Brain Structure Linking Delay Discounting and Academic Performance

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Abstract: As a component of self-discipline, delay discounting refers to the ability to wait longer for preferred rewards and plays a pivotal role in shaping students' academic performance. However, the neural basis of the association between delay discounting and academic performance remains largely unknown. Here, we examined the neuroanatomical substrates underlying delay discounting and academic performance in 214 adolescents via voxel-based morphometry (VBM) by performing structural magnetic resonance imaging (S-MRI). Behaviorally, we confirmed the significant correlation between delay discounting and academic performance. Neurally, whole-brain regression analyses indicated that regional gray matter volume (rGMV) of the left dorsolateral prefrontal cortex (DLPFC) was associated with both delay discounting and academic performance. Furthermore, delay discounting partly accounted for the association between academic performance and brain structure. Differences in the rGMV of the left DLPFC related to academic performance explained over one-third of the impact of delay discounting on academic performance. Overall, these results provide the first evidence for the common neural basis linking delay discounting and academic performance. *Hum Brain Mapp* 38:3917–3926, 2017. © 2017 Wiley Periodicals, Inc.

Key words: delay discounting; academic performance; dorsolateral prefrontal cortex; voxel-based morphometry; adolescents

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INTRODUCTION

What predicts or explains students' academic performance? General intelligence is commonly considered the most powerful and stable predictor of academic performance [Kuncel et al., 2004; Neisser et al., 1996; Sternberg et al., 2001]. Beyond general intelligence, nonintellectual factors (e.g., self-discipline and motivation) also play essential roles in shaping students' academic performance [Duckworth and Seligman, 2005; Richardson et al., 2012]. One of these factors, delay discounting, which refers to the ability to wait longer for preferred rewards [Kirby, 1997; Kirby et al., 1999] and is a component of self-discipline [Duckworth and Kern, 2011; Duckworth and Seligman, 2005], is consistently associated with academic performance. For example, evidence from the famous "Stanford marshmallow experiment" revealed that delayed behavior in preschoolers at 4 years of age predicted their subsequent SAT scores [Mischel et al., 1989; Shoda et al., 1990]. Furthermore, the ability of delay discounting to predict academic performance has been repeatedly reported in adolescent and college students [e.g., Farley and Kim-Spoon, 2015; Freeney and O'Connell, 2010; Kirby et al., 2005; Lee et al., 2012]. In summary, delay discounting may play a causal role in students' academic performance.

According to several structural brain imaging studies in healthy participants, individual differences in delay discounting are primarily associated with the regional gray matter volume (rGMV) or cortical thickness in the prefrontal cortex (PFC), including the dorsolateral PFC (DLPFC), the ventrolateral PFC (VLPFC), the medial PFC (MPFC), the anterior cingulate cortex (ACC) [Bjork et al., 2009; Cho et al., 2013; Drobetz et al., 2014], and the striatum, comprising the caudate and the putamen [Cho et al., 2013; Tschernegg et al., 2015]. However, these studies had several limitations that may limit the statistical power of their findings. First, the sample sizes were small, ranging from 29 to 70 participants. Second, the sample characteristics were highly heterogeneous (e.g., broad age range and disproportionate sex ratio). Third, some studies focused exclusively on several regions of interest (ROI) [e.g., PFC regions, Bjork et al., 2009; subcortical regions, Tschernegg et al., 2015] and employed considerably liberal statistical thresholds for multiple comparisons [e.g., Cho et al., 2013]. Because delay discounting is crucial for an individual's mental health and behavioral performance [Critchfield and Kollins, 2001; Reynolds, 2006; Shamosh et al., 2008; Shamosh and Gray, 2008], it is of importance to investigate the neuroanatomical correlates of delay discounting. On one hand, this would deepen our understanding of the neural substrates contributing delay discounting. On the other hand, it would provide potential neurobiological markers that can be used to develop corresponding intervening programs [e.g., the neurofeedback procedure; Scheinost et al., 2013] to promote effective delay discounting and well-being in healthy individuals and patients with mental disorders, and in particular, it also adds to

the development of psychoradiology (<https://radiopaedia.org/articles/psychoradiology>), a new field of radiology with growing intersection between the fields of psychiatry/psychology and clinical imaging (Kressel, 2017; Lui et al., 2016). Given the limitations in the previous structural brain studies on delay discounting, here we directly investigated the association between delay discounting and brain structure by performing whole-brain regression analyses in a large sample of healthy adolescent students ($N = 214$) with a narrow age range.

There are far fewer studies focusing on the neuroanatomical basis of academic performance. To the best of our knowledge, only one research has directly explored the structural brain basis underlying academic performance, reporting a correlation between better academic performance and greater cortical thickness in the temporal and occipital lobes [Mackey et al., 2015]. In addition, another VBM study based on ROI analysis found an association between higher academic performance and greater rGMV in the frontal and temporal lobes [Hair et al., 2015]. Because these studies had limitations similar to those reviewed above, we conducted whole-brain regression analyses to detect the neural correlates of academic performance and further explored the relationships between delay discounting, brain structure and academic performance.

To carry out our investigations, we employed a standard measurement of delay discounting, real-world academic performance, and VBM methodology. VBM analysis is a popular and well-validated approach for evaluating the amount of gray matter in different areas of the brain [Mechelli et al., 2005]. Given its task-free conditions and low-cost characteristics, VBM analysis has been widely employed to examine the brain basis of the human mind and behavior [DeYoung, 2010; Kanai and Rees, 2011]. First, we performed behavioral correlation analyses to confirm the association between delay discounting and academic performance. In light of the previous findings regarding the relationship between delay discounting and academic performance, we hypothesized that delay discounting would be associated with academic performance. Second, to identify the brain areas related to delay discounting, we conducted a whole-brain regression analysis. Given the prior findings on the brain structures of delay discounting, we speculated that structural variations in the PFC regions and striatum might predict individual differences in delay discounting. Third, we correlated the rGMV of each voxel across the brain with a national standard measure of academic performance to uncover the neural substrates of academic performance. Considering the limited neural evidence on academic performance, we speculated that structural variations of brain regions in the frontal, temporal and occipital lobes might predict individual differences in academic performance. Finally, we explored whether there were brain regions linked with both delay discounting and academic performance. We expected that some clusters in the PFC might be related to both delay discounting and academic performance.

METHODS

Participants

The participants were 234 healthy students ($M_{\text{age}} = 18.60$ years, $SD = 0.78$; 122 females) with no history of psychiatric or neurological illness from several local public high schools in Chengdu, China. All participants had recently graduated in June 2015 and were right-handed according to the Edinburgh Handedness Inventory [Oldfield, 1971]. We recruited these students from a larger project that aimed to investigate the determinants of social cognition, academic success and well-being among adolescents in Chengdu, China. We excluded 20 students from our sample who had an abnormal brain structure ($N = 3$) or no behavioral testing scores ($N = 17$). Thus, 214 participants ($M_{\text{age}} = 18.49$ years, $SD = 0.55$; 114 females) were included in our data analyses. Prior to testing, each participant gave written informed consent for the study. The local research ethics committee of the West China Hospital of Sichuan University approved this study. We performed all experiments from June 2015 to September 2015.

Assessment of Delay Discounting

We used the Monetary Choice Questionnaire (MCQ) to measure individual differences in delay discounting [Kirby et al., 1999]. The MCQ consists of 27 items that are grouped into three conditions (9 items per condition) based on the delayed reward magnitude: large (¥75–85¥), medium (¥50–60¥) and small (¥25–35¥), with delay times ranging from 7 days to 186 days. For each item, the participants were instructed to choose either a larger, delayed reward or a smaller, immediate reward. Example items included “Would you prefer ¥80 in 14 days or ¥33 today?” and “Would you prefer ¥27 today or ¥50 in 21 days?” The participants’ responses fit well with a hyperbolic function: $V = A / (1 + kD)$, where k refers to the discount rate parameter, D refers to the delayed time, A refers to the delayed reward, and V refers to the immediate reward [Mazur, 1987]. According to a procedure developed in previous studies [Kirby, 1997; Kirby et al., 1999], we computed the scores for delay discounting utilizing the following steps. First, for each item, we computed the k value that would yield indifference between the smaller and larger rewards by using the hyperbolic function [i.e., $V = A / (1 + kD)$]. An individual who chooses the larger reward on an item suggests the discounting rate is smaller than the indifference k for this item, whereas an individual who chooses the smaller reward suggests the discounting rate is greater than the indifference k . According to a participant’s responses on a given delayed reward condition (9 items), the range of k can be obtained. Then, we used the geometric mean of this range as the estimate of the delay discounting rate of the participant. If a participant chose all nine smaller rewards or larger rewards, we used the two endpoints of value k (0.25 and 0.00016) as the estimate of the delay discounting rate, respectively. Given that participants’ choices were not always consistent with a

single value of k , we assigned the k for each participant that can yield the highest consistency among his or her choices. If two or more k values exhibited equal consistency, we used their geometric mean as the estimate. Finally, we calculated the geometric mean of the k values of the three delayed reward conditions and then obtained a single k value for each participant. Higher k values resulted in higher impulsivity (i.e., more likely to select the immediate reward). Finally, we used a natural log transformation to normalize the k values ($\ln k$) because the raw k values were not normally distributed. According to prior studies, the MCQ shows good reliability and validity among adolescents and adults [Duckworth and Seligman, 2005; Kirby, 2009; Kirby et al., 1999]. The MCQ has been widely used in Chinese populations [e.g., Li et al., 2016; Liu et al., 2016]. To assess the internal reliability of the MCQ, we first computed the consistency value for each participant (i.e., the percent of the consistent responses) and then obtained the average consistency value for all participants. This average consistency value has been used in previous studies [e.g., Duckworth and Seligman, 2005]. The average consistency values in our dataset were $98.65\% \pm 3.64\%$, $98.65\% \pm 3.79\%$ and $98.81\% \pm 3.45\%$ for the large, medium and small delayed reward conditions, respectively. These high consistency values suggested the participants made their responses very carefully during testing.

Assessment of Academic Performance

We used the scores on the Chinese National College Entrance Examination (CNCEE) (also known as Gaokao), a sole criterion for admission to Chinese universities, to assess individual differences in academic performance. These scores were retrieved from the Chengdu Education Institute database. The CNCEE is administered in June each year and includes four curriculum subjects (Chinese, English, Mathematics and Comprehensive Ability). The scaled scores of the CNCEE range from 0 to 750, allowing for comparison across students within the same grade.

Assessment of General Intelligence

To rule out the possible influence of general intelligence on the relationships between delay discounting, academic performance and brain structure [Basten et al., 2015; Gong et al., 2005; Neisser et al., 1996; Shamosh and Gray, 2008], Raven’s Advanced Progressive Matrix (RAPM) was administered [Raven, 2000]. The RAPM is a widely used instrument for measuring general intelligence and comprises 36 nonverbal items referring to abstract reasoning. For each item, the participants were asked to choose the missing part for a graphical matrix. The number of the correct answers was calculated as the score for an individual’s general intelligence. The higher this score, the higher the level of general intelligence. In this study, Cronbach’s α value for RAPM was 0.82, showing an adequate internal consistency.

MRI Data Acquisition

We collected MRI data from a 3.0 T MRI scanner (Siemens-Trio Erlangen, Germany) equipped with a 12-channel head coil and located at the West China Hospital of Sichuan University. To obtain T1-weighted anatomical images, we employed a magnetization-prepared rapid gradient echo sequence with the following scanning parameters: repetition time, 1900 ms; echo time, 2.26 ms; inversion time, 900 ms; voxel size, 1 mm × 1 mm × 1 mm; matrix size, 256 × 256; flip angle, 9°; slice thickness, 1 mm; 176 slices.

Data Preprocessing for VBM

We carried out MRI data preprocessing using the Statistical Parametric Mapping program (SPM8, Wellcome Department of Cognitive Neurology, London, UK). A medical radiologist who was blind to the study design first visually inspected each image. Three participants were excluded due to abnormal brain structures (i.e., an unusual cyst). For each participant, we manually set the origin of the images to the anterior commissure for better registration. Next, we segmented the images into gray matter and white matter using the new segmentation in SPM8. Then, we performed registration, normalization and modulation analyses using Diffeomorphic Anatomical Registration Through Exponentiated Lie algebra (DARTEL) in SPM8 [Ashburner, 2007]. Specifically, we aligned and resampled the gray matter images to 2 mm × 2 mm × 2 mm and then normalized them to a study-specific template in Montreal Neurological Institute (MNI) space. To preserve the gray matter volume, we used Jacobian determinants to modulate the voxel values of gray matter. Finally, we employed an 8-mm full-width at half-maximum Gaussian kernel to smooth the modulated voxel values images. The resulting images representing the rGMV were used in the subsequent analyses.

Statistical Analysis of VBM

To investigate the relationships between delay discounting and brain structures, we carried out a whole-brain multiple regression analysis with the rGMV of each voxel as the dependent variable, the MCQ score as the independent variable, and age, gender, RAPM score and total gray matter volume (GMV) as the controlling variables. Moreover, we carried out another whole-brain multiple regression analysis to examine the relationships between academic performance and brain structures with the rGMV of each voxel as the dependent variable, CNCEE score as the independent variable, and age, gender, RAPM score and total GMV as the controlling variables. For these analyses, we applied an absolute threshold masking of 0.2 to rule out the noise voxels between white matter and gray matter. For multiple comparisons correction, we implemented nonstationary cluster correction using the

random field theory [Hayasaka et al., 2004]. The threshold for regions of significance was set as follows: $P < 0.05$ at the cluster level, combined with $P < 0.0025$ at the underlying voxel level. The nonisotropic cluster-size test has been widely employed in prior studies to analyze VBM data [e.g., Kong et al., 2015a; Takeuchi et al., 2015; Wei et al., 2015]. Moreover, prior evidence has suggested that in the nonisotropic cluster-size test, a relatively high cluster-determining threshold combined with high smoothing values of more than 6 voxels would cause appropriate conservativeness in real data [Silver et al., 2011]. With high smoothing values, an uncorrected threshold of $P < 0.001$ seems to cause conservativeness, whereas that of $P < 0.01$ seems to cause anticonservativeness. We conducted these analyses with SPM8 software.

Prediction Analysis

We carried out a machine learning approach to test the stability of the association between brain structure and behavioral performance. This approach is based on balanced cross-validation using linear regression [e.g., Kong et al., 2015a,b; Qin et al., 2014; Supekar et al., 2013]. In this analysis, we input delay discounting or academic performance as the dependent variable and the rGMV of different region(s) as the independent variable. Then, we used a four-fold balanced cross-validation procedure to calculate $r_{(\text{predicted}, \text{observed})}$, which represented the predictive ability of independent variable on dependent variable. Specifically, we first divided the data four-fold to ensure that the independent variable and dependent variable distributions across folds were balanced. Second, we used three folds to build a linear regression model, leaving out the fourth fold. Then, we employed this model to predict the fourth fold data (predicted values). We repeated this procedure four times to obtain a final $r_{(\text{predicted}, \text{observed})}$, which represented the correlation between the observed values and the values predicted by the regression model. Here, we applied a nonparametric testing method to determine the statistical significance of the model. Specifically, we generated 1000 surrogate datasets to estimate the empirical null distribution of $r_{(\text{predicted}, \text{observed})}$ where the null hypothesis corresponded to no association between behavioral performance and rGMV. Then, we permuted the labels of the observed data points to generate each surrogate dataset D_i of a size equal to the observed dataset. Next, we used the predicted labels with the four-fold balanced cross-validation procedure and the actual D_i labels to calculate the $r_{(\text{predicted}, \text{observed})}$ of D_i [i.e., $r_{(\text{predicted}, \text{observed})i}$]. Finally, we counted the number of $r_{(\text{predicted}, \text{observed})i}$ values greater than $r_{(\text{predicted}, \text{observed})}$ and then divided that count by the number of D_i datasets (1000). The resulting value was considered the statistical significance (P -value). In these analyses, the dependent variable scores were the standardized residuals of delay discounting or academic performance after regressing out age, gender, RAPM score and total GMV; the independent variable scores were the

TABLE I. Descriptive statistics for participant-level variables (N = 214)

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Age	18.49	0.55	16.76	20.44	0.49	1.68
Total GMV	0.67	0.06	0.53	0.82	0.10	-0.51
Delay discounting (<i>lnk</i>)	-4.23	1.30	-8.60	-1.39	-0.35	0.05
Academic performance	521.32	70.13	301.00	645.00	-0.46	0.06
General intelligence	24.16	5.60	6.00	36.00	-0.28	0.01

Note: N, number; SD, standard deviation; GMV, gray matter volume.

standardized residuals of rGMV after regressing out age, gender, RAPM score and total GMV.

RESULTS

Brain Structure of Delay Discounting and Academic Performance

Table I lists the descriptive statistics of all measures, including the mean, standard deviation, minimum, maximum, skewness and kurtosis. Total GMV was significantly correlated with academic performance ($r^* = 0.21$, $P = 0.003$)

and general intelligence ($r = 0.17$, $P = 0.012$) but not with delay discounting ($r = -0.07$, $P = 0.340$), after controlling for age and gender. Delay discounting was significantly related to academic performance ($r = -0.20$, $P = 0.004$), after adjusting for age, gender and total GMV. To test the specificity of the association between delay discounting and academic performance, we also included general intelligence as a confounding factor. Behaviorally, general intelligence was significantly correlated with delay discounting ($r = -0.14$, $P = 0.040$) and academic performance ($r = 0.31$, $P < 0.001$), after controlling for age and gender. After controlling for general intelligence as well as age,

Figure 1.

Brain regions related to delay discounting. (A) Brain images indicate the negative association between delay discounting and the rGMV in the left DLPFC. (B) The scatter plot depicts the correlation between delay discounting and the rGMV in the left DLPFC ($r = -0.33$, $P < 0.001$). The scores on the horizontal axis represent the standardized residuals of the delay discounting scores after regressing out age, gender, general intelligence and total

GMV. The scores on the vertical axis represent the standardized residuals of the mean rGMV values in the left DLPFC related to delay discounting (482 voxels) after regressing out age, gender, general intelligence and total GMV. The rGMV values were obtained from the imaging data preprocessing. DLPFC, dorsolateral prefrontal cortex; rGMV, regional gray matter volume. [Color figure can be viewed at wileyonlinelibrary.com]

*In this study, a given r value represents the correlation between two variables after controlling for other confounding variables. Specifically, we first calculated the standardized residual of a given variable after regressing out confounding variables. Then, we used the standardized residuals of two variables to compute the correlation between them (i.e., r value). This calculation method has been popularly used in previous studies (e.g., Kong et al., 2015a,b; Mackey et al., 2015).

TABLE II. Brain regions in which gray matter volume was correlated with delay discounting and academic performance

Region	Peak MNI coordinate			Peak T score	Cluster size (voxels)
	<i>x</i>	<i>y</i>	<i>z</i>		
Correlation with delay discounting					
Left DLPFC	-30	34	44	-4.44	482
Correlation with academic performance					
Left DLPFC	-30	58	28	4.64	578

Note: Significant regions were determined by calculating the non-stationary cluster correction with the following settings: $P < 0.05$ at the cluster level and $P < 0.0025$ at the voxel level. DLPFC, dorsolateral prefrontal cortex; MNI, Montreal Neurological Institute.

gender and total GMV, the association of delay discounting with academic performance was still significant ($r = -0.17$, $P = 0.013$), indicating the unique role of delay discounting in academic performance. Next, we investigated the neural substrates underlying delay discounting and academic performance.

First, we conducted whole-brain regression analyses to identify the structural correlates of delay discounting, with age, gender, general intelligence and total GMV as covariates. Higher delay discounting was significantly associated with smaller rGMV in the left DLPFC (the middle frontal gyrus; see Fig. 1 and Table II). We obtained no other

significant correlations. The location of the cluster observed in this study [peak MNI coordinate: (-30, 34, 44)] was comparable to the left DLPFC related to delay discounting that was reported in previous functional MRI (fMRI) studies [e.g., peak MNI coordinate: (-30, 34, 40), Weber and Huettel, 2008; peak MNI coordinate: (-34, 40, 34), Luo, et al., 2012]. Generally, the DLPFC mainly consists of Brodmann areas 8, 9 and 46 (Miller and Cohen, 2001; O'Reilly, 2010). Thus, our cluster including the sub-regions of Brodmann areas 8 and 9 was within this broader region. Then, we extracted the mean rGMV values in the left DLPFC related to delay discounting (482 voxels) and performed a correlation analysis. After controlling for age, gender, general intelligence and total GMV, delay discounting was significantly correlated with the rGMV in the left DLPFC (482 voxels; $r = -0.33$, $P < 0.001$; see Fig. 1). To evaluate the stability of the association between brain structure and delay discounting, we performed a prediction analysis using the machine learning approach. The rGMV in the left DLPFC (482 voxels) reliably predicted delay discounting [$r_{(\text{predicted}, \text{observed})} = -0.30$, $P < 0.001$], even after age, gender, general intelligence and total GMV were controlled for.

Next, we conducted whole-brain regression analyses to identify the structural correlates of academic performance, with age, gender, general intelligence and total GMV as covariates. Higher academic performance was significantly associated with greater rGMV in the left DLPFC (the middle frontal gyrus; see Fig. 2 and Table II). We obtained no

Figure 2.

Brain regions related to academic performance. (A) Brain images indicate the positive association between academic performance and the rGMV in the left DLPFC. (B) The scatter plot depicts the correlation between academic performance and the rGMV in the left DLPFC ($r = 0.28$, $P < 0.001$). The scores on the horizontal axis represent the standardized residuals of the CNCEE scores after regressing out age, gender, general intelligence and total GMV. The scores on the vertical axis represent the

standardized residuals of the mean rGMV values in the left DLPFC related to academic performance (578 voxels) after regressing out age, gender, general intelligence and total GMV. The rGMV values were obtained from the imaging data preprocessing. DLPFC, dorsolateral prefrontal cortex; rGMV, regional gray matter volume; CNCEE, Chinese National College Entrance Examination. [Color figure can be viewed at wileyonlinelibrary.com]

other significant correlations. Then, we extracted the mean rGMV values in the left DLPFC related to academic performance (578 voxels) and performed a correlation analysis. After controlling for age, gender, general intelligence and total GMV, academic performance was significantly correlated with the rGMV in the left DLPFC (578 voxels; $r = 0.28$, $P < 0.001$; see Fig. 2). To assess the stability of the association between brain structure and academic performance, we performed a prediction analysis using the machine learning approach. The rGMV in the left DLPFC (578 voxels) reliably predicted academic performance [$r_{(\text{predicted}, \text{observed})} = 0.25$, $P < 0.001$], even after age, gender, general intelligence and total GMV were controlled for. Based on the above results, the association between academic performance and the rGMV was similar to the pattern observed for the association between delay discounting and the rGMV. Quantitatively, 57 overlapping voxels in the left DLPFC were related to both academic performance and delay discounting. In summary, there may be common neural substrates in the left DLPFC linking delay discounting and academic performance.

Supplementary Analyses to Examine the Relationships between Delay Discounting, Academic Performance and rGMV

Then, we investigated how delay discounting affects the relationship between academic performance and brain structure. At the whole-brain level, after including delay discounting as well as age, gender, general intelligence and total GMV as covariates, multiple regression analyses demonstrated that no regions were significantly related to academic performance. Next, we extracted the mean rGMV values in the left DLPFC related to academic performance (578 voxels) and performed correlation analyses. After controlling for delay discounting as well as age, gender, general intelligence and total GMV, academic performance was still significantly correlated with the rGMV in the left DLPFC (578 voxels; $r = 0.25$, $P < 0.001$). Thus, adjusting for delay discounting reduced but did not remove the positive relationship between academic performance and the rGMV in the left DLPFC.

Finally, delay discounting did not significantly predict academic performance when controlling for the rGMV in the left DLPFC that was related to academic performance. The correlation between delay discounting and academic performance was -0.20 ($P = 0.004$), after controlling for age, gender and total GMV. When including the rGMV in the left DLPFC related to academic performance (578 voxels) as another covariate, this correlation was reduced to -0.13 ($P = 0.057$). This reduction might reflect the direct effects of the rGMV on academic performance or the effects of the unevaluated variances beyond delay discounting that were related to both academic performance and rGMV. However, based on our results, the rGMV in the left DLPFC related to academic performance explained

35% [i.e., $\frac{(-0.20) - (-0.13)}{(-0.20)} \times 100\%$] of the influence of delay discounting on academic performance in our dataset.

DISCUSSION

The current study reveals a neuroanatomical link between delay discounting and academic performance. Adolescent students with more impulsivity demonstrated worse performance in a national standard examination. Moreover, the rGMV in the left DLPFC was associated with both delay discounting and academic performance.

The association between academic performance and brain structure was partly explained by delay discounting. Differences in the rGMV of the left DLPFC related to academic performance explained over one-third of the influence of delay discounting on academic performance. Notably, our results were independent of general intelligence, suggesting the specificity of these effects. Taken together, this research presents the first evidence for the common neural basis linking delay discounting and academic performance.

Behaviorally, delay discounting was negatively and significantly related to academic performance, which fit well with previous findings [Farley and Kim-Spoon, 2015; Freeney and O'Connell, 2010; Kirby et al., 2005; Lee et al., 2012; Mischel et al., 1989; Shoda et al., 1990]. The Pearson's correlation coefficient between delay discounting and academic performance obtained for our sample ($r = -0.20$, $N = 214$) was comparable to values calculated using MCQ in previous studies in undergraduates [e.g., $r = -0.19$, $N = 247$; Kirby et al., 2005] and adolescents [e.g., $r = -0.23$, $N = 220$; Farley and Kim-Spoon, 2015]. Furthermore, delay discounting explained additional variance in academic performance beyond that explained by age, gender, general intelligence and total GMV. Thus, delay discounting might be a critical nonintellectual factor for cultivating students' academic performance.

Neurally, this study revealed a negative association between delay discounting and the rGMV in the left DLPFC. This result corroborated prior studies revealing a negative relationship between delay discounting and rGMV or cortical thickness in the DLPFC [Bjork et al., 2009; Drobetz et al., 2014]. Evidence from fMRI studies has also consistently indicated the crucial role of the DLPFC in delay discounting [for two systematic reviews, Peters and Büchel, 2011; Scheres et al., 2013]. In particular, a meta-analysis based on 18 fMRI studies in healthy participants reported that the functioning of the left DLPFC played a pivotal role in tasks of delay discounting [Wesley and Bickel, 2014]. Moreover, using repetitive transcranial magnetic stimulation (rTMS), Figner et al. [2010] reported that transient disruption of the left DLPFC led participants to select more immediate rewards, providing direct evidence for the causal role of the left DLPFC in delay discounting. Broadly, the DLPFC is generally considered a core brain region in self-regulation [Heatherly et al., 2011; Kelley et al., 2003].

2015], which is a prerequisite for delayed behavior [Metcalfe and Mischel, 1999; Mischel et al., 2011]. Therefore, our findings regarding the association between delay discounting and DLPFC volume may support the self-control account of delay discounting to a certain degree [Scheres et al., 2013].

In addition, the results regarding the association between the rGMV in the left DLPFC and academic performance were consistent with a prior structural brain imaging study, which revealed a positive association between the rGMV in the frontal lobe and academic performance [Hair et al., 2015]. Moreover, evidence from a functional MRI study indicated that activity in the DLPFC during working memory tasks is associated with individuals' educational attainments [Springer et al., 2005]. Similar findings were observed in an electroencephalography study in which students with higher academic performances exhibited greater frontal energy in the theta and delta frequencies when completing working memory tasks [Aguirre-Pérez et al., 2007]. Furthermore, a body of cognitive abilities (e.g., associative learning, working memory and word fluency) were defined as the DLPFC ability contributing to students' academic performance [Higgins et al., 2007]. Given the pivotal role of the DLPFC in self-regulation [Heatherston, 2011; Kelley et al., 2015], our findings suggest that the DLPFC might serve as a neural center at the intersection of cognitive and noncognitive functions.

Several limitations of this study deserve consideration in future investigations. First, the measurement of delay discounting was based on MCQ, which is a relatively old and crude measure of delay discounting because it determines the extent of delay discounting into bands. Future investigations should consider using newer dynamic adjusting procedures to measure delay discounting [e.g., Li, et al., 2013; Yim, et al., 2016], which may reduce measuring errors and improve psychometric properties. Second, although we used a national standard examination as the measure of academic performance, a single test may not adequately capture individuals' real-world achievements. Future studies should replicate our findings by utilizing test scores across time. Third, the current study only observed significant association of delay discounting with the left DLPFC but not with the other brain regions (e.g., the VLPFC, the MPFC, the ACC and the striatum), which have been found to be critical for measures of delay discounting [Peters and Büchel, 2011; Scheres, et al., 2013; Wesley and Bickel, 2014]. Given the present study used only rGMV as the measure of brain structure, future researchers should investigate this issue by utilizing other measures of brain structure (e.g., cortical surface area and cortical thickness) and brain function (e.g., resting-state brain activity and task-dependent brain activity) and then comparing the results obtained with different brain measures. Finally, the participants in this study consisted of a group of high school students with a narrow age range, which may limit the generalization of the findings. Future

studies are necessary to extend our study to include more diverse populations, such as undergraduates and primary school students.

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CONFLICT OF INTERESTS

The authors declare no competing interests.

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