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The regional homogeneity patterns of the dorsal medial prefrontal cortex predict individual differences in decision impulsivity

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ABSTRACT

Intertemporal choice refers to the process of making decisions by weighing short- and long-term benefits and costs. On average people prefer immediate rewards over delayed rewards with larger amounts, which is a form of decision impulsivity. Based on previous research showing the importance of the dorsal medial prefrontal cortex (DMPFC) in decision impulsivity, the present study examined whether regional homogeneity (ReHo) patterns in DMPFC were associated with individual differences in intertemporal choices. Two cohorts of college students (N = 239 and N = 227, respectively) were recruited and resting-state data were collected. Results from both univariate and multivariate pattern analyses of the two cohorts consistently showed that ReHo patterns in the DMPFC were associated with the delay discounting rate (i.e., log *k*). These results further support the important role of DMPFC in intertemporal choice and have potential practical implications for decision making in our daily life and at the level of national policies as well as for the treatment of clinical populations with decision impulsivity (e.g., gamblers, individuals with substance use disorders).

1. Introduction

Humans are not always rational decision makers (Peters and Büchel, 2011). For example, people on average have the tendency to favor the immediate smaller benefit rather than larger rewards in the future, a phenomenon called intertemporal choice or decision impulsivity. Intertemporal choice is very common in our daily life and it also occurs when making national policy decisions.

Frequently studied using a paradigm called the delay discounting task (i.e., choosing between options of immediate and delayed rewards), intertemporal choice is indexed by the delay discounting rate (*k*) parameter calculated following the hyperbolic function ($V = \frac{A}{1+k\times D}$), where V is the subjective value, A the reward magnitude, D the delay, and *k* the delay discounting rate (Ainslie, 1975). Clinical patient studies have suggested that choosing more immediate rewards (i.e., lager *k* value) is linked to various psychiatric disorders such as substance abuse (Bickel et al., 1999; Hu et al., 2015), pathological gambling (Alessi and Petry, 2003), and ADHD (Paloyelis et al., 2012).

With functional magnetic resonance imaging (fMRI), researchers have uncovered the underlying neural systems supporting intertemporal choice. For example, the frontal part of dorsal medial prefrontal cortex (DMPFC) and the right frontal pole (FP) have been suggested to represent delayed rewards, whereas the rear part of DMPFC represents immediate rewards (Kable and Glimcher, 2007; Luo et al., 2013; McClure et al.,

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2004). Peters and Büchel, 2011 reviewed published neuroimaging studies and identified three neural networks underlying decision impulsivity, including the valuation, cognitive control, and prospect networks. In the valuation network, the core nodes include the ventromedial prefrontal cortex (VMPFC), ventral striatum (VS), and posterior cingulate cortex (PCC). Increased activity in this system has been linked to more impulsive choice (i.e., lager *k* value) and action (Peters and Büchel, 2011).

Converging evidence from neuroimaging studies has suggested that the medial prefrontal cortex is the hub region supporting decision making. Specifically, this part of the brain is involved in representing the subjective values, including the subjective value of the delayed rewards (Kable and Glimcher, 2007) and subjective value under risk and ambiguity (Levy et al., 2010). It is also involved in the calculations of reward prediction (Knutson and Cooper, 2005) and decision values (Chib, Rangel, Shimojo and O'Doherty, 2009); the integration of different attribute value signals (such as visual appearance and semantic knowledge) (Kable and Glimcher, 2007); time processing, with recent time engaging posterior areas whereas distant time engaging anterior areas (Koritzky et al., 2013); cognitive control (Cavanagh and Frank, 2014; Ridderinkhof, van den Wildenberg, Segalowitz and Carter, 2004); and impulsivity (Luhmann et al., 2008; Mitchell et al., 2011; Sripada et al., 2011). In parallel with these studies, patients with damaged medial prefrontal cortex showed a larger delay discounting rate and most of them had no concern about the future consequences of their decisions (Bechara et al., 1994). Our previous study also found that DMPFC and FP represented the size of delayed rewards and regulated the ventral lateral prefrontal cortex to guide later decisions (Wang et al., 2014).

In addition to fMRI studies of the medial prefrontal cortex, structural studies have also revealed other neural correlates of intertemporal choices. For example, the grey matter volumes of the dorsal medial prefrontal cortex and the right FP (Bjork et al., 2009; Wang et al., 2016), the white matter volume of the right frontal lobe, and hippocampal and parahippocampal cortex were all correlated with decision impulsivity (Yu, 2012). The structural and functional connectivities between the lateral frontal lobe and ventral striatum (Peper et al., 2013; van den Bos et al., 2014) were also found to predict decision impulsivity.

Although resting state functional imaging is widely used in cognitive neuroscience literature, it has rarely been used to study the brain correlates of intertemporal choices. Resting state scans were normally used to construct functional connectivities or voxel wise regional homogeneity (ReHo) (Zang et al., 2004). ReHo is a voxel-based measure of brain activity that evaluates the similarity or synchronization between the time series of a given voxel and its nearest neighbors by calculating the Kendall's coefficient of concordance. ReHo has proven to be directly associated with task-based activation and deactivation (Zang et al., 2004). The default mode network (DMN), constructed using ReHo, was very similar to that constructed by other methods in resting state fMRI (Long et al., 2008). It was also similar to the pattern of DMN in cerebral blood flow (Zou et al., 2009), and to the spatial pattern of glucose metabolism (Aiello et al., 2015; Bernier et al., 2017). A number of studies have identified abnormal ReHo patterns in individuals with neurological and psychiatric disorders, such as Alzheimer's disease (He et al., 2013), schizophrenia (Liu et al., 2006), and Parkinson's disease (Wu et al., 2009).

Using resting-state fMRI, the present study investigated whether the ReHo patterns of DMPFC would be associated with individual differences in intertemporal choices. Two relatively large samples were recruited to cross-validate our results.

2. Materials and methods

2.1. Participants

A total of 497 college students participated in this study. These participants were from two cohorts, one from Beijing (N = 257) and the other from Chongqing (N = 240). Due to significant head motions (larger than 2 mm in any direction) during the scan, 18 subjects (7.5%) of the Beijing sample and 13 (5.7%) of the Chongqing sample were excluded from final data analysis, yielding the final samples of 239 (124 females, aged 23.6 ± 2.14 years) for the Beijing cohort and 227 (143 females, aged 20.9 ± 1.17 years) for the Chongqing cohort. The frame wise displacement and the correlation between head motion and *k* rate are shown in Table 1. None of the subjects had neurological or psychiatric history according to self-report. Written informed consent was obtained from subjects before experiments. This study was approved by the Institutional Review Boards of Beijing Normal University and Southwest University.

Table 1
The raw k-values, the relative frame wise displacement (FD) and their correlations.

		range	mean	SD
Beijing	raw k-value	1.235e-04 → 0.104	0.012	0.013
	FD	0.066 → 1.254	0.248	0.180
		r	p	
	Correlation between raw k and FD	r = 0.0005	p = 0.994	
Chongqing		range	mean	SD
	raw k-value	3.493e-04 - 0.123	0.022	0.021
	FD	0.043–0.255	0.108	0.044
		r	p	
	Correlation between raw k and FD	0.082	0.233	

2.2. Intertemporal choice task

Fig. 1 illustrates the stimuli and the experimental design of the intertemporal choice task with adaptive change of the *k* values (van den Bos et al., 2014; Wang et al., 2016). In this task, subjects had to choose between a fixed small sooner reward (SS, ¥60 received today) and a larger later (LL) reward. The amount of the LL reward was set from ¥78 to ¥108, and the delay (D) was set from 15 to 45 days in the future. It was made clear to the participants that the money in this choice task was hypothetical. Previous studies (Johnson and WK, 2002; Lagorio and Madden, 2005) have found no systematic differences in the delay discounting rate in response to real and hypothetical choices, suggesting that hypothetical rewards may serve as a valid proxy for real rewards in delay discounting research. The delay discounting rate parameter k was calculated according to the hyperbolic function. The initial k was set to 0.02. If the participants chose the immediate option, the delay discounting rate k was increased by having a lager LL on the next trial; if the participants chose the delayed option, the delay discounting rate k was decreased by having a small LL on the next trial. There were 60 trials in total. For the first 20 trials, the size of each step was 0.01 and for the remaining 40 trials the step size was 5% of the previous *k* value.

2.3. Functional imaging procedure

For the Chongqing sample, all brain imaging data were acquired on a 3T Siemens Trio scanner at Southwest University (Siemens Medical Systems, Erlangen, Germany). The anatomical structural scan was acquired using a T1-weighted MPRAGE sequence (TI = 900 ms; TR/TE = 1900 ms/2.52 ms; flip angle = 9°; 176 sagittal slices; 256 × 256 matrix size with spatial resolution as 1 × 1 × 1 mm^3). The resting state functional MRI data were scanned with gradient echo type plane echo imaging (GRE-EPI) sequence, and the scanning parameters were: TR/TE = 2000 ms/30 ms; Flip angle = 90°; FOV = 220 × 220 mm^2; 64 × 64 matrix size with a resolution of 3.4 × 3.4 × 4 mm^3.

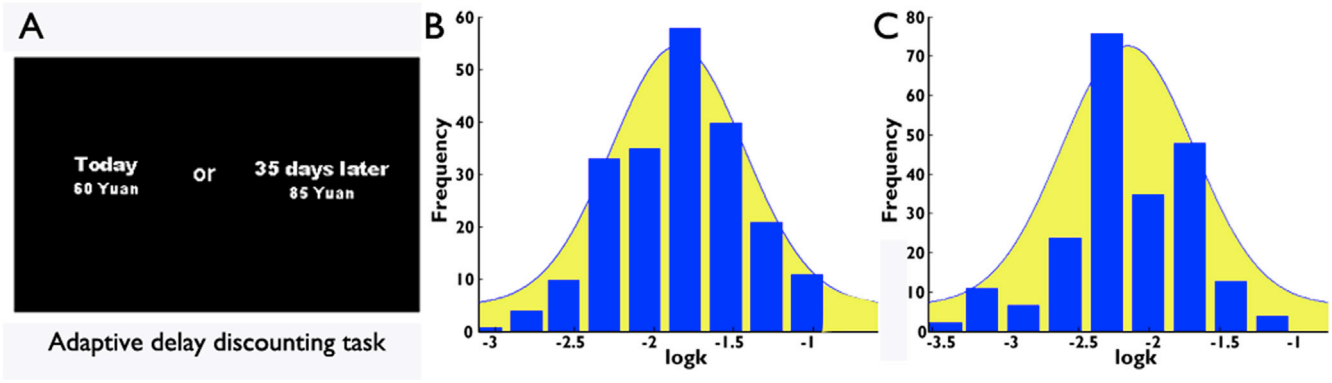

Fig. 1. Adaptive delay discounting task and the distributions of delay discounting rates. A. For each trial, subjects had to choose between a fixed reward (¥60) and a larger later reward. The delay period (D) for the larger later (LL) reward was randomly chosen from ¥78 to ¥108 between 15 and 45 days in the future. B. Normal distribution of the impulsive decisions (log k) of the Chongqing sample (kolmogorov-smirnov = 0.84, p = 0.48). C. Normal distribution of the impulsive decisions of the Beijing sample (kolmogorov-smirnov Z = 1.033, p = 0.24).

For the Beijing sample, imaging data were acquired on a 3T Siemens Trio scanner at Beijing Normal University with the same version of hardware/software as at Southwest University. Similarly, anatomical structural scan was acquired using a T1-weighted MPRAGE sequence (TI = 800 ms; TR/TE = 2530/3.1 ms; flip angle 10°; 208 sagittal slices; 256 × 256 matrix size with spatial resolution as 1 × 1 × 1 mm^3). Resting state fMRI data were acquired using the EPI sequence, and the specific parameters were: TI = 900 ms; TR/TE = 2000/25 ms; flip angle = 90°; matrix size = 64 × 64; and resolution = 3.4 × 3.4 × 4 mm^3. The slices were tilted 30° clockwise from the AC-PC plane to obtain better signals in the orbitofrontal cortex.

2.4. Behavioral data analysis

The statistical analysis of behavior data was completed by using MATLAB programming language (Mathworks Inc.). For the inter-temporal choice task, multidimensional unconstrained nonlinear minimum function *(fminsearch)* of MATLAB was used to fit the hyperbolic function. In order to better simulate the selection of trial each time, *softmax* function was used to calculate the probability of selecting the immediate option based on the difference between the immediate reward value and the delayed reward value: $P_{ss} = \frac{1}{1+e^{-(v_{ss}-v_{ll})\times m}}$, where m represents decision slope, P_{ss} the probability of choosing the sooner smaller option, and v_{ss} and v_{ll} the values of the sooner smaller and larger later options, respectively. Individual delay discounting rate (k) was determined by maximizing the likelihood of forecasting decisions. Since the original delay discounting rate was not normally distributed, a *log*10 transformation was applied (*log (k)*) (van den Bos et al., 2014; Wang et al., 2014).

2.5. Resting-state fMRI data analysis

The preprocessing of all resting state fMRI data was done using the DPARSF software on the MATLAB platform (http://www.rfmri.org/DPARSF). Because the signals at the beginning of scanning were unstable and the subjects needed to adapt to the scanning environment, the data of the first 10 time points were discarded. The data of the remaining 232 time points were corrected by different layer acquisition time (i.e., slice timing correction), and the acquisition time of all layers was corrected to the intermediate time of the image acquisition TR. The head motion correction was then performed, and then all functional images were registered to the standard image in the MNI space, and resampled to 3 × 3 × 3 mm^3. Images were smoothed with the 8 mm Gaussian kernel. White matter signal, cerebrospinal fluid signal, whole brain signal, and 6 head motion parameters were regressed as covariates (Dai et al., 2015; Fox et al., 2009). Data were then filtered with a band pass filter of 0.01–0.08 Hz (Hacker et al., 2012; Shin et al., 2014). ReHo was calculated voxel-wise and Fisher Z transformation was applied before the final statistical analysis.

2.6. Support vector regression (SVR) analysis

Epsilon-insensitive SVR of a linear kernel, implemented in PyMVPA (http://www.pymvpa.org), was used to test the multivariate prediction of brain activation and/or ReHo from individual delay discounting rates. High-dimensional regression Multivariable Pattern Analysis (MVPA) was performed using a searchlight procedure with a 3-voxel radius. This procedure allowed an evaluation of the pattern of ReHo across voxels without contamination from the mean signal differences within the searchlight. The epsilon was 0.01 based on previous studies (He et al., 2013; Huang et al., 2018; Wang et al., 2016).

Ten-fold cross-validation analyses were used. All participants were divided into 10 groups and matched by gender and corresponding behavioral performance (*log k*). For each iteration, 9 groups of individuals were selected for training according to the SVR model. The remaining group of subjects was predicted by the classifier obtained, and the predicted value and the real value (*log k*) were analyzed using Pearson correlation. Results from the 10 validations were averaged and assigned to this voxel. Finally, the generated whole brain r values were converted into a *z-map*. The threshold for the group images was based on cluster detection statistics, with a height threshold of $z > 2.3$ and a cluster probability of $p < 0.05$, corrected for whole-brain multiple comparisons using Gaussian Random Field Theory.

2.7. Univariate correlation analysis

In order to further illustrate the direction of correlations between ReHo values and behavioral delay discounting rate (*log k*), significant clusters in the MVPA analysis were used as region of interests (ROIs) to extract the average ReHo value for each ROI. Robust regression, implemented in the MATLAB Statistics Toolbox, was used for all correlations to minimize the impact of outliers. The analytical steps were the same for the two cohorts. To avoid the double dipping problem, we only reported the relevant directions, not the r and p values (Kriegeskorte et al., 2006).

3. Results

3.1. Behavioral results

The average delay discounting rates (*log k*) were −1.85 (SD = 0.42, ranging from −3.46∼-0.91) in the Chongqing sample and −2.15 (SD = 0.47, ranging from −3.91∼-0.98) in the Beijing sample. The *log k*

was normally distributed (Kolmogorov-Smirnov $Z = 0.84$, $p = 0.48$, in Chongqing and $Z = 1.033$, $p = 0.24$, in Beijing) (Fig. 1B and C). The *log k* was significantly higher in the Chongqing sample than in the Beijing sample ($t = 7.06$, $p < 0.0001$). The raw k-values are listed in Table 1.

4. Imaging results

4.1. ReHo

MVPA showed that in the Chongqing sample the ReHo of right dorsal medial prefrontal cortex was a predictor of the delay discounting rate (*log k*) (DMPFC; MNI = 12, 36, 28, prediction accuracy $r = 0.327$) (Fig. 2A). Other predictors included ReHo of the following brain regions: the right insula (MNI = 40, 16, −10, $r = 0.232$), left orbital frontal cortex (OFC; MNI = −50, 24, −12, $r = 0.21$), left superior frontal gyrus (SFG; MNI = −6, 16, 58, $r = 0.312$), left putamen (MNI = −22, 6, 0, $r = 0.219$), right posterior PFC (MNI = 30, 46, −18, $r = 0.237$), left frontal pole (FP; MNI = −18, 60, −10, $r = 0.223$), right cuneal cortex (MNI = 18, −72, 30, $r = 0.248$), left posterior occipital lobe (POC; MNI = −58,-28, 14, $r = 0.214$), right cerebellum (MNI = 10, −66, −22, $r = 0.251$), left lateral occipital lobe (LOC; MNI = −24, −78, 30, $r = 0.212$), and right occipital pole (OP; MNI = 4, −92, −14, $r = 0.194$) (Table 2). In order to investigate the direction of the association between the dorsal medial prefrontal cortex and impulsivity, further univariate correlation analysis showed that the ReHo of the DMPFC was negatively correlated with the delay discounting rate (Fig. 2B). It is worth noting that even when stricter criteria were used ($z > 3.1$, $p < 0.001$; FWE corrected $p < 0.05$), the above-mentioned results remained significant (Fig. 1 and Table 1).

Results from the Beijing sample replicated those of the Chongqing sample. Predictors of the delay discounting rate (*log k*) included ReHo of the left dorsal medial prefrontal cortex (DMPFC) (MNI = −4, 42, 14, $r = 0.198$) (Fig. 2C), the right insula, left posterior cingulate (PCC), right supramarginal gyrus (SMG), right lateral occipital cortex (LOC), left superior parietal lobule (SPL), right thalamus, right frontal pole, right auxiliary motor area (SMA), and right orbital frontal cortex (OFC) (Table 3). Further univariate correlation analysis confirmed that the ReHo of the DMPFC was negatively correlated with the delay discounting rate as for the Beijing sample (Fig. 2D). When we extracted the ReHo of DMPFC predefined based on the peak of DMPFC in the Chongqing sample, validation analysis revealed a significant correlation between ReHo in DMPFC and decision impulsivity ($r = 0.142$, $p = 0.035$) (Fig. S1).

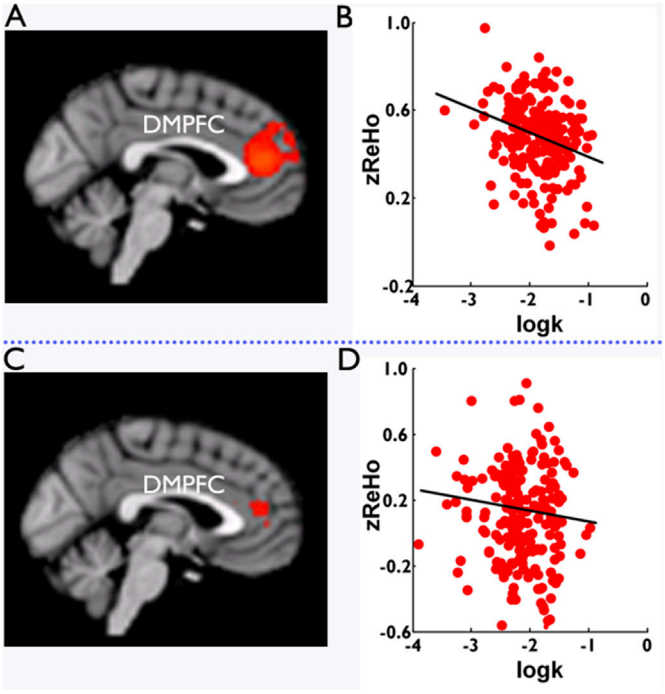

Fig. 2. The brain region whose ReHo was significantly correlated with delay discounting rate. A. The delay discounting rate k was successfully predicted by the ReHo of dorsal medial prefrontal cortex (DMPFC; MNI = 12, 36, 28, prediction accuracy r = 0.327) in the Chongqing sample. B. Scatterplot shows the significant negative correlation between the ReHo of DMPFC and the delay discounting rate in the Chongqing sample. C. The delay discounting rate k was successfully predicted by the ReHo of DMPFC (MNI = −4, 42, 14, r = 0.198) in the Beijing sample. D. Scatterplot shows the negative but not significant correlation between the ReHo of DMPFC and the delay discounting rate in the Beijing sample.

Table 2
Brain regions whose ReHo predicted delay discounting rate: MVPA of the Chongqing sample.

Brain Regions	L/R	No. Voxels	MNI Coordinates			Prediction Accuracy
			x	y	z	
DMPFC/FP	R	2716	12	36	28	0.327
Orbitofrontal cortex	L	327	−50	24	−12	0.210
Superior frontal gyrus	L	809	−6	16	58	0.312
Putamen	L	397	−22	6	0	0.219
Posterior PFC	R	706	30	46	−18	0.237
Frontal pole	L	442	−18	60	−10	0.223
insula	R	714	40	16	−10	0.232
Cuneal cortex	R	605	18	−72	30	0.248
POC	L	374	−58	−28	14	0.214
cerebellum	R	483	10	−66	−22	0.251
Lateral occipital cortex	L	371	−24	−78	30	0.212
Occipital pole	R	308	4	−92	−14	0.194

5. Discussion

With a large sample of college students, the present study examined whether regional homogeneity (ReHo) in the dorsal medial prefrontal cortex (DMPFC) was correlated with intertemporal choices. Both univariate and multivariate pattern analyses suggested that ReHo of the dorsal medial prefrontal cortex c was associated with decision impulsivity. Univariate analysis showed that they were negatively correlated, with higher ReHo being associated with lower decision impulsivity. This result was consistent between the two samples (Beijing and Chongqing). As far as we know, this study was the first to examine the relationship between the ReHo of medial prefrontal cortex and decision impulsivity. The results were consistent with our previous finding that different anatomical structures of the dorsal medial prefrontal cortex represented immediate and delayed reward size separately (Wang et al., 2014).

Evolutionary research has shown that the development of prefrontal cortex is later in human than in primates. In fact, the human prefrontal cortex does not mature until early adulthood, perhaps because it plays an unusually important role in human adaptation and higher functions, including human cognition, memory, thinking, reasoning, imagination, and various types of decision-making such as risk decision-making, intertemporal decision-making and social decision-making (Wang et al., 2014).

Evidence from lesion studies showed that patients with medial prefrontal cortex injury were more likely to ignore the future and to focus only on current benefits (Bechara et al., 1994; Bechara et al., 2000). Sripada et al. (2011) used Barrett Impulsivity Scale (BIS) to measure trait impulsivity and also scanned the subjects while they performed the intertemporal choice task. They found a significant negative correlation between the activation level of medial prefrontal cortex and trait impulsivity score. Luhmann et al. (2008) also found that activation in the medial prefrontal cortex was negatively correlated with choosing delayed rewards. Our previous study also showed that the anterior part of the dorsal medial prefrontal cortex represented the subjective value of delayed rewards (Wang et al., 2014). Therefore, we believe that the

Table 3
Brain regions whose ReHo predicted delay discounting rate: MVPA of the Beijing sample.

Brain Regions	L/R	No. Voxels	MNI Coordinates			Prediction Accuracy
			x	y	z	
DMPFC	L	90	−4	42	14	0.198
PCC	L	1385	−4	−36	24	0.286
Pallidum/insula	R	1202	16	4	−4	0.260
Supramarginal gyrus	R	690	54	−36	24	0.217
Lateral occipital cortex	R	649	46	−72	−22	0.226
Superior parietal lobule	L	591	−24	−54	44	0.253
Thalamus	R	587	18	−36	0	0.230
Frontal pole	R	539	12	72	14	0.264
SMA	R	411	6	−10	66	0.218
Lateral occipital cortex	R	389	24	−76	54	0.247
Orbital frontal cortex	R	291	14	30	−26	0.236

dorsal medial prefrontal cortex mainly represents delayed rewards, so its ReHo patterns are associated with decision impulsivity.

Intertemporal decision reflects decision impulsivity. The research on the mechanism of decision impulsivity mainly emphasizes the participation of three neural network systems, namely, the value, cognitive control, and prospect network systems (Peters and Büchel, 2011). A number of studies have shown that the value network system is regulated by the prefrontal cortex, as well as by upstream input from the hippocampus (Hare et al., 2009; van den Bos et al., 2014). Our results replicated these findings, confirming the importance of the value network, particularly the medial prefrontal cortex, in the representation of delayed rewards. Specifically, the posterior medial prefrontal cortex (pDMPFC) represents immediate reward and the anterior medial prefrontal cortex (aDMPFC) represents of delayed reward. In addition, the ventromedial prefrontal cortex (VMPFC), the posterior cingulate cortex (PCC) and the nucleus accumbens (NAcc) are mainly responsible for representing decision values, while the anterior cingulate cortex is responsible for decision difficulty (Wang et al., 2014). The dorsal medial prefrontal cortex plays a role in intertemporal choice through two mechanisms. One was the functional connectivity between the dorsal medial prefrontal cortex and the hippocampus. The other was the functional connectivity among the dorsal medial prefrontal cortex/frontal pole, the ventral prefrontal cortex, and ventral striatum. The dorsal medial prefrontal cortex, which is responsible for representing the value of delayed rewards, regulates the ventral lateral prefrontal cortex to represent the value of decision-making and thereby affect subsequent selections.

MVPA has important advantages over univariate analysis when exploring the neural representation of rewards and the neural mechanism behind intertemporal decision making. For example, it takes full advantage of the information from the voxels that do not show significant activation at the univariate level. MVPA is more sensitive than the univariate analysis in detecting differences in cognitive state because it uses relatively raw data. Finally, MVPA can detect signal changes of the polypheromones to better capture the inherently multivariate characteristics of brain imaging data.

Although we have found that the ReHo of the medial prefrontal cortex and brain activation patterns play an important role in decision impulsivity, our study had some shortcomings that need to be mentioned. First, our study only correlated brain function and behavior performance, so it was unable to address the question of causality. Second, our study did not examine the reasons behind the relationship between the ReHo of the dorsal medial prefrontal cortex and decision impulsivity. Further research is still needed to understand how the dorsal medial frontal cortex regulates intertemporal choice. Future research needs to verify and repeat the above results from the perspective of nerve fibers. Third, although ReHo had proven to be able to construct long range connectivities such as the default mode network (Long et al., 2008), and it still only considers the information of the nearest voxels (i.e., short connectivity). Future studies should examine if the long distance connectivity contributes to decision impulsivity. Last, the effect size of this relationship was modest and we call future studies to replicate the results of the present study.

In summary, this study used two independent large samples for the first time to investigate the neural mechanism of individual differences in intertemporal choice. This study also adopted multi-voxel pattern analysis (MVPA) for the first time with cross validation, which improved the sensitivity of the test results. Results showed that the ReHo patterns of dorsal medial prefrontal cortex was a predictor of decision impulsivity, with higher ReHo predicting lower decision impulsivity. These results were replicated between the two samples. Our results provide not only important empirical support for theoretical models of the neural basis of intertemporal choice but also practical implications for effective intervention with decision impulsivity.

Disclosures

All authors declared that they have no conflict of interest.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2019.07.015.

References

Aiello, M., Salvatore, E., Cachia, A., Pappata, S., Cavaliere, C., Prinster, A., et al., 2015. Relationship between simultaneously acquired resting-state regional cerebral glucose metabolism and functional MRI: a PET/MR hybrid scanner study. Neuroimage 113, 111–121. https://doi.org/10.1016/j.neuroimage.2015.03.017.

Ainslie, G., 1975. Specious reward: a behavioral theory of impulsiveness and impulse control. Psychol. Bull. 82 (4), 463–496.

Alessi, S.M., Petry, N.M., 2003. Pathological gambling severity is associated with impulsivity in a delay discounting procedure. Behav. Process. 64 (3), 345–354.

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.

Bechara, A., Tranel, D., Damasio, H., 2000. Characterization of the decision-making deficit of patients with ventromedial prefrontal cortex lesions. Brain 123 (11), 2189–2202.

Bernier, M., Croteau, E., Castellano, C.A., Cunnane, S.C., Whittingstall, K., 2017. Spatial distribution of resting-state BOLD regional homogeneity as a predictor of brain glucose uptake: a study in healthy aging. Neuroimage 150, 14–22. https://doi.org/10.1016/j.neuroimage.2017.01.055.

Bickel, W.K., Odum, A.L., Madden, G.J., 1999. Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. Psychopharmacology 146 (4), 447–454.

Bjork, J.M., Momenan, R., Hommer, D.W., 2009. Delay discounting correlates with proportional lateral frontal cortex volumes. Biol. Psychiatry 65 (8), 710–713. https://doi.org/10.1016/j.biopsych.2008.11.023.

Cavanagh, J.F., Frank, M.J., 2014. Frontal theta as a mechanism for cognitive control. Trends Cognit. Sci. 18 (8), 414–421. https://doi.org/10.1016/j.tics.2014.04.012.

Chib, V.S., Rangel, A., Shimojo, S., O'Doherty, J.P., 2009. Evidence for a common representation of decision values for dissimilar goods in human ventromedial prefrontal cortex. J. Neurosci. 29 (39), 12315–12320. https://doi.org/10.1523/JNEUROSCI.2575-09.2009.

Dai, Z., Yan, C., Li, K., Wang, Z., Wang, J., Cao, M., et al., 2015. Identifying and mapping connectivity patterns of brain network hubs in alzheimer's disease. Cerebr. Cortex 25 (10), 3723–3742. https://doi.org/10.1093/cercor/bhu246.

Fox, M.D., Zhang, D., Snyder, A.Z., Raichle, M.E., 2009. The global signal and observed anticorrelated resting state brain networks. J. Neurophysiol. 101 (6), 3270–3283.
Hacker, C.D., Perlmutter, J.S., Criswell, S.R., Ances, B.M., Snyder, A.Z., 2012. Resting state functional connectivity of the striatum in Parkinson's disease. Brain 135 (Pt 12), 3699–3711. https://doi.org/10.1093/brain/aws281.
Hare, T.A., Camerer, C.F., Rangel, A., 2009. Self-control in decision-making involves modulation of the vmPFC valuation system. Science 324 (5927), 646–648.
He, Xue, G., Chen, C., Chen, C., Lu, Z.L., Dong, Q., 2013. Decoding the neuroanatomical basis of reading ability: a multivoxel morphometric study. J. Neurosci. 33 (31), 12835–12843. https://doi.org/10.1523/JNEUROSCI.0449-13.2013.
Hu, S., Ide, J.S., Sheng, Z., Sinha, R., Li, C.S.R., 2015. Conflict anticipation in alcohol dependence — a model-based fMRI study of stop signal task. Neuroimage Clin. 8 (C), 39–50.
Huang, X., Zhang, H., Chen, C., Xue, G., He, Q., 2018. The neuroanatomical basis of the Gambler's fallacy: a univariate and multivariate morphometric study. Hum. Brain Mapp. 0 (0) https://doi.org/10.1002/hbm.24425.
Johnson, M.W., WK, B., 2002. Within-subject comparison of real and hypothetical money rewards in delay discounting. J. Exp. Anal. Behav. 77 (2), 129–146.
Kable, J.W., Glimcher, P.W., 2007. The neural correlates of subjective value during intertemporal choice. Nat. Neurosci. 10 (12), 1625–1633. https://doi.org/10.1038/nn2007.
Knutson, B., Cooper, J.C., 2005. Functional magnetic resonance imaging of reward prediction. Curr. Opin. Neurol. 18 (4), 411–417.
Koritzky, G., He, Q., Xue, G., Wong, S., Xiao, L., Bechara, A., 2013. Processing of time within the prefrontal cortex: recent time engages posterior areas whereas distant time engages anterior areas. Neuroimage 72, 280–286. https://doi.org/10.1016/j.neuroimage.2013.01.056.
Kriegeskorte, N., Goebel, R., P.,B., 2006. Information-based functional brain mapping. Proc. Natl. Acad. Sci. U. S. A (10), 3863-38.
Lagorio, C.H., Madden, G.J., 2005. Delay discounting of real and hypothetical rewards III: steady-state assessments, forced-choice trials, and all real rewards. Behav. Process. 69 (2), 173–187. https://doi.org/10.1016/j.beproc.2005.02.003.
Levy, I., Snell, J., Nelson, A.J., Rustichini, A., Glimcher, P.W., 2010. Neural representation of subjective value under risk and ambiguity. J. Neurophysiol. 103 (2), 1036–1047. https://doi.org/10.1152/jn.00853.2009.
Liu, H., Liu, Z., Liang, M., Hao, Y., Tan, L., Kuang, F., et al., 2006. Decreased Regional Homogeneity in Schizophrenia: a Resting State Functional Magnetic Resonance Imaging Study. Neuroreport.
Long, X.Y., Zuo, X.N., Kiviniemi, V., Yang, Y., Zou, Q.H., Zhu, C.Z., et al., 2008. Default mode network as revealed with multiple methods for resting-state functional MRI analysis. J. Neurosci. Methods 171 (2), 349–355. https://doi.org/10.1016/j.jneumeth.2008.03.021.
Luhmann, C.C., Chun, M.M., Yi, D.J., Lee, D., Wang, X.J., 2008. Neural dissociation of delay and uncertainty in intertemporal choice. J. Neurosci. 28 (53), 14459–14466. https://doi.org/10.1523/JNEUROSCI.5058-08.2008.
Luo, X., Zhang, S., Hu, S., Bednarski, S.R., Erdman, E., Farr, O.M., et al., 2013. Error processing and gender-shared and -specific neural predictors of relapse in cocaine dependence. Brain 136 (4), 1231–1244.
McClure, S.M., Laibson, D.I., George, L., Cohen, J.D., 2004. Separate neural systems value immediate and delayed monetary rewards. Science 306 (5695), 503–507.
Mitchell, J.P., Schirmer, J., Ames, D.L., Gilbert, D.T., 2011. Medial prefrontal cortex predicts intertemporal choice. J. Cogn. Neurosci. 23 (4), 857–866.
Paloyelis, Y., Mehta, M.A., Faraone, S.V., Asherson, P., Kuntsi, J., 2012. Striatal sensitivity during reward processing in attention-deficit/hyperactivity disorder. J. Am. Acad. Child Adolesc. Psychiatry 51 (7), 722–732 e729.
Peper, J.S., Mandl, R.C., Braams, B.R., de Water, E., Heijboer, A.C., Koolschijn, P.C., Crone, E.A., 2013. Delay discounting and frontostriatal fiber tracts: a combined DTI and MTR study on impulsive choices in healthy young adults. Cerebr. Cortex 23 (7), 1695–1702. https://doi.org/10.1093/cercor/bhs163.
Peters, Büchel, C., 2011. The neural mechanisms of inter-temporal decision-making: understanding variability. Trends Cognit. Sci. 15 (5), 227–239. https://doi.org/10.1016/j.tics.2011.03.002.
Ridderinkhof, K.R., van den Wildenberg, W.P., Segalowitz, S.J., Carter, C.S., 2004. Neurocognitive mechanisms of cognitive control: the role of prefrontal cortex in action selection, response inhibition, performance monitoring, and reward-based learning. Brain Cogn. 56 (2), 129–140. https://doi.org/10.1016/j.bandc.2004.09.016.
Shin, D.J., Jung, W.H., He, Y., Wang, J., Shim, G., Byun, M.S., et al., 2014. The effects of pharmacological treatment on functional brain connectome in obsessive-compulsive disorder. Biol. Psychiatry 75 (8), 606–614. https://doi.org/10.1016/j.biopsych.2013.09.002.
Sripada, C.S., Gonzalez, R., Phan, K.L., Liberzon, I., 2011. The neural correlates of intertemporal decision-making: contributions of subjective value, stimulus type, and trait impulsivity. Hum. Brain Mapp. 32 (10), 1637–1648. https://doi.org/10.1002/hbm.21136.
van den Bos, W., Rodriguez, C.A., Schweitzer, J.B., McClure, S.M., 2014. Connectivity strength of dissociable striatal tracts predict individual differences in temporal discounting. J. Neurosci. 34 (31), 10298–10310. https://doi.org/10.1523/JNEUROSCI.4105-13.2014.
Wang, Q., Chen, C., Cai, Y., Li, S., Zhao, X., Zheng, L., et al., 2016. Dissociated neural substrates underlying impulsive choice and impulsive action. Neuroimage 134, 540–549.
Wang, Q., Luo, S., Monterosso, J., Zhang, J., Fang, X., Dong, Q., Xue, G., 2014. Distributed value representation in the medial prefrontal cortex during intertemporal choices. J. Neurosci. 34 (22), 7522–7530. https://doi.org/10.1523/JNEUROSCI.0351-14.2014.
Wu, T., Long, X., Zang, Y., Wang, L., Hallett, M., Li, K., Chan, P., 2009. Regional homogeneity changes in patients with Parkinson's disease. Hum. Brain Mapp. 30 (5), 1502–1510. https://doi.org/10.1002/hbm.20622.
Yu, R., 2012. Regional white matter volumes correlate with delay discounting. PLoS One 7 (2), e32595. https://doi.org/10.1371/journal.pone.0032595.
Zang, Y., Jiang, T., Lu, Y., He, Y., Tian, L., 2004. Regional homogeneity approach to fMRI data analysis. Neuroimage 22 (1), 394–400. https://doi.org/10.1016/j.neuroimage.2003.12.030.
Zou, Q., Wu, C.W., Stein, E.A., Zang, Y., Yang, Y., 2009. Static and dynamic characteristics of cerebral blood flow during the resting state. Neuroimage 48 (3), 515–524. https://doi.org/10.1016/j.neuroimage.2009.07.006.