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Coupling and segregation of large-scale brain networks predict individual differences in delay discounting

Zhiyi Chen[a,1], Yiqun Guo[a,1], Tao Suo[b,**], Tingyong Feng[a,c,*]

[a] Faculty of Psychology, Southwest University, Chongqing, China
[b] Institute of Psychology and Behavior, School of Education, Henan University, Kaifeng, China
[c] Key Laboratory of Cognition and Personality, Ministry of Education, China

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ABSTRACT

Decision-making about rewards, which requires us to choose between different time points, generally refers to intertemporal choice. Converging evidence suggests that some of the brain networks recruited in the delay discounting task have been well characterized for intertemporal choice. However, little is known about how the connectivity patterns of these large-scale brain networks are associated with delay discounting. Here, we use a resting-state functional connectivity MRI (rs-fcMRI) and a graph theoretical analysis to address this question. We found that the delay discounting rates showed a positive correlation with the functional network connectivity (FNC) between the cingulo-opercular network (CON) and the default mode network (DMN), while they showed a negative correlation with the FNC of both the CON-SAN (salience network) and the SAN-FPN (fronto-parietal network). Our results showed the association of both coupling and segregating processes with large-scale brain networks in delay discounting. Thus, the present study highlights the pivotal role of the functional connectivity patterns of intrinsic large-scale brain networks in delay discounting and extends our perspective on the neural mechanism of delay discounting.

1. Introduction

Every day we make decisions that involve trade-offs between outcomes that occur at different points in time, and this type of decision is called as intertemporal choice. For instance, our long-term financial position largely relies on our patience to forsake the short-run satisfaction of immediate consumption for long-term pay-off. In such intertemporal decision-making, individuals generally prefer smaller but immediate rewards over larger but delayed ones, and this is termed delay discounting (Kable & Glimcher, 2010). Steep discounting of delayed rewards has been implicated in a series of suboptimal behaviors such as obesity (Weller, Cook, Avsar, & Cox, 2008), overeating (Appelhans et al., 2011), substance abuse, and nonresponse to climate change (Alessi & Petry, 2003; Bickel, Quisenberry, Moody, & Wilson, 2015; Kirby & Petry, 2004). To investigate the underlying neural mechanism of delay discounting, previous studies mainly used region-based multimodal methods such as the task-state functional magnetic resonance imaging (fMRI), voxel-based morphometry (VBM), and resting-state functional connectivity MRI (rs-fcMRI) (Kable & Glimcher, 2007; Li et al., 2013; Olson et al., 2009). However, little is known about the neural correlates of delay discounting from a network-based perspective, especially in the connectivity patterns of intrinsic large-scale functional brain networks.

Task-state fMRI studies have shown that delay discounting recruits three distinct brain networks: the reward valuation network (such as the ventral striatum (VS), orbitofrontal cortex (OFC), and medial prefrontal cortex (mPFC)); the cognitive control network (such as the anterior cingulate cortex (ACC) and dorsolateral prefrontal cortex (dlPFC)); and the prospection network (such as the hippocampus and amygdala); these networks have been found to correspond to the core subprocesses of intertemporal choice (Glimcher, 2009, 2010; ; Mcclure, Laibson, Loewenstein, & Cohen, 2004; Peters & Büchel, 2011). Specifically, the reward valuation network plays a vital role in the representation of subjective reward values, while the cognitive control network is responsible for the top-down control of subjective value signals from the reward valuation network. Simultaneously, the prospection network also makes a great contribution to delay discounting through the representation of decision outcomes. In addition, studies involving the resting-state analysis have indicated that the functional connectivity (FC) of the brain regions (such as VS, ACC, and dlPFC) is

* Corresponding author at: School of Psychology, Southwest University, No.2, Tian Sheng RD., Beibei, ChongQing 400715, China.
** Corresponding author at: Institute of Psychology and Behavior, School of Education, Henan University, Jin Ming Avenue, Kaifeng, Henan, 475004, China.
E-mail addresses: suotao810815@163.com (T. Suo), fengty0@swu.edu.cn (T. Feng).
[1] Zhiyi Chen and Yiqun Guo contributed equally to this work.

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associated with delay discounting (Costa et al., 2013; Li et al., 2013; Schmaal, Goudriaan, Meer, Brink, & Veltman, 2012). Neuroanatomical studies have also revealed the associations between gray matter volume (GMV) of VS, OFC, dlPFC, and parahippocampal gyrus and delay discounting (Mohammadi et al., 2016; Sang et al., 2013; Wang & Dvorak, 2010). Collectively, these findings converge on the conclusion that brain regions, which are associated with delay discounting, play an important role in value representation, cognitive control, and prospection.

Although relatively numerous neuroimaging studies have identified the neural mechanism underlying delay discounting, little is known about how the FC patterns of intrinsic large-scale brain networks reflect delay discounting. A recent debate in neuroscience emphasizes that neural responses to a series of decision-making challenges are reflected not only by a change in activity in certain regions of the brain but also by the connectivity pattern of global reorganization (Bressler & Menon, 2010; Larson-Prior et al., 2011; Sylvester et al., 2012; Varela, Lachaux, Rodriguez, & Martinerie, 2001). Many studies indicate that our understanding about the neural underpinning of complex decision-making (such as intertemporal choice) should be updated from a network-based classification to a network-interacted scheme (Bressler & Menon, 2010; Rubinov & Sporns, 2010; Sporns, Chialvo, Kaiser, & Hilgetag, 2004). Importantly, because of the strong influence of high-level cognitive control on intertemporal choices, the interaction between a set of cognitive-related networks including the fronto-parietal network (FPN), salience network (SAN), and cingulo-opercular network (CON) has been considered to be robust for understanding the neural basis of temporal discounting (Boettiger et al., 2007; Menon, 2011; Monterosso et al., 2007; Stanger et al., 2013; Worhunsky et al., 2013). Hence, in contrast to the identification of isolated brain regions or within a single defined network, we hypothesize that the coupling of these cognitive-related functional networks (e.g., CON-SAN, FPN-SAN, and CON-FPN) is potentially involved in temporal discounting. Furthermore, our previous connectome-based work suggests the pivotal role of the default mode network (DMN) in the regulation of cognitive resources (Chen, Guo, & Feng, 2017). Thus, we also expect that the bridge between DMN and the cognitive-related networks (e.g., CON-DMN, FPN-DMN, and SAN-DMN) could be another predictor for delay discounting.

In the current study, we conducted a graph analysis using the method by Power et al. (2011) to reconstruct the intrinsic large-scale brain networks from whole-brain areas. Recent studies indicated that the template used by Power et al. provided a well-formed brain graph to define nodes and showed a higher test-retest reliability for global and local network properties relative to anatomical automatic labeling (AAL) and other atlas (Cole, Pathak, & Schneider, 2010; Power, Schlaggar, Lessovschlaggar, & Petersen, 2013; Spreng, Sepulcre, Turner, & Stevens, 2013; Yan, Craddock, Zuo, Zang, & Milham, 2013). In this vein, we first used a community detection algorithm (Gordon et al., 2016; Power et al., 2011) to assign 10 well-established large-scale networks from the original 264 nodes defined by Power et al. (2011). These established networks were demonstrated to be representative of the intrinsic brain networks (Gordon et al., 2016). Then, we calculated FC between all these well-established large-scale brain networks and further estimated the connections within them. Finally, we employed the partial Spearman rank-order correlation analysis to explore the associations between the connectivity patterns of large-scale brain networks and delay discounting, particularly in correlates of the FC of these cognitive-related networks (also extends to DMN) on delay discounting.

2. Materials and methods

2.1. Participants

Sixty-two healthy subjects participated in the present study, and the age ranged from 19 to 24 years (M = 20.312 years; 15 male and 46 female). One subject was excluded from further analyses after quality control because of excessive head movement (absolute displacement with regard to the reference scan exceeded 2 mm). The detailed demographic characteristics of participants are summarized in Table 1. No significant differences were found for all behavioral measures between genders. In addition, sample sizes were chosen to ensure adequate power to detect medium-size effect (effect size $d = 0.5$, type I error $\alpha = 0.05$, power $1 - b = 0.7$) on the basis of a G*Power calculation (http://www.softpedia.com/get/Science-CAD/G-Power), which resulted in a minimum sample size of 49 subjects for the present analysis (Faul, Erdfelder, Lang, & Buchner, 2007). All participants had no history of psychiatric or neurological illness as confirmed by psychiatric clinical assessment, and they were paid for their participation (for detailed procedures, see below). The experimental protocol was approved by the Institutional Review Board (IRB) of the Southwest University.

Table 1
Participants' demographic information for the current study. Participants' personality trait and anxiety are respectively assessed by two standard psychological scales, namely, NEO Personality Inventory (NEO-PI; Costa & McCrae, 1992) and Trait Anxiety Inventory (TAI). *t* represents the *t* value of contrast between males and females on these variables using the independent *t* test, and the corresponding *p* value is also reported. *r* indicates the order-rank correlation coefficient for the association between AUC of all the participants and these variables, and the corresponding *p* value is also reported.

Variables (Mean ± S.D.)	Female	Male	*t* (*p* value)	*r* (*p* value)
Big-five personality				
Conscientiousness	42.20 ± 6.41	40.93 ± 6.01	0.91 (0.68)	−0.04 (0.71)
Extraversion	40.17 ± 5.76	40.06 ± 7.04	0.06 (0.07)	0.03 (0.78)
Neuroticism	34.53 ± 8.04	34.25 ± 5.69	0.12 (0.17)	0.03 (0.77)
Agreeableness	40.31 ± 4.75	40.31 ± 6.01	−0.01 (0.23)	−0.09 (0.45)
Openness	41.62 ± 5.89	39.75 ± 6.78	1.04 (0.73)	0.01 (0.95)
Trait anxiety	53.00 ± 10.47	54.00 ± 10.53	−0.32 (0.69)	−0.02 (0.87)

2.2. Monetary delay discounting task

We conducted a monetary delay discounting task, in which participants made a series of hypothetical monetary choices between a fixed immediate reward (sooner but smaller option) and a varied delayed reward (later but larger option) (Kable & Glimcher, 2007). The amount of sooner but smaller option was CNY (¥) 20 on all trials. The larger delayed option was constructed using one of the five delays (7, 15, 30, 60, and 120 days) and one of the ten add-percentages of the immediate reward (¥ 22–92); thus, there were 50 unique choices in one session. The entire task contained four sessions, for a total of 200 trials. Participants were allowed as much time as they desired to make decision.

To ensure the relatively high ecological validity for our study, the participants would be paid with the actual money as remuneration, according to their real responses in the intertemporal choices task. Such remuneration procedures were instructed in detail for each participant before formal experiment. We had also double-checked whether they completely understood these procedures before the experiment, guaranteeing that all the participants could make real decisions in this task. Specifically, the remuneration was divided into two parts: (1) fixed reward (before the formal experiment, participants were informed that we would pay ¥ 20 [≈ $ 3.0734] for their participation); (2) monetary task-related reward (participants were told at the outset that one of their choices from the task would be randomly picked and that they would receive the amount of money they chose on that trial with the actual money, at the delay specified. In other words, if they chose the immediate option on the randomly selected trial, they would receive