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ORIGINAL RESEARCH

Activation patterns of the dorsal medial prefrontal cortex and frontal pole predict individual differences in decision impulsivity

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Abstract

Intertemporal choice refers to decisions that need to weigh different rewards at different time points in the future. Decision impulsivity manifests in the tendency of choosing smaller immediate options rather than larger later ones. Previous studies have suggested that decision impulsivity in intertemporal decision-making shares similar cognitive and neural mechanisms with risky decision-making. The present study theorizes on and examines whether the activation patterns of the dorsal medial prefrontal cortex (DMPFC) and the frontal pole (FP) during the risk-taking "cups task", as captured in the scanner, can predict the delay discounting rate (*k*) based on an intertemporal decision task performed outside the scanner. To this end, we scanned with functional magnetic resonance imaging (fMRI) techniques a sample of 257 college students (N = 257) while performing the cups task. Univariate analyses showed that activation levels of the DMPFC and the FP were inversely correlated with risk preference, but not with the delay discounting rate *k*. Multivariate pattern analysis, which can overcome key limitations of the univariate analyses, showed that activation patterns of these two regions predict the delay discounting rate *k*. These results confirmed the important roles of DMPFC and FP in decision impulsivity and the utility of using multivariate pattern analysis with fMRI data involving decision making tasks.

Keywords Intertemporal choice · decision impulsivity · dorsal medial prefrontal cortex · frontal pole · multivariate pattern analysis

Introduction

Two types of economic decision making have been extensively studied by researchers: Intertemporal choice and risky decision making. In intertemporal choice decisions, participants are faced with the choice between a smaller immediate reward and a larger later reward (Frederick et al. 2002; Loewenstein 1988). On average, participants prefer smaller immediate rewards over larger later rewards. This phenomenon has been called decision impulsivity (Lv et al. 2019; Wang et al. 2016), because it reflects little reflection on the possibility that larger later rewards are beneficial. To describe individual variations in decision impulsivity, a delay discounting rate (*k)* is calculated with the data from the intertemporal choice task (Frederick et al. 2002; Loewenstein 1988), by the hyperbolic function ($SV = \frac{A}{1+k\times D}$), where SV is the subjective value, A

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the reward magnitude, D the delay, and k the delay discounting rate (Ainslie 1975). Larger k represents higher decision impulsivity, as manifested from the preference for immediate, but smaller rewards.

In risky decision making, participants are faced with the choice between the certainty of receiving a smaller reward (the safe option) and a chance to receive a bigger reward (the risky option) (Clark et al. 2008; Peters and Büchel 2009; Xue et al. 2010). One of the most widely used risky decision making tasks is the "cups task" (Weller et al. 2007). In this task, participants choose between one option of a single cup, which represents a sure option with a fixed amount of gain or loss, and a second option of multiple cups, which represents a risky decision with probabilities for greater gains but also for greater losses.

Although it has been suggested that these two types of decision making have similar cognitive and neural mechanisms, and that risky decision making can be perceived as a form of decision impulsivity (Peters and Büchel 2009; Xue et al. 2010), empirical evidence in support of this perspective have been mixed. On the one hand, several behavioral studies have found common cognitive mechanisms for intertemporal choice and risky decision making (Green and Myerson 2004; Luhmann et al. 2008). For example, these two decision types can be represented by the same mathematical function. On the other hand, some studies have found that reward size matters for intertemporal choice (the bigger the reward, the more likely people would choose the delayed reward), but not for risky decision making (Green et al. 1999; Myerson et al. 2003), suggesting different cognitive mechanisms for the two decision making types.

Similarly, evidence from brain imaging studies has suggested overlapping but distinct neural processing mechanisms of intertemporal choice and risky decision making. The overlapping regions include the ventral striatum (VS), orbitofrontal cortex (OFC)/medial prefrontal cortex, and anterior cingulate cortex (ACC) (Kable and Glimcher 2007; Peters and Büchel 2009). Specifically, decision impulsivity has been linked to three neural networks: the cognitive control, prospect, and valuation networks (Peters and Büchel 2011). The cognitive control network is mainly localized to the prefrontal cortex (McClure et al. 2004), whereas the prospect network includes the hippocampus' regulation of the medial prefrontal cortex. For example, Peters and Büchel found that the functional connection between the anterior cingulate gyrus and the hippocampus predicts individual decision impulsivity (Peters and Büchel 2010).

The valuation network includes the following core nodes: medial prefrontal cortex, ventral striatum, and posterior cingulate cortex. When the level of neural activity of the system is increased, individuals show decision-making impulsivity. For instance, Beck et al. (2009) found that ventral striatal activation during reward anticipation was correlated with impulsivity in alcoholics. Others found that the neural activation of the medial prefrontal cortex could predict the level of decision impulsivity (Luhmann et al. 2008; Mitchell et al. 2011; Sripada et al. 2011). However, risky decision making is believed to result from the interaction between the "social emotional" and "cognitive control" systems in the brain according to the dual systems model (Steinberg 2010). A meta-analysis showed that DMPFC is a main faculty of the "social emotional" system (Phan et al. 2002).

The above literature review suggests that the prefrontal cortex plays an important role in both decision impulsivity and risky decision making. Other studies have shown that MPFC and fontal pole (FP) are especially essential for both types of decision making. Specifically, lesions of the MPFC and FP have been found to lead to risky decisions and excessive discounting (Bechara et al. 2000, 1996). People with such lesions had been found to make decisions based on their likes and dislikes, regardless of the future consequences of their decisions. Our previous work also found that DMPFC and FP represent the size of delayed rewards, which was responsible for decision-making value representation through the regulation of the ventral lateral prefrontal cortex, guiding follow-up decisions (Wang et al. 2014). Moreover, the grey-matter volumes in the right FP and left middle frontal gyrus (MFG) were predictive of the decision impulsivity parameter k in an intertemporal choice task (Wang et al. 2016).

Similarly, the MPFC has been identified as one critical structure in a neural system subserving risky decision making (Bechara, 2005; Glimcher and Aldo 2004; Spence 1995). Patients with MPFC lesions are less consistent in their choices in very simple preference judgment tasks (Fellows and Farah 2007). Individuals with drug abuse problems also show abnormal sensitivity to reward and elevated risk seeking behavior in comparison to healthy controls (Bechara 2005; Bechara et al. 2002; Tanabe et al. 2010). These finding suggest that the PFC and FP are important for risky decision-making and intertemporal choice (Lee et al. 2007).

In line with this perspective, a previous study (Wang et al. 2014) has found that the dorsomedial prefrontal cortex represents the delayed reward size. To further investigate whether the function of this region can be associated with individual differences in decision-making impulsivity, we used the brain activation patterns during one task to predict behavioral outcomes of another. Based on the abovementioned similarities between the psychological and neural mechanisms of risky and intertemporal choice decision making, the present study aimed at investigating whether risky and intertemporal choice decision making are correlated. It further aimed at examining whether the abovementioned activation patterns of the DMPFC and FP when performing one risky decision making task (the cups task) in a scanner would predict behavioral outcomes of the intertemporal choice task

outside the scanner. In doing so we follow similar approaches taken by previous research. For example, based on the state of human brain activity before the emergence of stimulation, researchers predicted subsequent risky decisions (Huang et al. 2014). To test our assertions, we recruited a large sample of Chinese college students (n = 257) and employed multivariate pattern analyses.

Materials and Methods

Participants

Two hundred and fifty-seven college students from Beijing Normal University volunteered to participate in the present study. This sample is the same Beijing cohort mentioned in a previously published study (Lv et al. 2019). Of the total sample, 18 (7.5%) participants were excluded from further analysis because of severe head motion (larger than 2 mm mean displacement in any direction) during the scan, leaving 239 participants (124 females, aged 23.6 ± 2.14 years) in the final analysis. All of them were free of any neurological or psychiatric disorder according to self-reports. A written informed consent form, which was approved with all other procedures by Beijing Normal University's Institutional Review Board, was signed by each participant before the experiment. All subjects first performed the behavioral test of intertemporal choice and were then subjected to an fMRI scan.

The intertemporal choice task

Participants performed one session of intertemporal choice task to determine their decision impulsivity as illustrated in Fig. 1. They were instructed to choose between a fixed smaller sooner reward (SS, ¥60 received today) and a larger later (LL) reward. The amount of the LL reward was randomly assigned from ¥78 to ¥108, and the delay (D) was either 15 days or 45 days in the future. The decision impulsivity index (i.e., the delay discounting rate parameter, k) was calculated according to the hyperbolic function: $SV = \frac{A}{1+k\times D}$, where SV represents the subjective value, D represents the delay period and A represents the amount of the LL reward. Following previous studies (Luo et al. 2012; Luo et al. 2009; Wang et al. 2014), adaptive track was induced to accurately measure the parameter k. In brief, the initial k was set to 0.02 which represents the average k value from a previous study (Wang et al. 2014). From trial to trial, it was adjusted (increased or decreased) as a result of participants' choices. Specifically, if the participants chose the immediate option, the k was increased by one step (i.e., next trial would have a lager LL) and if the participants chose the delayed option, the k was decreased by one step (i.e., next trial would have a smaller LL). With a total of 60 trials, each step for the k was set as 0.01 for the first 20 trials and as 5% of the previous k value for the remaining 40 trials. The final k was calculated as the mean of the last 16 trials and represented the decision impulsivity in this study.

The cups task

In order to investigate the brain activation patterns in risky decisions, we used a computerized version of the cups task (Xue et al. 2009) inside the fMRI scanner. The cups task includes a Gain domain and a Loss domain (Fig. 2A). In the Gain domain, subjects were asked to win as much money as possible and in the Loss domain, they were asked to lose as little money as possible. During each trial, participants were asked to choose between a risky option and a safe option. The safe option was set to win or lose ¥1 for sure, while the risky option was to win a larger amount (e.g., ¥2, ¥3, ¥5) with a certain probability (e.g., 0.20, 0.33 or 0.50) in the Gain domain, and to lose a larger amount (e.g., ¥2, ¥3, or ¥5) with a certain probability (e.g., 0.20, 0.33 or 0.50) in the Loss domain. In the cups task, multiple combinations were involved, including the combinations of equal expected value (EQEV) for the risky and safe options, such as 0.20 × 5 (5 cups to win ¥5), 0.33 × 3 (3 cups to win ¥3), and 0.50 × 2 (2 cups to win ¥2) on both Gain and Loss domains, which were all equal to the expected value of the safe option 1. Some combinations were slightly risk-advantageous (RA), meaning that their expected values (EVs), namely, 0.33 × 5 (3 cups to win ¥5) and 0.50 × 3 (2 cups to win ¥3), were higher than the expected value of the safe option in the Gain domain or that their EVs, namely, 0.20 × 3 (5 cups to lose ¥3) and 0.33 × 2 (3 cups to lose ¥2), were less than the expected value of the safe option in the Loss domain. Some combinations were slightly risk-disadvantageous (RD), meaning that the EVs were less than the safe option in the Gain domain [0.20 × 3 (5 cups to win ¥3) and 0.33 × 2 (3 cups to win ¥2)] or more than the safe option in the Loss domain [0.33 × 5 (3 cups to lose ¥5) and 0.50 × 3 (2 cups to lose ¥5)]. Finally, the 2 combinations with the biggest differences in EV between risky and safe options (i.e., 0.20 × 2 and 0.50 × 5) were excluded in the present study because our previous research (Xue et al. 2009) found that these combinations were sensitive to subjects' risk attitudes.

On each trial, an array of 2, 3, or 5 cups was shown on one side of the screen, with either (+) or (-) and an amount of money presented above the cups to indicate that if the right cup was chosen it would yield a gain or loss, respectively (Fig. 2A). On the other side of the screen was the safe option, where only one cup with ¥1 was shown. To make the task easier to implement in the scanner, subjects were not asked to choose the specific cup in the risky option as in previous studies (Xue et al. 2009). Instead, subjects only needed to decide whether to risk or not by pressing the corresponding left or right button

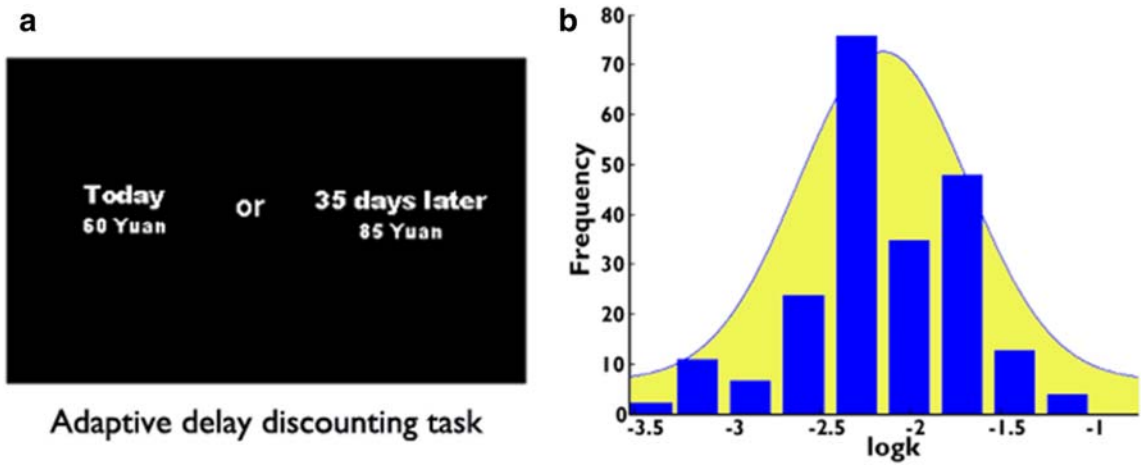

Fig. 1 Intertemporal choice task and the distribution of delay discounting rates. A. For each trial, subjects had to choose between a smaller sooner (SS) fixed reward (¥60) and a larger later reward. The delay period (D) for the larger later (LL) reward was randomly chosen from ¥78 to ¥108 between 15 and 45 days in the future. B. Normal distribution of the impulsive decisions (kolmogorov-smirnov Z = 1.033, p = 0.24).

via the response box. The subjects were shown the consequence of their choice immediately and were informed that gains or losses in all trials were accumulated to determine their actual earnings.

Functional imaging procedure

Imaging data were acquired on a 3T Siemens scanner at Beijing Normal University. Anatomical structural scan was acquired using an 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). The 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. The slices were tilted 30 degrees clockwise from the AC-PC plane to obtain better signals in the orbitofrontal cortex.

Behavioral data analysis

The statistical analysis of behavioral data was conducted with R2012 MATLAB (Mathworks Inc.). To fit the model to intertemporal choice task, we used multidimensional unconstrained nonlinear minimum function *(fminsearch)* in MATLAB. The hyperbolic function $SV = \frac{A}{1+k\times D}$ was used to calculate the subjective value of the delayed rewards. In order to better simulate trial selection, *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: $P_{ss} = \frac{1}{1+e^{-1\times m\times(V_{SS}-V_{LL})}}$, where m represents decision slope, P_{SS} represents the probability of choosing the smaller sooner option, V_{SS} and V_{LL} represent the value of the smaller sooner and larger later options, respectively. Individual delay discounting rate was determined by maximizing the likelihood of forecasting decisions. Since the original delay

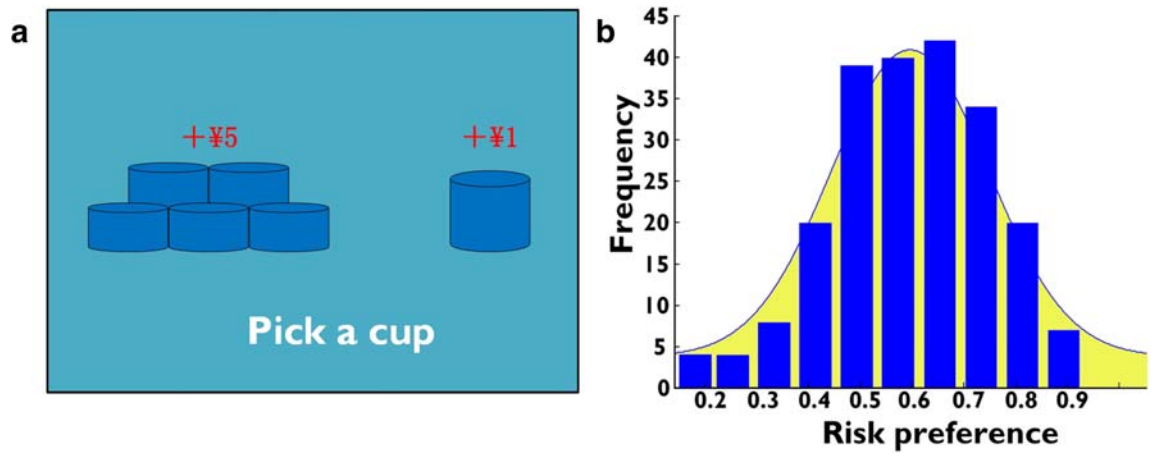

Fig. 2 The cups task and the distribution of risk preference. A. The cups task includes a Gain domain and a Loss domain. Each trial consists of a safe option with ¥1 in one cup, and a risky option with a probability of 1/2–1/5 (as determined by the number of cups) of larger gain or loss (±¥2 to ±¥5). B. The risk rate on the EQEV trials provided an estimation of individual's risk preference. The distribution of risk preference of the cups task was normal (kolmogorov-smirnov $Z = 0.93$, $p = 0.39$).

discounting rate was not normally distributed, a log10 transformation was applied to it (van den Bos et al. 2014; Wang et al. 2014)). For the cups task, the probability of the risky option was selected as the risk preference index according to the participant's risk preference in the EQEV combination only.

Univariate fMRI data analysis

Image preprocessing and statistical analyses were performed by using the fMRI Expert Analysis Tool (FEAT v6.00, https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/FEAT). The first 3 images before the task were automatically discarded by the scanner to allow for T1 equilibrium. The remaining images were then realigned to correct for head motion. Data were spatially smoothed with a 5-mm full-width at half-maximum (FWHM) Gaussian kernel to increase the signal-to-noise ratio and filtered in the temporal domain using a nonlinear high-pass filter with a 90 s cutoff. EPI images were then registered into standard 3-dimensional Montreal Neurological Institute (MNI) space. A two-step registration procedure was used whereby EPI images were first registered to the MPRAGE structural image, and then into standard MNI space, using affine transformations (Jenkinson & Smith, 2001). Registration from MPRAGE structural image to standard space was further refined using FNIRT nonlinear registration (Andersson et al. 2007a, b).

A general linear model (GLM) was used to analyze the contributions of the different experimental factors to the blood oxygenation level-dependent (BOLD) responses using both parametric analysis and category analysis. The parametric analysis was used to quantitatively describe the relationship between brain activation and decision parameters. There were 5 regressors generated for each trial and entered a GLM model: the magnitude of the possible outcome of the risky choice (Mag), the probability (Prob, as determined by the number of cups), the relative EV of the risky option, the experienced reward and the experienced risk. The relative EV of the risky option was calculated by subtracting the EV of the safe choice from that of the risky choice (¥1 or -¥1 for the Gain and Loss domain, respectively). Following the existing studies (Holt and Laury 2002; Kim et al. 2006; Tobler et al. 2007), risk in the present study was defined as the variance of the outcome, which was calculated using the following formula: $\text{Risk} = (1 - \text{Prob}) \times (0 - \text{EV})^2 + \text{Prob} \times (\text{Mag} - \text{EV})^2$. In order to examine the neural mechanism of experienced risk, we multiplied the decision risk parameter by the subject's actual choice coded as 1 (risky choice) or 0 (safe choice). More importantly, in this study, we ensured that the risk and reward experiences were orthogonal to each other. In the parametric analysis, we used smoothed data to obtain the activation maps and the unsmoothed data for multivoxel pattern analysis (MVPA).

For the category analysis, the following events were modeled based on participants' responses: RiskyLoss_Gain-domain, RiskyWin_Gain-domain, NoRisk_Gain-domain, RiskyLoss_Loss-domain, RiskyWin_Loss-domain, NoRisk_Loss-domain, and nuisance events consisting of the instructions. It should be noted that the response to RiskyLoss under the Gain domain does not mean that the subjects lose money, but only reflects the loss relative to the certainty of winning money. Similarly, RiskyWin under the Loss domain does not mean that the subjects win money, but only reflects the relative certainty of losing money. The purposes of this analysis were to extract the activation values of DMPFC and FP, and to examine their relationships with risk preference.

Multivariate pattern analysis

Combined with epsilon-insensitive SVR of a linear kernel, as implemented in PyMVPA (http://www.pymvpa.org), we used brain activation with risk experience during the cups task to predict the delay discounting rate. High-dimensional regression MVPA was performed using a searchlight procedure with a 3-voxel radius. This procedure allowed an evaluation of the pattern of activity across voxels without contamination from the mean signal differences within the searchlight. Based on previous studies (He et al. 2013; Huang et al. 2019; Wang et al. 2016), the epsilon was set to 0.01.

Brain-behavior correlation analysis

In order to further investigate the direction of correlation between risk-related activation values and behavioral delay discounting rate, log(k), we selected the significantly predicted multivariate brain region as the seed point ROI, then extracted the activation value related to risk in the seed brain region. After that, we correlated them with the delay discounting rate k based on behavioral data. To avoid the double dipping problem (Kriegeskorte et al. 2009), we only reported the relevant directions, not the r and p values.

Results

Behavioral results

Behavioral results suggested that the average value of impulsive decision index ($log\ k$) was −2.15 (SD = 0.47, ranging from −3.91~-0.98). The distribution of impulsive decisions ($log\ k$) was normal (Kolmogorov-Smirnov $Z = 1.033$, $p = 0.24$) (Fig. 1. **B**). Similarly, the distribution of risk preferences in the cups task was also normal (Kolmogorov-Smirnov $Z = 0.93$, $p = 0.39$) (Fig. 2. **B**). Risky decision-making was positively correlated with impulsive decision-making ($r = 0.278$, $p < 0.01$), suggesting those who preferred risky choices also tended to have higher decision impulsivity. In addition, sex information was available for 230 participants (9 participants

did not report their sex). Males showed significant higher delay discount rate in the delay discounting task than females (logk) ($t(228) = 2.13$, $p = 0.03$).

Imaging results

Using a multivariate MVPA approach, we found that in the brain regions correlated with risk experience during the cups task, activation levels in the right DMPFC (MNI = 8, 26, 44, $r = 0.341$) (Fig. 3. **A**) and right FP (MNI = 30, 36, 32, $r = 0.333$) (Fig. 3C) predicted delay discounting rate *k*. Other brain regions that also predicted the delay discounting rate included the right medial temporal gyrus (MTG; MNI = 56, -36, -12, $r = 0.303$), left dorsal anterior cingulate cortex (dACC; MNI = -4, 18, 24, $r = 0.334$), right supramarginal gyrus (SMG; MNI = 58, -30, 48, $r = 0.296$), left frontal operculum cortex (MNI = -42, 28, 2, $r = 0.317$), posterior PFC (MNI = 30, 46, -18, $r = 0.237$), frontal pole (FP; MNI = -18, 60, -10, $r = 0.223$), right cerebellum (MNI = 26, -46, -32, $r = 0.287$) and left superior temporal gyrus (STG; MNI = -66, -20, 12, $r = 0.256$) (Table 1). Univariate analysis showed that activation levels of the DMPFC and the FP were significantly negatively correlated with risk preference (Fig. 3B, D). However, no significant correlation was found between activation levels and the delay discounting rate k.

Discussion

The present study sought to investigate whether the activation patterns of DMPFC and FP in a risky decision-making task would predict the behavior on an intertemporal choice task. A large sample of Chinese college students was recruited and multivariate pattern analysis (as well as univariate analyses) was conducted. Risky decision-making showed a positive correlation with decision impulsivity. Neuroimaging results suggested that activation patterns in the DMPFC and FP in the cups task could predict decision impulsivity, as manifested in behavior on another task. This result was consistent with our previous findings that the MPFC plays an important role in intertemporal decision-making (Lv et al. 2019; Wang et al. 2014) and hence further verified the relationship between MPFC/FP and decision impulsivity based on MVPA. These results can further help understanding the shared neural basis of intertemporal choice decisions and risky decision-making.

Our finding of a significant positive correlation between risky decision making and decision impulsivity is also consistent with the idea that these two types of decision making are similar. First, they have similar mathematical models and assumptions in traditional economics. Delay discounting is described with the discount utility function (DUT) model in intertemporal decision-making, whereas the expected utility

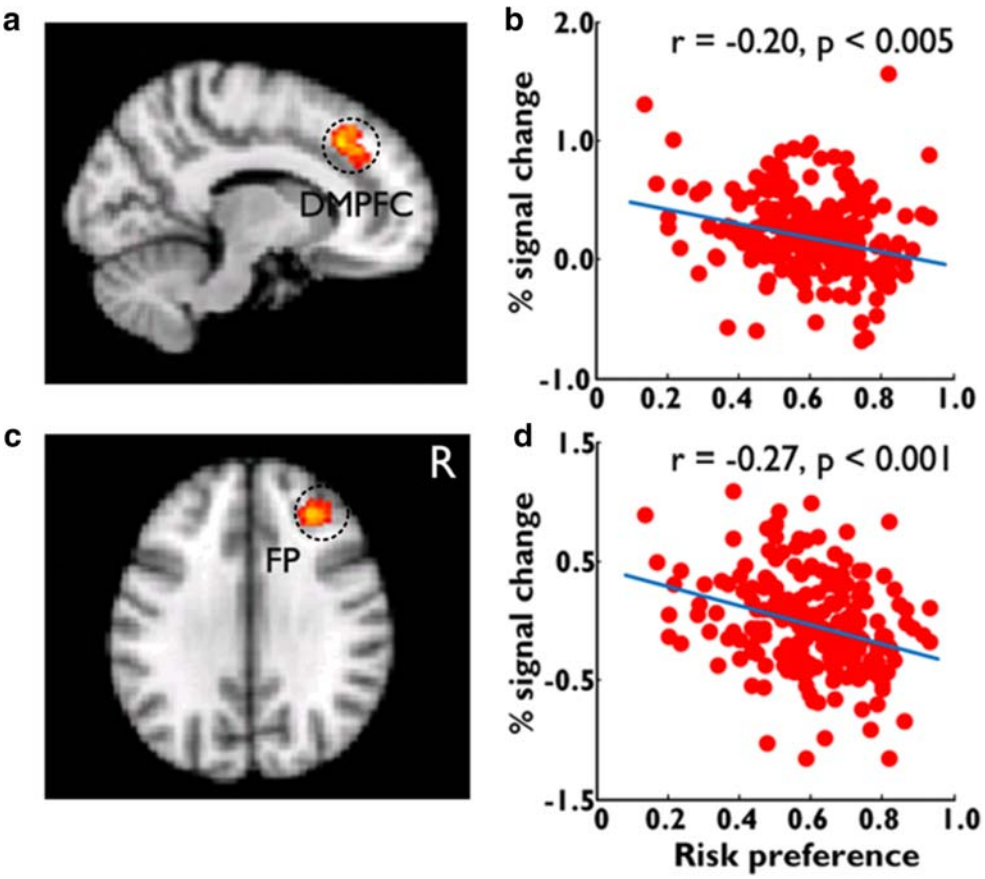

Fig. 3 Brain activation patterns significantly predicted decision impulsivity. Activation levels in the dorsal medial prefrontal cortex (DMPFC; MNI = 8, 26, 44, r = 0.341) (A) and the frontal pole (FP; MNI = 30, 36, 32, r = 0.333) (C) predicted the delay discounting rate k. Univariate analysis showed that activation levels of the dorsal medial prefrontal cortex (B) and the frontal pole (D) were negatively correlated with risk preference.

Table 1 Brain regions significantly correlated with the delay discounting rate.

Brain Regions	L/R	No. Voxels	MNI Coordinates			Prediction Accuracy
			x	y	z	
DMPFC	R	664	8	26	44	0.341
Frontal pole	R	227	30	36	32	0.333
Middle Temporal gyrus	R	574	56	-36	-12	0.303
dACC	L	431	-4	18	24	0.334
Supramarginal gyrus	R	295	58	-30	48	0.296
Frontal operculum cortex	L	262	-42	28	2	0.317
cerebellum	R	386	26	-46	-32	0.287
Superior temporal gyrus	L	342	-66	-20	12	0.256

function (EUT) model is used to describe probability discounting in risky decision-making. Both delay discount function and probability discount function can be described by hyperbolic curve (Green and Myerson 2004). Furthermore, some studies have found a significant positive correlation between delay discounting and probability discounting in the same individual (Myerson et al. 2003). These findings have promising clinical implications. People with mental or neurological diseases often exhibit decision-making impulsivity; for example, attention-deficit disorder, gambling disorder and substance use disorder cases. Our findings can extend the battery of instrument out there for measuring decision-making impulsivity when diagnosing or treating such patients. Future research can investigate whether applying this approach can improve diagnostic sensitivity and specificity.

Our result that activation levels of the DMPFC and FP during the cups task could predict the delay discounting rate k was consistent with the experimental results of Xue (2009). Using functional magnetic resonance imaging (fMRI) and a risky decision making task, Xue et al. found that the MPFC was activated when a risky decision was made, but the intensity of activation was negatively correlated with the subjects' risk preference. On the contrary, the activation of the ventral MPFC was positively correlated with the individual's risk preference. These results indicate that the dorsal and ventral MPFC may transmit different decision signals. Previous studies have shown that intertemporal choice decisions and risky decision-making may share similar neural systems. Specifically, Peters and Büchel (2009) found that the ventral striatum and OFC coded the subjective value of both delayed and probabilistic monetary rewards in a common system.

In contrast, some animal studies have found differences in the brain mechanisms that mediate time discounting and probability discounting (Acheson et al. 2006). Similarly, previous studies have shown that the lesion of the ventromedial prefrontal cortex has no impact on learning, memory and attention, but can influence the integration of emotions into decision making. For example, patients with damaged ventromedial prefrontal cortex tend to make impulsive decisions in real life, ignore long-term interests, expected emotions, and show defects in experimental tasks that require balancing rewards, punishment and risks (Shiv et al. 2002). Our results are consistent with the notion that there are overlapping neural mechanisms between these two types of decisions.

A large sample is also the highlight of this study. We recruited a large sample for this study for several reasons. First, small samples inevitably lead to sampling error, which limits the generalization of experimental results. Second, the statistical tests of small samples tend to be unstable, which reduces its replicability potential. Third, large samples afford many-repeated sub-samplings, which can increase the robustness of estimates. Therefore, inferring neural basis of individual differences from large sample databases can be advantageous, accurate, reliable and replicable.

Lastly, it is worth noting that both traditional univariate and advanced MVPA were used in this study. These two methods differ in several ways (Mur et al. 2009). First, in terms of the purpose of the analysis, traditional brain imaging analysis focuses on activated brain regions associated with a specific task to detect brain regions involved in a mental process. In contrast, MVPA aims to detect the content of representation. Second, in terms of the experimental conditions, traditional brain imaging focuses on differences in brain activation between different mental activities, while MVPA focuses on differences in contents of representation between different objects. Third, in terms of data analysis, the traditional brain imaging method compares the difference of the activation of the brain regions under different conditions, while MVPA compares the difference of activation patterns under different conditions. Fourth, whereas univariate analysis focuses on significantly activated voxels, multivariate pattern analysis considers those voxels that were not significantly activated. Fifth, in terms of spatial resolution, traditional brain imaging analysis is limited by the smoothed size, while MVPA can make use of elaborate spatial information. Last, MVPA uses cross-validation and consequently, its results are more reliable. Specifically, compared with

traditional univariate analysis, MVPA uses repeated subsampling with a leave-one-out approach or other methods. The produced output is based on the average value, and can include distributional parameters for estimates. This allows for more robust and reliable results, compared to univariate approaches.

Several limitations of this study need to be mentioned. First, our study was correlational in nature and cannot be used for inferring causality. Second, previous studies showed that the educational background (e.g., students major in psychology or economics) significantly influences decisions in risky choice or time discounting tasks. We did not record major information in our study, and should be accounted for in future research. Third, sex differences in delay discounting parameters were observed here, and should be more deeply examined din future research. Because such sex differences were not the main aim of this study, the number of males and females was imbalanced. Fourth, the paradigm used in this study followed Xue et al. (2009), and used accumulated earnings to motivate subjects. Although in each trial we only presented one time gain or loss but not the accumulated gains or losses, it may be a potential confounding factor to influence the brain activity. Lastly, the lack of fMRI data for the intertemporal choice task is a limitation. It would have been useful to have it and link brain activations on both tasks. We call for future research to supplement our results with such brain imaging data.

Conclusion

Our study found that the brain activation patterns of the DMPFC and the FP were associated with decision impulsivity. It extended our understanding of the neural basis of intertemporal choice and the links between time-reward and risk-reward discounting.

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Author contributions QW, CC, GX, and QH designed the study, QW and QH collected the data, QW and QH performed the analysis, CL and QH finished the first draft of the manuscript. All authors made critical revisions to the manuscript and the final version of the manuscript was approved by all authors.

Compliance with ethical standards

All procedures performed in studies involving human participants were in accordance with the ethical standards of the Institutional Review Board of the Beijing Normal University.

Conflict of interest The authors declare no conflict of interest.

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