https://doi.org/10.1037/0894-4105.18.1.152

Bolt, T., Laurienti, P. J., Lyday, R., Morgan, A., & Dagenbach, D. (2016). Graph-theoretical study of functional changes associated with the iowa gambling task. *Frontiers in Human Neuroscience, 10*. https://doi.org/10.3389/fnhum.2016.00314

Bowman, C. H., & Turnbull, O. H. (2003). Real versus facsimile reinforcers on the Iowa Gambling Task. *Brain and Cognition, 53*(2), 207–210. https://doi.org/10.1016/S0278-2626(03)00111-8

Buela-Casal, G., Guillén-Riquelme, A., & Cubero, N. S. (2015). Manual STAI, Cuestionario de Ansiedad Estado Rasgo. *Tea Ediciones*.

Buelow, M. T., & Suhr, J. A. (2009). Construct validity of the Iowa gambling task. *Neuropsychology Review, 19*(1), 102–114. https://doi.org/10.1007/s11065-009-9083-4

Bush, G. (2011). Cingulate, frontal, and parietal cortical dysfunction in attention-deficit/hyperactivity disorder. *Biological Psychiatry, 69*(12). https://doi.org/10.1016/j.biopsych.2011.01.022

Capa, R. L., & Bouquet, C. A. (2018). Individual differences in reward sensitivity modulate the distinctive effects of conscious and unconscious rewards on executive performance. *Frontiers in Psychology, 9*. https://doi.org/10.3389/fpsyg.2018.00148

Cavedini, P., Gorini, A., & Bellodi, L. (2006). Understanding obsessive-compulsive disorder: Focus on decision making. *Neuropsychology Review, 16*(1), 3–15. https://doi.org/10.1007/s11065-006-9001-y

Cole, M. W., Reynolds, J. R., Power, J. D., Repovs, G., Anticevic, A., & Braver, T. S. (2013). Multi-task connectivity reveals flexible hubs for adaptive task control. *Nature Neuroscience, 16*(9), 1348–1355. https://doi.org/10.1038/nn.3470

Cuthbert, B. N. (2020). The role of RDoC in future classification of mental disorders. *Dialogues in Clinical Neuroscience, 22*(1), 81–85. https://doi.org/10.31887/DCNS.2020.22.1/bcuthbert

Delibaş, D. H., Akseki, H. S., Erdoğan, E., Zorlu, N., & Gülseren, Ş. (2018). Impulsivity, sensation seeking, and decision-making in long-term abstinent cannabis dependent patients. *Noropsikiyatri Arsivi, 55*(4), 315–319. https://doi.org/10.5152/npa.2017.19304

Duan, L., Zhang, Y. J., & Zhu, C. Z. (2012). Quantitative comparison of resting-state functional connectivity derived from fNIRS and fMRI: A simultaneous recording study. *NeuroImage, 60*(4), 2008–2018. https://doi.org/10.1016/j.neuroimage.2012.02.014

Ernst, M., Kimes, A. S., London, E. D., Matochik, J. A., Eldreth, D., Tata, S., Contoreggi, C., Leff, M., & Bolla, K. (2003). Neural substrates of decision making in adults with attention deficit hyperactivity disorder. *American Journal of Psychiatry, 160*(6), 1061–1070. https://doi.org/10.1176/appi.ajp.160.6.1061

Evans, C. E. Y., Kemish, K., & Turnbull, O. H. (2004). Paradoxical effects of education on the Iowa Gambling Task. *Brain and Cognition, 54*(3), 240–244. https://doi.org/10.1016/j.bandc.2004.02.022

Feurer, C., Jimmy, J., Chang, F., Langenecker, S. A., Phan, K. L., Ajilore, O., & Klumpp, H. (2021). Resting state functional connectivity correlates of rumination and worry in internalizing psychopathologies. *Depression and Anxiety, 38*(5), 488–497. https://doi.org/10.1002/da.23142

Fullana, M. A., Tortella-Feliu, M., Caseras, X., Andión, Ó., Torrubia, R., & Mataix-Cols, D. (2005). Psychometric properties of the Spanish version of the Obsessive-Compulsive Inventory - Revised in a non-clinical sample. *Journal of Anxiety Disorders, 19*(8), 893–903. https://doi.org/10.1016/j.janxdis.2004.10.004

Gao, Y., Shuai, D., Bu, X., Hu, X., Tang, S., Zhang, L., Li, H., Hu, X., Lu, L., Gong., Q., & Huang, X. (2019). Impairments of large-scale functional networks in attention-deficit/hyperactivity disorder: A meta-analysis of resting-state functional connectivity. *Psychological Medicine. 49*(15), 2475-2485. doi: 10.1017/S003329171900237X.

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science, 7*(4), 457–472. https://doi.org/10.1214/ss/1177011136

Gordon, E. M., Devaney, J. M., Bean, S., & Vaidya, C. J. (2015). Resting-state striato-frontal functional connectivity is sensitive to DAT1 genotype and predicts executive function. *Cerebral Cortex, 25*(2), 336–345. https://doi.org/10.1093/cercor/bht229

Groen, Y., Gaastra, G. F., Lewis-Evans, B., & Tucha, O. (2013). Risky Behavior in Gambling Tasks in Individuals with ADHD - A Systematic Literature Review. *PLoS ONE, 8*(9). https://doi.org/10.1371/journal.pone.0074909

Gürsel, D. A., Avram, M., Sorg, C., Brandl, F., & Koch, K. (2018). Frontoparietal areas link impairments of large-scale intrinsic brain networks with aberrant fronto-striatal interactions in OCD: A meta-analysis of resting-state functional connectivity. *Neuroscience and Biobehavioral Reviews, 87*, 151–160. https://doi.org/10.1016/j.neubiorev.2018.01.016

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage learning.

Hobkirk, A. L., Bell, R. P., Utevsky, A. v., Huettel, S., & Meade, C. S. (2019). Reward and executive control network resting-state functional connectivity is associated with impulsivity during reward-based decision making for cocaine users. *Drug and Alcohol Dependence, 194*, 32–39. doi: 10.1016/j.drugalcdep.2018.09.013.

Horstmann, A., Villringer, A., & Neumann, J. (2012). Iowa gambling task: There is more to consider than long-term outcome. Using a linear equation model to disentangle the impact of outcome and frequency of gains and losses. *Frontiers in Neuroscience, 6*. https://doi.org/10.3389/fnins.2012.00061

Huppert, T. J. (2016). Commentary on the statistical properties of noise and its implication on general linear models in functional near-infrared spectroscopy. *Neurophotonics, 3*(1), Article 010401. https://doi.org/10.1117/1.nph.3.1.010401

Ieong, H. F. H., & Yuan, Z. (2017). Abnormal resting-state functional connectivity in the orbitofrontal cortex of heroin users and its relationship with anxiety: A pilot fNIRS study. *Scientific Reports, 7*, 1–14. https://doi.org/10.1038/srep46522

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*(2), 263–292. https://doi.org/10.2307/1914185

Kovács, I., Richman, M. J., Janka, Z., Maraz, A., & Andó, B. (2017). Decision making measured by the Iowa Gambling Task in alcohol use disorder and gambling disorder: A systematic review and meta-analysis. *Drug and Alcohol Dependence, 181*, 152–161. https://doi.org/10.1016/j.drugalcdep.2017.09.023

Kruschke, J. K. (2011). Bayesian assessment of null values via parameter estimation and model comparison. *Perspectives on Psychological Science*, *6*(3), 299–312. doi: 10.1177/1745691611406925.

Kruschke, J. K. (2015). Doing Bayesian Data Analysis. A tutorial with R, JAGS, and Stan (Second Edition). Academic Press. doi: 10.1016/B978-0-12-405888-0.09993-1.

Kumar, R., Janakiprasad Kumar, K., & Benegal, V. (2019). Underlying decision making processes on Iowa Gambling Task. *Asian Journal of Psychiatry, 39*, 63–69. https://doi.org/10.1016/j.ajp.2018.12.006

Lawrence, N. S., Wooderson, S., Mataix-Cols, D., David, R., Speckens, A., & Phillips, M. L. (2006). Decision making and set shifting impairments are associated with distinct symptom dimensions in obsessive-compulsive disorder. *Neuropsychology, 20*(4), 409–419. https://doi.org/10.1037/0894-4105.20.4.409

Li, N., Ma, N., Liu, Y., He, X. S., Sun, D. L., Fu, X. M., Zhang, X., Han, S., & Zhang, D. R. (2013). Resting-state functional connectivity predicts impulsivity in economic decision-making. *Journal of Neuroscience, 33*(11), 4886–4895. https://doi.org/10.1523/JNEUROSCI.1342-12.2013

Li, X., Lu, Z. L., D'Argembeau, A., Ng, M., & Bechara, A. (2010). The Iowa Gambling Task in fMRI images. *Human brain mapping, 31*(3), 410–423. https://doi.org/10.1002/hbm.20875

Ligneul, R. (2019). Sequential exploration in the iowa gambling task: Validation of a new computational model in a large dataset of young and old healthy participants. *PLoS Computational Biology, 15*(6). https://doi.org/10.1371/journal.pcbi.1006989

Lin, C. H., Chiu, Y. C., Lee, P. L., & Hsieh, J. C. (2007). Is deck B a disadvantageous deck in the Iowa Gambling Task? *Behavioral and Brain Functions, 3*(16). https://doi.org/10.1186/1744-9081-3-16

Lin, H. Y., Tseng, W. Y. I., Lai, M. C., Matsuo, K., & Gau, S. S. F. (2015). Altered resting-state frontoparietal control network in children with attention-deficit/hyperactivity disorder. *Journal of the International Neuropsychological Society, 21*(4), 271–284. https://doi.org/10.1017/S135561771500020X

Liu, J., Cao, L., Li, H., Gao, Y., Bu, X., Liang, K., Bao, W., Zhang, S., Qiu, H., Li, X., Hu, X., Lu, L., Zhang, L., Hu, X., Huang, X., & Gong, Q. (2022). Abnormal resting-state functional connectivity in patients with obsessive-compulsive disorder: A systematic review and meta-analysis. *Neuroscience and Biobehavioral Reviews, 135*. https://doi.org/10.1016/j.neubiorev.2022.104574

Ma, S., Zang, Y., Cheung, V., & Chan, C. C. H. (2015). Importance of punishment frequency in the Iowa gambling task: An fMRI study. *Brain Imaging and Behavior, 9*(4), 899–909. https://doi.org/10.1007/s11682-015-9353-0

Malloy-Diniz, L. F., Fuentes, D., Borges-Leite, W., Correa, H., & Bechara, A. (2007). Impulsive behavior in adults with attention deficit/hyperactivity disorder: Characterization of attentional, motor and cognitive impulsiveness. *Journal of the International Neuropsychological Society, 13*(4), 693–698. https://doi.org/10.1017/S1355617707070889

Marek, S., & Dosenbach, N. U. F. (2018). The frontoparietal network: Function, electrophysiology, and importance of individual precision mapping. *Dialogues in Clinical Neuroscience, 20*(2), 133–140. https://doi.org/10.31887/dcns.2018.20.2/smarek

Marek, S., Tervo-Clemmens, B., Calabro, F. J., Montez, D. F., Kay, B. P., Hatoum, A. S., … Dosenbach, N. U. F. (2022). Reproducible brain-wide association studies require thousands of individuals. *Nature, 603*(7902), 654–660. https://doi.org/10.1038/s41586-022-04492-9

Markett, S., Reuter, M., Montag, C., Voigt, G., Lachmann, B., Rudorf, S., Elger, C. E., & Weber, B. (2014). Assessing the function of the fronto-parietal attention network: Insights from resting-state fMRI and the attentional network test. *Human Brain Mapping, 35*(4), 1700–1709. https://doi.org/10.1002/hbm.22285

Mostert, J. C., Shumskaya, E., Mennes, M., Onnink, A. M. H., Hoogman, M., Kan, C. C., Arias Vasquez, A., Buitelaar, J., Franke, B., & Norris, D. G. (2016). Characterising resting-state functional connectivity in a large sample of adults with ADHD. *Progress in Neuro-Psychopharmacology and Biological Psychiatry, 67*, 82–91. https://doi.org/10.1016/j.pnpbp.2016.01.011

Niendam, T. A., Laird, A. R., Ray, K. L., Dean, Y. M., Glahn, D. C., & Carter, C. S. (2012). Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective and Behavioral Neuroscience, 12*(2), 241–268. https://doi.org/10.3758/s13415-011-0083-5

Norman, L. J., Carlisi, C. O., Christakou, A., Murphy, C. M., Chantiluke, K., Giampietro, V., Simmons, A., Brammer, M., Mataix-Cols, D., & Rubia, K. (2018). Frontostriatal Dysfunction During Decision Making in Attention-Deficit/Hyperactivity Disorder and Obsessive-Compulsive Disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging, 3*(8), 694–703. https://doi.org/10.1016/j.bpsc.2018.03.009

Park, I. H., Lee, B. C., Kim, J. J., Kim, J. il, & Koo, M. S. (2017). Effort-based reinforcement processing and functional connectivity underlying amotivation in medicated patients with depression and schizophrenia. *Journal of Neuroscience, 37*(16), 4370–4380. doi: 10.1523/JNEUROSCI.2524-16.2017.

Penolazzi, B., Gremigni, P., & Russo, P. M. (2012). Impulsivity and Reward Sensitivity differentially influence affective and deliberative risky decision making. *Personality and Individual Differences, 53*(5), 655–659. https://doi.org/10.1016/j.paid.2012.05.018

R Core Team. (2021). R: A Language and Environment for Statistical Computing. *R Foundation for Statistical Computing, Vienna, Austria*.

Raichle, M. E. (2015). The Brain's Default Mode Network. *Annual Review of Neuroscience, 38*, 433–447. https://doi.org/10.1146/annurev-neuro-071013-014030

Richarte, V., Corrales, M., Pozuelo, M., Serra-Pla, J., Ibáñez, P., Calvo, E., Corominas, M., Bosch, R., Casas, M., & Ramos-Quiroga, J. A. (2017). Validación al español de la ADHD Rating Scale (ADHD-RS) en adultos: Relevancia de los subtipos clínicos. *Revista de Psiquiatría y Salud Mental, 10*(4), 185–191. https://doi.org/10.1016/j.rpsm.2017.06.003

Santosa, H., Aarabi, A., Perlman, S. B., & Huppert, T. J. (2017). Characterization and correction of the false-discovery rates in resting state connectivity using functional near-infrared spectroscopy. *Journal of Biomedical Optics, 22*(5), Article 055002. https://doi.org/10.1117/1.jbo.22.5.055002

Santosa, H., Zhai, X., Fishburn, F., & Huppert, T. (2018). *The NIRS Brain AnalyzIR toolbox. Algorithms, 11*(5), 73. https://doi.org/10.3390/A11050073

Sanz, J., Perdigón, A. L., & Vázquez, C. (2003). Adaptación española del Inventario para la Depresión de Beck-II (BDI-II): 2.Propiedades psicométricas en población general. *Clínica y Salud, 14*(3), 249–280.

Sharma, A., Wolf, D. H., Ciric, R., Kable, J. W., Moore, T. M., Vandekar, S. N., Katchmar, N., Daldal, A., Ruparel, K., Davatzikos, C., Elliott, M. A., Calkins, M. E., Shinohara, R. T., Bassett, D. S., & Satterthwaite, T. D. (2017). Common dimensional reward deficits across mood and psychotic disorders: A connectome-wide association study. *American Journal of Psychiatry, 174*(7), 657–666. https://doi.org/10.1176/appi.ajp.2016.16070774

Silk, T. J., Vance, A., Rinehart, N., Bradshaw, J. L., & Cunnington, R. (2008). Dysfunction in the fronto-parietal network in attention deficit hyperactivity disorder (ADHD): An fMRI study. *Brain Imaging and Behavior, 2*(2), 123–131. https://doi.org/10.1007/s11682-008-9021-8

Siugzdaite, R., Bathelt, J., Holmes, J., & Astle, D. E. (2020). Transdiagnostic Brain Mapping in Developmental Disorders. *Current Biology, 30*(7), 1245–1257. https://doi.org/10.1016/j.cub.2020.01.078

Smallwood, J., Bernhardt, B. C., Leech, R., Bzdok, D., Jefferies, E., & Margulies, D. S. (2021). The default mode network in cognition: A topographical perspective. *Nature Reviews Neuroscience, 22*(8), 503–513. https://doi.org/10.1038/s41583-021-00474-4

Stan Development Team. (2022). Stan Modeling Language User's Guide and Reference Manual, Version 2.19.2. *Interaction Flow Modeling Language*.

Steingroever, H., Wetzels, R., Horstmann, A., Neumann, J., & Wagenmakers, E. J. (2013). Performance of healthy participants on the Iowa Gambling Task. *Psychological Assessment, 25*(1), 180–193. https://doi.org/10.1037/a0029929

Stern, E. R., Fitzgerald, K. D., Welsh, R. C., Abelson, J. L., & Taylor, S. F. (2012). Resting-state functional connectivity between fronto-parietal and default mode networks in obsessive-compulsive disorder. *PLoS ONE, 7*(5), e36356.

Taebi, A., Becker, B., Klugah-Brown, B., Roecher, E., Biswal, B., Zweerings, J., & Mathiak, K. (2022). Shared network-level functional alterations across substance use disorders: A multi-level kernel density meta-analysis of resting-state functional connectivity studies. *Addiction Biology, 27*(4), e13200.

Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society. Series B: Statistical Methodology, 63*(2), 411–423. https://doi.org/10.1111/1467-9868.00293

Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The neural basis of loss aversion in decision-making under risk. *Science, 315*(5811), 515–1508. https://doi.org/10.1126/science.1134239

Toplak, M. E., Jain, U., & Tannock, R. (2005). Executive and motivational processes in adolescents with Attention-Deficit-Hyperactivity Disorder (ADHD). *Behavioral and Brain Functions, 1*(8). https://doi.org/10.1186/1744-9081-1-8

Turner, B. O., Paul, E. J., Miller, M. B., & Barbey, A. K. (2018). Small sample sizes reduce the replicability of task-based fMRI studies. *Communications Biology, 1*, 62. https://doi.org/10.1038/s42003-018-0073-z

Ursache, A., & Raver, C. C. (2015). Iowa Gambling Task performance and executive function predict low-income urban preadolescents' risky behaviors. *Personality and Individual Differences, 79*, 1–6. https://doi.org/10.1016/j.paid.2015.01.010

Vaghi, M. M., Vértes, P. E., Kitzbichler, M. G., Apergis-Schoute, A. M., van der Flier, F. E., Fineberg, N. A., Sule, A., Zaman, R., Voon, V., Kundu, P., Bullmore, E. T., & Robbins, T. W. (2017). Specific Frontostriatal Circuits for Impaired Cognitive Flexibility and Goal-Directed Planning in Obsessive-Compulsive Disorder: Evidence From Resting-State Functional Connectivity. *Biological Psychiatry, 81*(8), 708–717. https://doi.org/10.1016/j.biopsych.2016.08.009

Vaidya, C. J., & Gordon, E. M. (2013). Phenotypic Variability in Resting-State Functional Connectivity: Current Status. *Brain Connectivity, 3*(2), 99–120. https://doi.org/10.1089/brain.2012.0110

van den Bos, R., Homberg, J., & de Visser, L. (2013). A critical review of sex differences in decision-making tasks: Focus on the Iowa Gambling Task. *Behavioural Brain Research, 238*(1), 95–108. https://doi.org/10.1016/j.bbr.2012.10.002

van den Heuvel, M. P., Mandl, R. C. W., Kahn, R. S., & Hulshoff Pol, H. E. (2009). Functionally linked resting-state networks reflect the underlying structural connectivity architecture of the human brain. *Human Brain Mapping, 30*(10), 3127–3141. https://doi.org/10.1002/hbm.20737

Verdejo-Garcia, A., Garcia-Fernandez, G., & Dom, G. (2022). Cognition and addiction. *Dialogues in Clinical Neuroscience, 21*(3), 281–290. https://doi.org/10.31887/DCNS.2019.21.3/gdom

Verdejo-García, A. J., Perales, J. C., & Pérez-García, M. (2007). Cognitive impulsivity in cocaine and heroin polysubstance abusers. *Addictive Behaviors, 32*(5), 950–966. https://doi.org/10.1016/j.addbeh.2006.06.032

Wei, Y., Womer, F., Sun, K., Zhu, Y., Sun, D., Duan, J., … Wang, F. (2022). Applying dimensional psychopathology: Transdiagnostic prediction of executive cognition using brain connectivity and inflammatory biomarkers. *Psychological Medicine*, 1–11. https://doi.org/10.1017/S0033291722000174

Wei, Z., Yang, N., Liu, Y., Yang, L., Wang, Y., Han, L., Zha, R., Huang, R., Zhang, P., Zhou, Y., & Zhang, X. (2016). Resting-state functional connectivity between the

dorsal anterior cingulate cortex and thalamus is associated with risky decision-making in nicotine addicts. *Scientific Reports, 6*, 21778. https://doi.org/10.1038/srep21778

Zanto, T. P., & Gazzaley, A. (2013). Fronto-parietal network: Flexible hub of cognitive control. *Trends in Cognitive Sciences, 17*(12), 602–603. https://doi.org/10.1016/j.tics.2013.10.001

Zorlu, N., Karavul Ucman, T., Gelal, F., Colak Kalayci, C., Polat, S., Saricicek, A., Kurtgöz Zorlu, P., & Gulseren, S. (2014). Abnormal white matter integrity in long-term abstinent alcohol dependent patients. *Psychiatry Research - Neuroimaging, 224*(1), 42–48. https://doi.org/10.1016/j.pscychresns.2014.07.006