Growth mindset promotes children's working memory performance through cortico-striatal interaction and fronto-parietal activation

Yuyao Zhao[1,2], Jiahua Xu[1,2], Menglu Chen[1,2], Lei Hao[1,2,6], Ying He[1,2], Hui Wang[7], Yanpei Wang[1], Daoyang Wang[1,5], Zhuo Rachel Han[1,2], Shuping Tan[3], Weiwei Men[4], Jiahong Gao[4], Yong He[1, 2], Sha Tao[1], Qi Dong[1], Shaozheng Qin[1, 2, 8*]

1. State Key Laboratory of Cognitive Neuroscience and Learning & IDG/McGovern Institute for Brain Research, Beijing Normal University, Beijing, 100875, China
2. Beijing Key Laboratory of Brain Imaging and Connectomics, Beijing Normal University, Beijing, 100875, China
3. Beijing HuiLongGuan Hospital, Peking University, Beijing, 100096, China
4. Center for MRI Research, Academy for Advanced Interdisciplinary Studies & McGovern Institute for Brain Research, Peking University, Beijing, 100871, China
5. Department of Psychology, Hangzhou Normal University, Hangzhou, 311121, China
6. College of Teacher Education, Southwest University, Chongqing, 400715, China
7. Faculty of Psychology, School of Artificial Intelligence, Beijing Normal University, Beijing, 100875, China
8. Chinese Institute for Brain Research, Beijing, 102206, China

* Correspondence should be addressed to Shaozheng Qin Ph.D. (szqin@bnu.edu.cn).

Abstract

Children with growth mindset tend to believe that personal abilities and traits are improvable through continuous efforts. This belief boosts intrinsic motivation and benefits cognitive abilities in children, in the long term resulting in improved academic performance. However, little is known regarding its neurocognitive mechanisms in the processing of cognitive tasks. Using functional brain imaging and an n-back task in school-aged children (ages 8-12), we demonstrated that growth mindset promotes working memory performance through enhanced response in the fronto-parietal network, salience network, and caudate nucleus. While growth mindset predicted lower connectivity between caudate and insula irrespective of memory load, the connectivity between caudate and posterior cingulate cortex was selectively correlated with growth mindset in the high load condition. The cortico-striatal connectivity together with cortical response played a key mediatory role in the promotion effect of growth mindset towards working memory. Our findings suggest a neurocognitive mechanism accounts for how growth mindset promotes children's working memory in demanding tasks via modulation of motivational neural systems and information processing.

Introduction

To meet the challenges ahead, children develop positive inner beliefs that enable them to continue their efforts without external support. The belief that human attributes and skills are malleable and improvable is called growth mindset (Dweck and Yeager, 2019). It benefits cognitive control performance (Moser et al. 2011; Schroder et al. 2017) and further results in better academic achievements in school-aged children (Claro et al., 2016; Good et al., 2003; Yeager et al., 2019). This merit covers a large range of age groups from age 7 to adulthood (Sarrasin et al., 2018) and the effect lasted for years (Blackwell et al., 2007). Such a substantial effect of growth mindset is proposed to root in higher intrinsic motivation (Ng 2018; Xu et al. 2020) and modulation of working memory processing (Mangels et al. 2006). Despite decades of application and research in education, however, little is known about the underlying

neurocognitive mechanism by which growth mindset impacts cognitive control in children.

Growth mindset impacts positively on motivation, as implicated by both behavioral and neural evidence. Students induced growth mindset tended to attach importance to academics and have higher positive beliefs about effort (Aronson et al. 2002; Blackwell et al. 2007; Yeager et al. 2016). It also led to process-related change: growth mindset intervention caused lower perceived intrinsic and extraneous load in students (Xu et al. 2020). Recordings of brain signals related growth mindset with more effortful coding of task-related information, and localized the effect to brain regions including frontal, cingulate and parietal cortex (Moser et al. 2011; Schroder et al. 2014). Furthermore, growth mindset predicted higher activation in caudate nucleus (Bejjani et al. 2019), a core region of motivation (Liljeholm and O'Doherty 2012). A task-free study revealed mindset-related cortico-striatal connectivity, with dorsal striatum coupling with prefrontal, precentral and cingulate cortex (Myers et al. 2016). In brief, the direct effect of growth mindset on motivation is repeatedly tested from childhood to adulthood. However, how growth mindset modulates task-related processing through motivational neural mechanisms needs further investigation.

Striatum and cortical networks are involved in the motivational process during cognitive control. Since high-demand task with higher engagement of control systems is inherently more costly, it need to be specifically motivated (Botvinick and Braver 2015; Sidarus et al. 2019). The striatum, especially the caudate nucleus, is involved in the motivational process during cognitively demanding tasks through the evaluation between benefit and cost (Westbrook et al. 2021). Higher activation of caudate nucleus causes a higher willingness to conduct effortful working memory tasks (Westbrook et al. 2020). This preference for high-demand tasks affects working memory processing: the activation of caudate itself and its interaction with cortical regions govern the updating of task-related information (McNab and Klingberg 2008; Baier et al. 2010; Kühn et al. 2013). Though most studies focused on the coupling of

caudate to core fronto-parietal regions including prefrontal, anterior cingulate, and superior parietal cortex (Nee and Brown 2013; Jarbo and Verstynen 2015), connectivity and dopamine release of caudate to PCC is also related to cognitive demand (Braskie et al. 2011; Vatansever et al. 2018). Since cortico-striatal interaction serves for information updating, subsequent processing of this input information in working memory may lie on well-known task-related cortical networks, including fronto-parietal network (FPN), salience network (SN), and default mode network (DMN) (Owen et al. 2005; Cai et al. 2021). Thus, we examine both local response and interactions within cortical networks and striatum, and suppose it to be a potential neural mechanism of growth mindset.

We tested the above hypotheses using blood-oxygen-level-dependent functional magnetic resonance imaging (BOLD-fMRI) and a numerical n-back working memory task. The working memory task allowed us to test for neural response under different cognitive demand levels, and is suitable for children in consideration of difficulty. Regarding the crucial role of childhood in cognitive control development, a large sample of children (N = 375; ages 8-12 years old; **Fig. 1A**) were recruited for the current study. They first completed the growth mindset measurement, then conducted the n-back task in an MRI scanner. Whole-brain multiple regression analyses discovered that striatum, cortical network regions were associated with growth mindset in the working memory task, especially in high demand condition. Further connectivity analysis identified specific cortico-striatal pathways related to growth mindset. Finally, mediation analyses revealed that growth mindset affects working memory performance through cortico-striatal pathways and cortical network activation.

Methods and materials

Participants

A total number of 375 children (8-12 years old, M±SD = 9.833±1.039 years, 207 males and 168 females) **(Fig. 1D)** were recruited in the current study. The written informed consent form was obtained from each participant and their caregivers or legal guardians. The study procedures were approved by local ethics following the standards of the Declaration of Helsinki. Participants had no obstacle in vision and reported no history of neurological or psychiatric disorders and no current use of any medication or recreational drugs. Participants with excessive head motions (more than 1/3 frames with standardized DVARS >1.5 or frame displacement > 0.5), incomplete scales or scanning were excluded from further analyses **(Fig. 1A)**. A final sample of 306 children (8-12 years old, M±SD = 9.869±1.024 years,163 males and 143 females) were sent for imaging analysis.

The measure of growth mindset

The mindset was assessed using the Growth Mindset Scale (GMS) (Dweck 2006). It consists of 20 items (e.g., No matter who you are, you always can change your intelligence a lot), with 14 items about the individuals' theory of ability and 6 items about the individuals' theory of personality (Chinese version used in Wang et al. 2020, 2021). Participants were asked to rate their agreement with each statement using a 4-point Likert-type scale (0 = Strongly Disagree, 1 = Disagree, 2 = Agree, 3 = Strongly agree). The final score from 0 to 60 with higher scores represents higher growth mindset level.

N-back Task procedure

A classic numerical n-back task was used to assess participants' working memory performance. This task consisted of three conditions with different workloads (0-back, 1-back, and 2-back) and each condition consisted of 4 blocks. In each block, the participants first viewed a 2-second cue that indicated the workload of this block

(0-back, 1-back, and 2-back). Followed by a sequence of 15 pseudorandom digits in which each digit was presented for 400 milliseconds. In the 0-back condition, participants were instructed to respond to the digit "1". While in the 1-back condition, participants were asked to respond to the digit which was just the same as the previous one. In the 2-back condition, participants needed to respond to the digit which was the same as the previous two. Stimuli were presented via E-Prime 2.0 (http://www.pstnet.com; Psychology Software Tools, Inc., Pittsburgh, PA). Both participants' response and reaction time (RT) were recorded, then we calculated participants' accuracy based on their responses. The accuracy and RT were used as indicators of individual working memory performance.

Behavioral data analysis

The accuracy was assessed by d' based on the signal detection theory (Green and Swets 1966). All trials for each participant were assigned into the following categories: (1) hits: responses to targets; (2) misses: no response to targets; (3) false alarms: responses to non-targets; (4) correct rejections: no response to non-targets. The hit rate and false alarm rate were defined as follows:

$$hit\ rate = \frac{hits}{hits + misses}$$

$$false\ alarm\ rate = \frac{false\ alarms}{false\ alarms + correct\ rejections}$$

The aforementioned hit rate and false alarm rate were Z transformed with inversed cumulative Gaussian distribution to calculate d' (Finc et al. 2020):

$$d' = Z(hit\ rate) - Z(false\ alarm\ rate)$$

To get finite *d'* values in case either hit rate or false alarm rate was equal to 0 or 1, modified values 0.01 or 0.99 was used instead. This *d'* measurement was defined as accuracy and used to assess participants' working memory performance together with RT in all analyses.

Behavioral measurements were analyzed with R (version 4.0.2, https://www.r-project.org, Platform: x86_64-apple-darwin17.0 (64-bit)). Restricted by participants' schedules as students, some participants finished their scales after the fMRI scanning (M = 63.360 days, SD = 58.603 days), we used the scanning date to calculate each participant's age.

Image data acquisition

Data were acquired using the same type of 3.0T scanner (Magnetom Prisma syngo MR D13D, Erlangen, Germany) with a 64-channel head coil. High-resolution anatomical images were acquired by a three-dimensional sagittal T1-weighted magnetization-prepared rapid gradient echo (MPRAGE) sequence (TR = 2530 ms, TE = 2.98 ms, TI = 1100ms, flip angle = 7°, voxel size 0.5 x 0.5 x 1.0 mm^3, matrix size = 256 × 224, FOV = 256 x 224 mm^2, brand width = 240 Hz/Px, 192 slices with 1 mm thickness). Functional images with 33 axial slices (3.5 mm thick, 0.7 mm skip) parallel to the anterior and posterior commissural line (AC-PC) were acquired using a T2*-sensitive echo-planar imaging (EPI) sequence (TR = 2000ms, TE = 30ms, flip angle = 90°, voxel size = 3.5 x 3.5 x 3.5 mm^3, FOV = 224 x 224 mm^2). The whole n-back task consisted of 232 volumes and lasted for 464s.

Image data preprocessing

Brain images were preprocessed with the fMRIPrep 1.4.1 (Esteban et al. 2019) pipeline implemented in Nipype 1.2.0 (Gorgolewski et al. 2011). The first 4 volumes of n-back task were discarded for signal stability and adaptation of participants. For each participant, the following preprocessing procedures were conducted. First, each T1w volume was skull-stripped and a BOLD reference was estimated. Slice time correction was then performed and all slices were realigned in time to the middle of each TR using 3dTshift from AFNI. Motion correction was done using mcflirt (FSL) and 6 head-motion parameters (three rotations, three translations) were estimated. The EPI data was corrected for susceptibility distortions based on a field map and co-registered to the anatomical reference using boundary-based registration with nine degrees of

freedom. Finally, these preprocessed BOLD functional images in the original space were resampled into the well-known 'MNI152NLin6Asym' space. Head-motion transformation, susceptibility distortion correction, BOLD-to-T1w transformation and T1w-to-template (MNI) warp were concatenated and applied in a single step using antsApplyTransforms (ANTs) using Lanczos interpolation.

ICA-based Automatic Removal of Motion Artifacts (ICA-AROMA) was used to automatically remove motion artifacts non-aggressively after removal of non-steady volumes and spatial smoothing with an isotropic, Gaussian kernel of 6 mm full-width half-maximum (FWHM). Physiological noise regressors were extracted applying CompCor and two CompCor variants were estimated: temporal (tCompCor) and anatomical (aCompCor). Framewise displacement (FD) and DVARS were calculated using Nipype. In addition to 6 head-motion parameters and global signals, their temporal derivatives and quadratic terms were also estimated. Outliers were defined as frames that exceeded a threshold of 0.5 mm FD and 1.5 standardized DVARS and were annotated. All these parameters were taken as aggressive noise regressors and were placed in the corresponding confounds file. For credible results, individuals with more than 1/3 frames as outliers were excluded in the following analyses (n = 22).

General linear model (GLM) analysis

To identify working memory-related brain systems and their relations to growth mindset, we constructed GLMs on both individual and group levels using SPM12 (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/). To assess task-invoked neural response to different workloads, the 0-, 1-, and 2-back conditions were modeled as separate boxcar regressors and convolved with the canonical hemodynamic response function (HRF) built in SPM12. To regress out effects related to noise, signals within cerebrospinal fluid (CSF) and white matter (WM) from each participant were included as a nuisance in the model (Parkes et al., 2018). A high-pass filter of 1/128Hz was

applied and temporal autocorrelations in fMRI were corrected using a first-order autoregressive model (AR(1)).

Relevant contrast parameter estimate images were initially generated at the individual-subject level, then submitted to group-level analyses by treating participants as a random variable. Contrast images of 2-back > 0-back, 2-back > 1-back, and 1-back > 0-back were submitted to separate multiple regression analyses with participants' growth mindset as a covariate of interest, gender and age as nuisances. Coefficients of the multiple regression were tested using one-sample t-test. Significant clusters were determined at a voxel level false discovery rate (FDR) correction (pFDR < 0.05) on the whole brain. For visualization of results, significant clusters were displayed using Surf Ice (https://www.nitrc.org/projects/surfice/) and MRIcroGL (https://www.nitrc.org/projects/mricrogl/).

Regions of interest (ROIs) analysis

ROIs of three networks were generated from meta-analysis images using the Neurosynth database (http://neurosynth.org). The whole-brain result and meta-analysis results were overlapped for comparison. Mask of multiple comparison only included continuous clusters with more than 10 voxels passed the threshold of $p < 0.05$ (corrected for multiple comparison using FDR) in the 2-back > 0-back contrast. And the meta-analysis masks of the term "working memory" and "default mode" included clusters with more than 10 voxels satisfied $Z > 3$ ($p<0.001$).

Based on this criterion, we then picked dorsal lateral prefrontal cortex (dlPFC), frontal eye field (FEF), and inferior parietal sulcus (IPS) for FPN; anterior Insula (aInsula) and anterior cingulate cortex (ACC) for SN from the meta-analysis map of the term "working memory". Similarly, clusters of angular gyrus (AG), posterior cingulate cortex (PCC), and ventral medial prefrontal cortex (vmPFC) were selected from the meta-analysis map of the term "default mode". Besides, bilateral

hippocampus/parahippocampus (HCP/PHC) was also included based on the result of whole-brain multiple regression. Finally, ROIs generated from the original meta-analysis maps include: dlPFC, FEF, and IPS nucleus for FPN; aInsula and ACC for SN; vmPFC, AG, PCC, and HCP/PHC for DMN (Fig. S1A & B). Parameter estimates from each ROI and each participant were extracted from the individual-level 2-back > 0-back contrast using MarsBaR (http://marsbar.sourceforge.net/) to characterize activation during the task in each ROI.

Functional connectivity analysis

To assess the effect of cortico-striatal interaction, connectivity between bilateral caudate and whole cortical regions was calculated using the generalized psychophysiological interaction (gPPI) method (McLaren et al. 2012). The bilateral caudate seed was defined as the group-level significant clusters after FDR correction in the 2-back > 0-back contrast, which is located in the dorsolateral caudate. The gPPI approach assessed task-dependent functional connectivity of the seed region with all voxels within global gray matter. Specifically, the mean time series of voxels within the seed region were extracted and subsequently deconvolved to uncover neural activity (physiological variable). The estimated neural activities were then multiplied with task design vectors (0-back, 1-back, 2-back; psychological variable) and convolved with a canonical HRF to form the PPI regressors of interest. Besides, physiological/psychological variables, as well as signals within CSF and WM were also included in individual GLM to account for potential confounds and remove the effects of common driving inputs on brain connectivity. Individual-level contrast images of gPPI effects were then submitted to second-level multiple regression analyses with participants' growth mindset as a covariate of interest while gender and age as nuisances. The significance threshold was determined by Monte Carlo Simulation using 3dClustSim in AFNI (Cox et al. 2017) at a height threshold of $p < 0.001$, and an extent threshold of $p < 0.05$. Parameter estimates were extracted from significant clusters using the same method noted above.

Mediation analysis

The mediation models were constructed and statistics were tested by the 'mediation' package (https://cran.r-project.org/web/packages/mediation/) in R. A number of 5000 Monte Carlo draws were done for nonparametric bootstrap and 95% bias-corrected and accelerated (BCa) confidence intervals were estimated. If the confidence interval did not include zero, the effect was considered significant. Age was included in the models as a covariate of no interest.

Results

Growth mindset predicts higher working memory performance in young children

We first verified the effectiveness of our workload manipulation. We conducted repeated-measures analysis of variance (ANOVA) on accuracy and RT respectively with workloads as within-subject factors. Both accuracy and RT showed robust main effects (Accuracy: $F(1.94, 724.95) = 471.913$, $p < 0.001$, $\eta^2 = 0.308$; RT: $F(1.71, 624.61) = 325.855$, $p < 0.001$, $\eta^2 = 0.228$). Following separate pairwise comparisons revealed lower accuracy in higher workload condition (paired t-test, two-sided: 1- and 0-back: $t(374) = -7.946$; 2- and 1-back: $t(374) = -23.075$, both $p < 0.001$, Bonferroni-corrected; **Fig. 1B**). And participants responded slower while workload increasing (paired t-test, two-sided: 1- and 0-back: $t(370) = 15.712$; 2- and 1-back: $t(367) = 11.415$, both $p < 0.001$, Bonferroni-corrected; **Fig. 1C**). Furthermore, we performed Pearson correlation between working memory performance and age, which revealed improvement in both accuracy and RT in children from 8 to 12 years old (**Fig. S2**). Improvements of RTs in all three workloads were roughly the same (0-back: $r = -0.289$, $p < 0.001$; 1-back: $r = -0.281$, $p < 0.001$; 2-back: $r = -0.203$, $p < 0.001$), while larger improvement in higher workload was observed in accuracy (0-back: $r = 0.078$, $p = 0.131$; 1-back: $r = 0.159$, $p = 0.002 < 0.005$; 2-back: $r = 0.258$, $p < 0.001$).

Next, we examined the behavioral relationship between mindset and working memory performance using partial correlation with age and gender as covariates of no interest (**Fig. 1E**). These analyses revealed that mindset score positively correlated with

accuracy under all three workloads (0-back: $r = 0.194$, $p < 0.001$; 1-back: $r = 0.134$, $p = 0.009 < 0.01$; 2-back: $r = 0.213$, $p < 0.001$), while RT also showed the same pattern but no significance was found (0-back: $r = -0.007$, $p = 0.892$; 1-back: $r = -0.042$, $p = 0.419$; 2-back: $r = 0.010$, $p = 0.846$) (**Fig. S3**). Age and mindset score showed no interaction effect in all workloads. Moreover, we conducted correlation analyses to test whether mindset also developed as children grew up. This analysis revealed no significant correlation ($r = 0.018$, $p = 0.730$), indicating that mindset is a relatively stable trait from 8 to 12 and its effect towards working memory is independent of development.

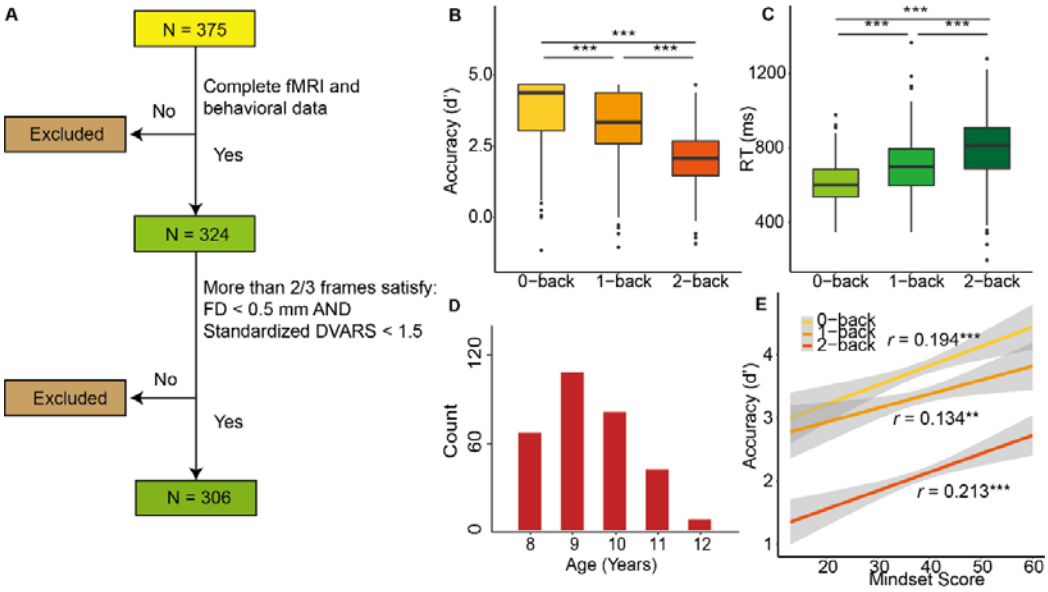

Fig. 1. A. Participant selection procedure for fMRI analysis. A total number of 375 children were included in the behavioral analysis. Children with incomplete data (n = 51) or excessive head motion during functional imaging (n = 18) were excluded from the fMRI analysis. The final sample size for fMRI analysis was 306. **B.** ANOVA and paired t-test results for accuracy. Participants' responses to 1-back condition were significantly less accurate than 0-back condition, and the difference was even larger between 2-back and 1-back conditions. **C.** ANOVA and paired t-test results for RT. RT decreased with task workload increased. The thick black line in each box represents the median. The upper and lower edges of each box correspond to the 25th and 75th percentiles, respectively. The upper and lower error bars each represent the largest and smallest values within 1.5 times IQR (inter-quartile range, the distance between the

25th and 75th percentiles) above 75th percentile and below 25th percentile. **D.** Age distribution of the final sample (n = 306). Participants' ages ranged from 8 to 12 years old. **E.** Correlation between mindset and accuracy with age and gender as covariates (n = 375). Accuracy was positively correlated with mindset score under all three workloads. Shading represents 95% CI (confidence interval). Largest correlation was observed under 2-back condition. $^{***}p < 0.001$, $^{**}p < 0.01$, Bonferroni-corrected.

Growth mindset predicts higher WM-related FPN, SN and striatal activity

To investigate the neural bases of how growth mindset benefits working memory performance, we applied whole-brain multiple regression analysis. Multiple regression has been applied for 2-back > 0-back, 2-back > 1-back and 1-back > 0-back contrasts (derived from first-level analysis) to extract brain response specific to the working memory process and emphasize the difference between workloads.

For 2-back > 0-back contrast, main results were found within FPN. Besides, growth mindset was also found to be related to striatum, together with core SN regions including cingulate cortex and insula (**Table S1** and **Fig. 2A**). Regions in the FPN were positively correlated with growth mindset, including the bilateral IPS, bilateral superior parietal lobe, right inferior frontal gyrus (IFG), right dlPFC, bilateral FEF, left precentral region and left supplementary motor area (SMA). As expected, we identified significant clusters in the striatum (right putamen and bilateral caudate nucleus), with higher growth mindset score predictive of higher striatal activation. Moreover, growth mindset also predicted higher activations in SN (right anterior cingulate cortex, right insula) and other regions within visual area (bilateral precuneus, right lingual gyrus and left calcarine sulcus). Interestingly, activation in PCC and bilateral parahippocampus, which belong to DMN, is linked to lower growth mindset (**Table S2**). A similar pattern was also observed in the 2-back > 1-back contrast: higher activation in bilateral IPS, left SMA, right FEF and part of the visual cortex predicted higher growth mindset (**Table S1**). Whereas contrast between 1-back and 0-back did not reveal any significant cluster.

We then compared our whole-brain multiple regression results mentioned above with the meta-analysis of working memory from Neurosynth database (http://neurosynth.org). Our multiple regression results were highly overlapped with the meta-analysis map, with conjunct clusters mainly distributed in FPN, including bilateral IPS, bilateral FEF, right dlPFC, and left SMA (**Table S3A** and **Fig. 2B**). Other regions were also identified, including left caudate nucleus, right insula and bilateral precuneus. Considering the aforementioned negative correlation found in parahippocampus and regions around PCC, we also compared the negative map of multiple regression analysis with meta-analysis of DMN. The result showed conjunct clusters in right parahippocampus, left calcarine and bilateral precuneus (**Table S3B**). Together, these results indicate that working memory-related activation in FPN, SN and DMN regions were associated with individual differences in growth mindset.

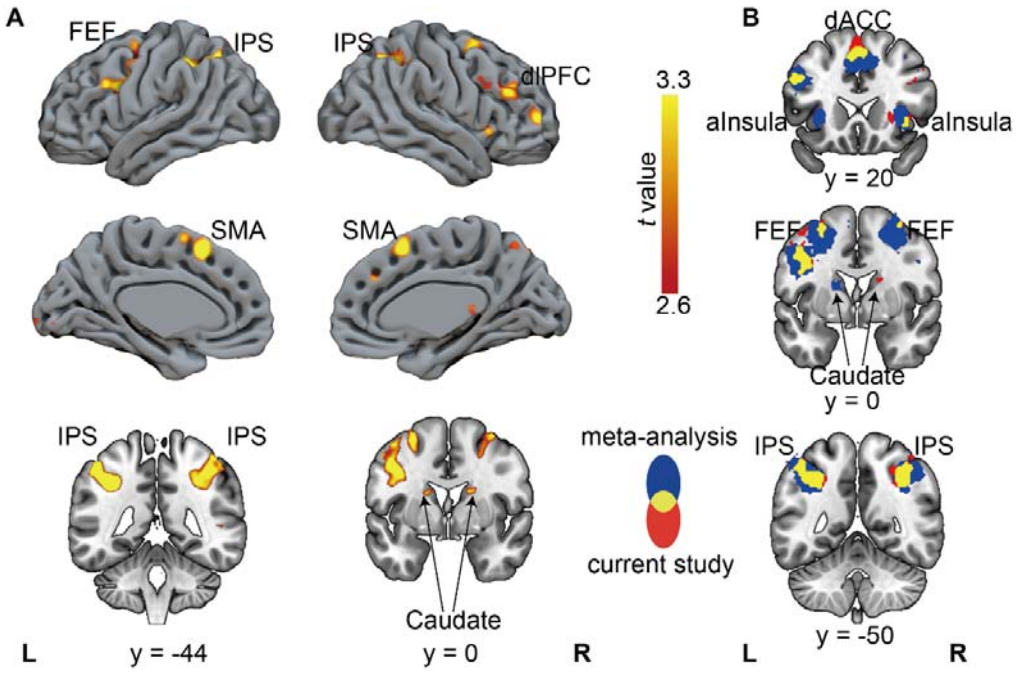

Fig. 2. A. Multiple regression result of mindset score for 2-back > 0-back with age controlled (n = 306). Clusters passed the threshold of uncorrected $p < 0.005$ were presented for visualization purpose. Fronto-parietal area and striatum showed the strongest positive correlation with growth mindset. **B**. Conjunction map of whole-brain

multiple comparison and meta-analysis result. Regions that linked to higher growth mindset were highly overlapped with areas crucial for working memory task, especially in fronto-parietal area. Blue: meta-analysis map of working memory with threshold of Z >3. Red: Whole-brain multiple comparison results of current study with $p < 0.05$ (corrected for multiple comparison using FDR). Yellow: overlap of meta-analysis result and multiple regression results. Only clusters larger than 10 voxels were presented. dlPFC: dorsal lateral prefrontal cortex, IPS: inferior parietal sulcus, SMA: supplementary motor area.

Growth mindset affects cortico-striatal connectivity

We then tested how growth mindset modulates intrinsic cortico-striatal connectivity. Bilateral caudate regions identified above were used as seed for functional connectivity analysis (**Fig. 3A**; see Methods for details). Whole brain multiple regression analysis of growth mindset was conducted for connectivity targets in 2->0-back and 1- > 0-back contrasts, with age and gender as covariates. Higher growth mindset caused decoupling between caudate and cortical regions in 2->0-back contrast. Interestingly, connectivity between caudate and PCC was predicted by interaction between growth mindset and workload ($t(304) = 2.75$, $p = 0.006$) (**Fig. 3C**). Only under high workload condition, growth mindset predicts lower intrinsic connectivity (2->0-back: $r = -0.266$, $p < 0.001$; 1->0-back: $r = -0.093$, $p = 0.106$). Compared with PCC, connectivity to precuneus and insula was not influenced by workload, but only predicted by growth mindset (precuneus: 2-back>0-back: $r = -0.244$, $p < 0.001$; 1->0-back: $r = -0.166$, $p = 0.004$; insula: 2->0-back: $r = -0.257$, $p < 0.001$; 1->0-back: $r = -0.204$, $p < 0.001$) (**Fig. 3B, D**). Connectivity between caudate and PCC was also distinctive in its association with behavioral performance: caudate-PCC connectivity negatively predicted accuracy in high workload condition (2->0-back: $r = -0.152$, $p = 0.008$; 1->0-back: $r = -0.084$, $p = 0.146$) (**Fig. 3C**). By comparison, caudate-precuneus connectivity showed weak correlation and caudate-insula connectivity did not have such effect (precuneus: 2-back>0-back: $r = -0.120$, $p = 0.036$; 1->0-back: $r = -0.069$, $p = 0.229$; insula: 2->0-back: $r = -0.049$, $p =$

0.398; 1->0-back: r = -0.003, p = 0.953) (**Fig. 3B, D**). We then tested mediation effect of caudate-PCC connectivity in the association between growth mindset and behavioral performance. Analysis showed that growth mindset affects working memory performance via caudate-PCC connectivity in high load condition (indirect Est. = 0.004, 95% CI = [0.0004, 0.009]) (**Fig. 3E**). These results revealed that growth mindset modulates cortico-striatal connectivity. Specially, caudate-PCC connectivity mediates the association between growth mindset and behavioral performance in high workload.

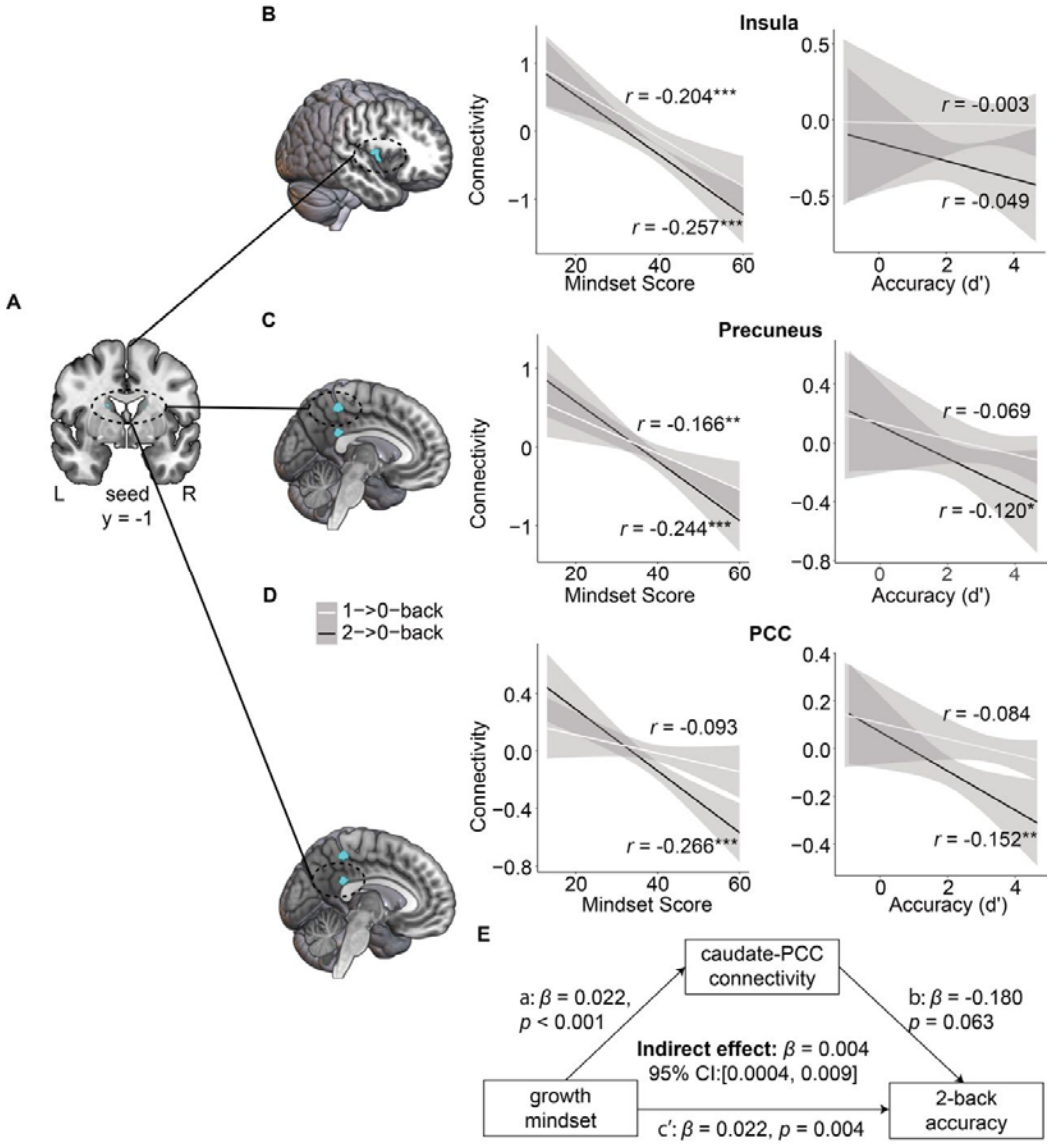

Fig. 3. Higher growth mindset predicts decoupling between caudate and cortical regions. **A.** Caudate seed region used in connectivity analysis (n = 306). **B, C, D.**

Significant clusters in insula/precuneus/PCC that showed negative correlations between growth mindset and connectivity with caudate. Accuracy of 1-back and 2-back was used in calculation with 2->0-back/1->0-back contrast connectivity respectively. **E.** Mediation model exhibited a mediatory role of caudate-PCC connectivity on the effect of growth mindset towards accuracy in 2-back condition. Age and gender were set as nuisances. PCC: posterior cingulate cortex. Shading represents 95% CI. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Growth mindset predicts working memory performance via cortical network activation

To elucidate how cortical activation alone associates with growth mindset and behavior in a network view, we focused our analysis on 9 core FPN, SN and DMN regions based on meta-analysis map of working memory. As expected, each ROI from FPN and SN showed positive activation while regions from DMN deactivated in two contrasts (**Fig. S1D**). Overall activation of ROIs from FPN and SN was significantly different from that of ROIs from DMN (paired t-test, two-sided: FPN-DMN: $t(305) = 29.730$, $p < 0.001$; SN-DMN: $t(305) = 27.504$, $p < 0.001$; Bonferroni-corrected), and FPN showed highest activation compared with SN (paired t-test, two-sided: $t(305) = 2.634$, $p = 0.030$, Bonferroni-corrected; see **Table S4** for details).

Network response was also associated with both mindset and working memory performance (**Fig. S4**): Activation strength of all FPN and SN regions was positively correlated with mindset score and predicted higher accuracy. Among FPN regions, strongest activation was evoked in IPS, which was associated with higher mindset score ($r = 0.253$, $p < 0.001$) and accuracy ($r = 0.210$, $p < 0.001$). Both FEF and dlPFC had similar but weaker effect (FEF and mindset score: $r = 0.181$, $p = 0.001$; FEF and accuracy: $r = 0.246$, $p < 0.001$; dlPFC and mindset score: $r = 0.207$, $p < 0.001$; dlPFC and accuracy: $r = 0.115$, $p = 0.046$). Neural response in SN regions also showed correlation with both mindset score (dACC: $r = 0.201$, $p < 0.001$; aInsula: $r = 0.167$, $p = 0.003$) and accuracy (dACC: $r = 0.209$, $p < 0.001$; aInsula: $r = 0.221$, $p < 0.001$). On the contrary, only activation in HPC/PHC was negatively correlated with both mindset

score (r = -0.117, p = 0.042) and accuracy (r = -0.217, p < 0.001). Activation of PCC and vmPFC only showed negative correlation with accuracy (PCC: r = -0.143, p = 0.012; vmPFC: r = -0.227, p < 0.001), while no association was found in AG. These results implicated that neural response in network regions may serve as neural mediator under the direct effect from growth mindset to behavioral performance.

To validate this assumption, we then investigated whether growth mindset benefits working memory performance via neural response in FPN, SN and DMN regions. We used the accuracy in 2-back condition regarding its high correlation with growth mindset compared to 1-back condition. With age and gender set as nuisances, analysis showed that activation in FEF and IPS from FPN mediated the relationship between growth mindset and working memory accuracy (FEF: indirect Est. = 0.005, 95% CI = [0.002, 0.011]; IPS: indirect Est. = 0.006, 95% CI = [0.002, 0.012]) (**Fig. 4**). Similar mediation effect was also found in SN regions (aInsula: indirect Est. = 0.004, 95% CI = [0.001, 0.010]; dACC: indirect Est. = 0.005, 95% CI = [0.002, 0.010]). In contrast, mediation effects of all DMN regions showed no significance. These results indicate that neural response in both FPN and SN regions played a mediatory role in the promoting effect of growth mindset on working memory performance.

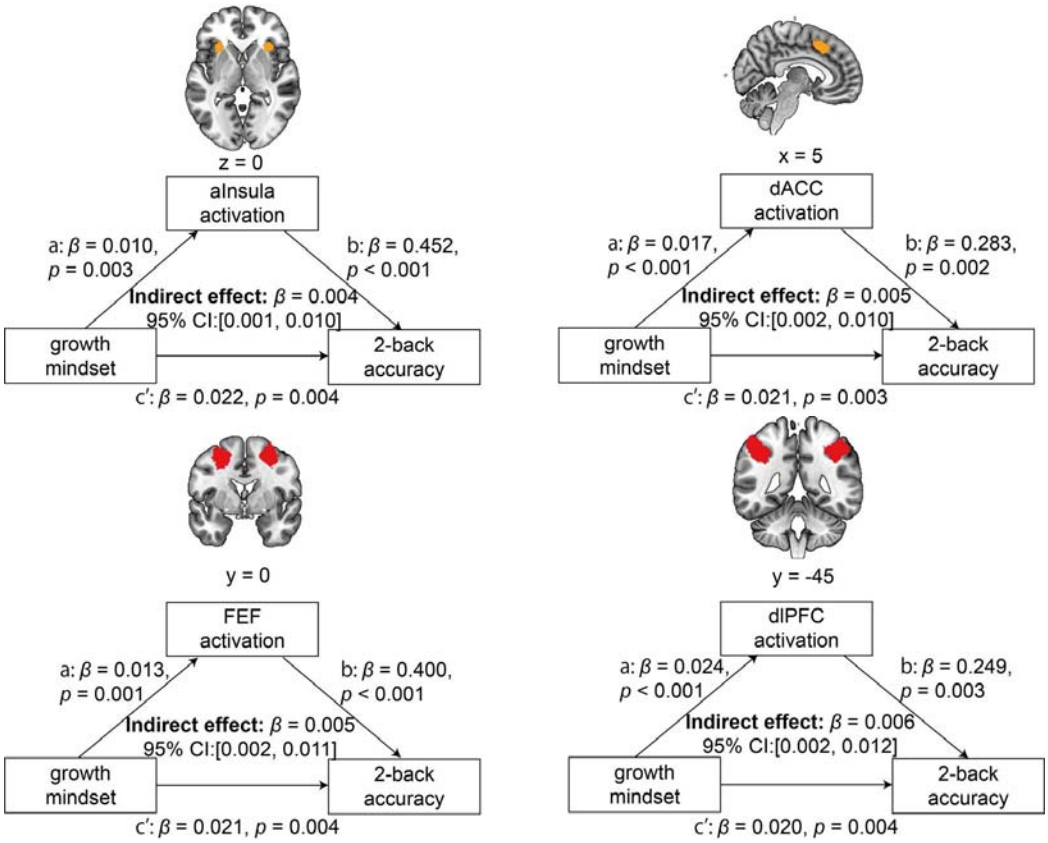

Fig. 4. Mediation models of ROIs. Activation of regions in SN (dACC and aInsula) and regions in FPN (FEF and IPS) from 2- > 0-back contrast showed a significant indirect effect in the association between mindset score and accuracy in 2-back task (n = 306). Age and gender were set as nuisances. aInsula: anterior insula, dACC: dorsal anterior cingulate cortex, FEF: frontal eye field, IPS: inferior parietal sulcus. CI: confidence interval.

Growth mindset predicts working memory performance via cortico-striatal connectivity and cortical activation

The cortical activation and connectivity analysis identified proximal regions in PCC and insula. This may implicate cortical response to cortico-striatal interaction. Thus, we then examined the relationship between connectivity and cortical response. Analysis revealed significant positive correlation between caudate-PCC connectivity and PCC response in 2->0-back contrast (r = 0.141, p = 0.014) **(Fig. 5B)**; but negative correlation between caudate-aInsula connectivity and insula response in 2->0-back

contrast (r = -0.201, p < 0.001) **(Fig. 5D)**. This caudate-cortical information processing may also serve in the effect of growth mindset to performance. Further chain mediation analysis supported this assumption: for processing in PCC, higher growth mindset level was linked to lower caudate-PCC connectivity, which then related to lower PCC response, and caused higher accuracy in 2-back condition (indirect Est. = 0.0005, 95% CI = [0, 0.002]) **(Fig. 5A)**; for processing in insula, higher growth mindset level related to lower caudate-insula connectivity, but then caused higher aInsula response, and led to higher accuracy in 2-back condition (indirect Est. = 0.001, 95% CI = [0.0003, 0.003]) **(Fig. 5C)**. Parallel analyses for low workload condition and precuneus region were also conducted but found no effects. Other alternative models showed null effects. These results further expanded the mediation effect through caudate-cortical interaction, and implicated that caudate-cortical gating affects cortical response in reaction to change in information processing.

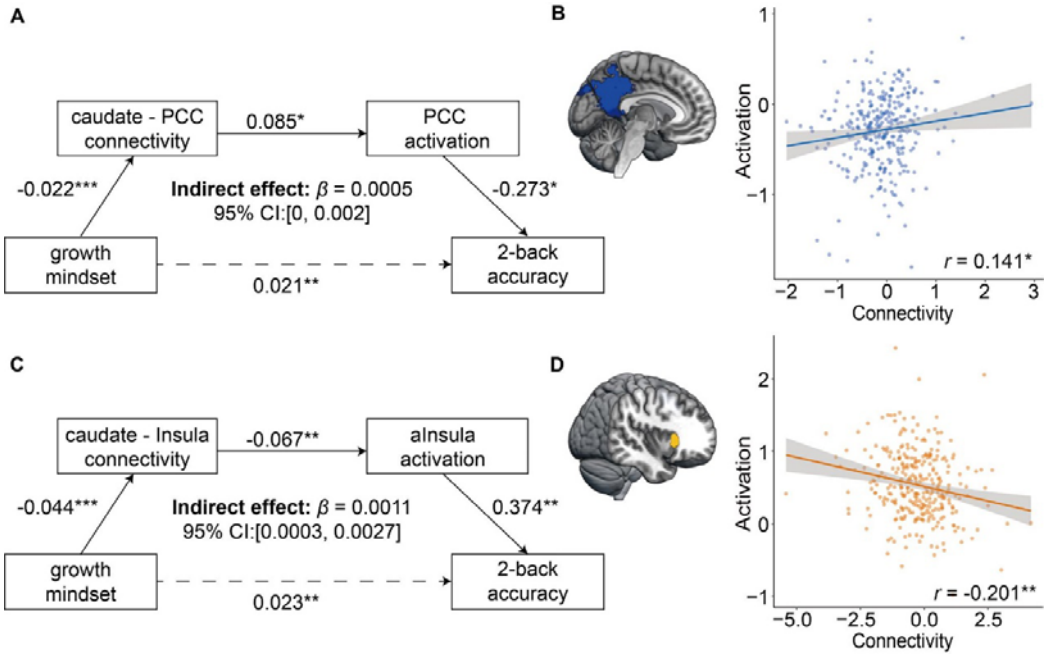

Fig. 5. Mediation models of connectivity and activation in PCC/insula. **A.** Caudate-PCC connectivity and activation in PCC showed a significant indirect effect in the association between mindset score and accuracy in 2-back condition. **B.** Representation of PCC ROI and correlation between caudate-PCC connectivity and PCC activation. **C, D.** same as **A, B,** but in insula region. Age and gender were set as

nuisances. aInsula: anterior insula, PCC: posterior cingulate cortex. CI: confidence interval. Shading represents 95% CI. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Discussion

In current study, we investigated how growth mindset affects the working memory process through neural mechanisms in children. As expected, children with growth mindset performed better in working memory task. Critically, higher growth mindset was associated with enhanced response in FPN and SN core regions. These cortical responses mediated the association between growth mindset and working memory performance. Furthermore, growth mindset predicts lower caudate-insula and caudate-PCC connectivity. The cortico-striatal interaction affected cortical information processing, and together acted as a mediator in the beneficial effect of growth mindset on working memory performance. Our findings revealed that growth mindset affects working memory performance through modulating cortico-striatal interaction and cortical response in children. These neural correlates indicate latent motivational driven response and modulation in information processing of growth mindset.

Growth mindset promotes working memory performance

We examined children's working memory performance with different workloads. Our results showed that growth mindset predicted higher accuracy in working memory task irrespective of age and gender. Of note, the most prominent effect was found in the high workload condition. This is with our assumption that growth mindset motivates more effortful tasks. As an imitation of daily effort in real life, current paradigm was with no feedback. Thus, the effect of growth mindset is supposed to support by intrinsic motivation. Higher intrinsic motivation facilitates performance in high workloads and involves both cortical and striatal underlying mechanisms (Satterthwaite et al. 2012; Di Domenico and Ryan 2017). Previous intervention evidence also exhibited this effect: interventions of growth mindset caused increased challenge-seeking behavior and higher enrollment in advanced math courses (Yeager and Dweck 2012; Rege et al. 2020). At-risk students, especially, benefited more from growth mindset interventions since they faced more challenges and demanded more cognitive resources dealing with schoolwork (Yeager et al. 2016; Sarrasin et al. 2018).

The neurocognitive mechanisms underlying this phenomenon are subsequently discussed below.

Growth mindset facilitates working memory via enhancing FPN and SN activity

Imaging analysis revealed that growth mindset was associated with higher activation in fronto-parietal, anterior cingulate cortex and insula areas in high workload condition. On contrary, higher deactivation was observed in parahippocampus and PCC. These regions are commonly involved in working memory tasks as indicated by meta-analysis. In particular, activations in FEF, IPS, dACC and aInsula mediated the association between growth mindset and working memory performance in high workload condition. These regions are associated with subjective estimation of efforts (Massar et al. 2015; Arulpragasam et al. 2018), while higher activation in DMN predicts demand avoidance (Sayalı and Badre 2019).

Similar to current results, increasing activation within FPN and SN was observed under high cognitive demand (Dima et al. 2014), and predicted higher accuracy (Taghia et al. 2018). The enhanced neural response in these cortical regions reflects higher efficiency of information processing within working memory, but in distinct ways. It has long been recognized that frontal and parietal regions are critical for maintaining and adaptively updating information during working memory process (Cohen et al., 1997; Roth et al., 2006). In detail, both FEF and IPS top-down control attention towards target stimuli during cognitive demanding task (Bressler et al., 2008), while also serving to maintain and update memory representations (Takahama et al., 2010). Among frontal regions, FEF is considered to direct response and control sensory systems regarding working memory content (Badre and Nee 2018). Posterior regions such as IPS are especially involved in symbolic manipulation (Davis et al., 2018) and number processing (Bugden et al., 2012). Higher involvement of fronto-parietal regions in the demanding condition indicates more effortful updating and maintenance, together with increased control over the sensory-motor system. Distinct from FPN, anterior cingulate and insula cortex detect salience and regulate access to attentional resources depending on task demand (Taghia et al. 2018). During

the task, aInsula acts as an afferent cortical hub for perceiving autonomic feedback, and ACC was the efferent hub for responses (Seeley 2019). Thus, we suggest that growth mindset contributes to efficient cortical information processing in demanding tasks, which involves updating, manipulation, and control over the sensorimotor system, then subsequently leads to better performance in children.

Dorsolateral caudate activation and cortico-striatal connectivity reflect modulation to the motivational and updating process of growth mindset

Higher activation in caudate was also observed in children with growth mindset. The beneficial effect of dorsolateral caudate in cognitively demanding tasks has been widely observed (Arulpragasam et al. 2018), and is proposed to be involved in the evaluation of benefit and cost in the effortful task (Westbrook et al. 2020). Compared with other striatum regions, the cortico-striatal connectivity of dorsal caudate is unique in human (Liu et al. 2021) and supports cognitive demanding tasks (Hedden and Gabrieli 2010). The high engagement of caudate thus indicates modulation of the motivational process of growth mindset in cognitive tasks.

Further connectivity analysis yielded that growth mindset is associated with lower cortico-striatal connectivity. Connectivity between caudate and insula/precuneus showed consistent negative correlations in different workloads. However, caudate-PCC connectivity only exhibited this tendency in the high workload condition and played a mediatory role in the association between growth mindset and performance. This is correspondent to the association between higher dopamine synthesis capacity in dorsal caudate and greater PCC deactivation in the working memory task (Braskie et al. 2011).

The cortico-striatal interaction serves as a basis for information transfer to support working memory updating while protecting current content from interference. This contradictory need is supposed to be met via the striatum gating mechanism (Frank et al. 2001). High workload during task calls for higher efficiency of information updating, satisfied by a higher level of gate-opening to allow for more input information. This process is accompanied by higher caudate, insula, ACC, and

fronto-parietal activity (Nir-Cohen et al. 2020). Though this cortico-striatal interaction is supported by evidence of coactivation and interventions (McNab and Klingberg 2008; Baier et al. 2010; Broadway et al. 2018), few studies directly tested this coupling. One study observed increased frontostriatal coupling during high-level context updates (Nee and Brown 2013), and another study observed little evidence of input gating (Chatham et al. 2014). In contrast to the necessity to constrain information from competing information in these studies, the high workload condition in the current study calls for a lower level of gating but higher efficiency of updating. Future studies comparing different contexts of working memory may clarify this discrepancy. Thus, we proposed that decreased coupling predicted by growth mindset reflects more input information and less controlled gating.

The gating process and cortical response together serve to benefit behavioral performance in children with growth mindset

Changes in the input-gating process triggered higher involvement of insula while higher deactivation in PCC. On one hand, rapid updating of working memory content offers more task-related information in time and allows for a higher possibility of accurate response. On the other hand, this expanded working memory content includes both task stimuli and distractions, calling for more efficient processing in cortical regions. For FPN and SN networks, higher engagement in high workload indicates local assessing of information to guide appropriate behavior. As mentioned above, aInusla is a major afferent cortical hub (Seeley 2019). Within the insula region, related content is assessed to guide salience detection, attention shifting (Wager and Barrett 2017) and update internal estimation (Namkung et al. 2017). As for PCC, task-independent distractions and self-referential thinking are suppressed (Mason et al. 2007; Qin and Northoff 2011) to reserve cognitive resources and resist disturbance, as reflected by deactivation in high workload. Taken together, caudate-striatal connectivity and resultant cortical response jointly formed the neurocognitive model by which growth mindset affects working memory performance in children.

Limitations

First, the cortico-striatal loop is not solely based on functional connectivity, cortical response to striatal dopamine also reliably affects the working memory process. Additional tests of dopaminergic projection are needed. Future studies should also account for projections from different subregions of caudate and other striatum regions of higher spatial resolution. Second, though we recruited children from schools of the same standard, many other variables such as motivation, intelligence, and general cognitive capabilities should be taken into account in future studies. Third, although we have identified key regions and pathways involved in working memory in relation to growth mindset, the neurobiological mechanisms of how growth mindset affects the maturation of large-scale brain networks and cognitive development should be further investigated.

Conclusions

Our study highlights the mediatory role of cortico-striatal interaction together with fronto-parietal response in the positive association between children's growth mindset and working memory performance. Lower caudate-insula and caudate-PCC connectivity in children with higher growth mindset implicate efficient updating and more input information during working memory, whereas enhanced frontoparietal network and salience network engagement reflects more effective cognitive control and motivational processes. Our findings suggest a neurocognitive account for how growth mindset promotes working memory via functional organization of widely distributed brain systems, which informs further utilization of growth mindset in learning and education.

CRediT authorship contribution statement

Yuyao Zhao: Conceptualization, Software, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. **Jiahua Xu, Menglu Chen, Lei Hao, Ying He:** Software, Investigation, Resoueces, Writing – Review & Editing. **Hui Wang, Yanpei Wang, Daoyang Wang, Zhuo Rachel Han, Shuping Tan, Weiwei Men, Jiahong Gao, Yong He, Shao Tao, Qi Dong, Shaozheng Qin:** Conceptualization, Methodology, Resources, Writing – Review & Editing, Supervision, Project administration.

Acknowledgements

This study was supported by the National Natural Science Foundation of China (32130045, 31522028, 82021004, 81571056); The Beijing Brain Initiative of Beijing Municipal Science & Technology Commission (Z181100001518003); the Open Research Fund of the State Key Laboratory of Cognitive Neuroscience and Learning (CNLZD1503, CNLZD1703); the Major Project of National Social Science Foundation (19ZDA363, 20&ZD153); the 111 Project (BP0719032).

Data and code availability statement

Data availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability: The code used to run the behavioral analysis, multiple comparison, gPPI and mediation analysis is available in the following Github repository: [https://github.com/zhaoyuyao/Growth_mindset_working_memory].

Declaration of competing interest

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

References

Aronson J, Fried CB, Good C. 2002. Reducing the effects of stereotype threat on African American college students by shaping theories of intelligence. J Exp Soc Psychol. 38:113–125.

Arulpragasam AR, Cooper JA, Nuutinen MR, Treadway MT. 2018. Corticoinsular circuits encode subjective value expectation and violation for effortful goal-directed behavior. Proc Natl Acad Sci U S A. 115:E5233–E5242.

Badre D, Nee DE. 2018. Frontal Cortex and the Hierarchical Control of Behavior. Trends Cogn Sci.

Baier B, Karnath HO, Dieterich M, Birklein F, Heinze C, Müller NG. 2010. Keeping memory clear and stable - The contribution of human basal ganglia and prefrontal cortex to working memory. J Neurosci. 30:9788–9792.

Bejjani C, Depasque S, Tricomi E. 2019. Intelligence mindset shapes neural learning signals and memory. Biol Psychol. 146:107715.

Blackwell LS, Trzesniewski KH, Dweck CS. 2007. Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. Child Dev. 78:246–263.

Botvinick M, Braver T. 2015. Motivation and cognitive control: From behavior to neural mechanism. Annu Rev Psychol. 66:83–113.

Braskie MN, Landau SM, Wilcox CE, Taylor SD, O'Neil JP, Baker SL, Madison CM, Jagust WJ. 2011. Correlations of striatal dopamine synthesis with default network deactivations during working memory in younger adults. Hum Brain Mapp. 32:947–961.

Broadway JM, Frank MJ, Cavanagh JF. 2018. Dopamine D2 agonist affects visuospatial working memory distractor interference depending on individual differences in baseline working memory span. Cogn Affect Behav Neurosci. 18:509–520.

Cai W, Ryali S, Pasumarthy R, Talasila V, Menon V. 2021. Dynamic causal brain circuits during working memory and their functional controllability. Nat Commun. 12:3314.

Chatham CH, Frank MJ, Badre D. 2014. Corticostriatal output gating during selection from working memory. Neuron. 81:930–942.

Cox RW, Chen G, Glen DR, Reynolds RC, Taylor PA. 2017. FMRI Clustering in AFNI: False-Positive Rates Redux. Brain Connect. 7:152–171.

Di Domenico SI, Ryan RM. 2017. The emerging neuroscience of intrinsic motivation: A new frontier in self-determination research. Front Hum Neurosci.

Dima D, Jogia J, Frangou S. 2014. Dynamic causal modeling of load-dependent modulation of effective connectivity within the verbal working memory network. Hum Brain Mapp. 35:3025–3035.

Dweck CS. 2006. Mindset: The new psychology of success., Mindset: The new psychology of success. New York, NY, US: Random House.

Esteban O, Markiewicz CJ, Blair RW, Moodie CA, Isik AI, Erramuzpe A, Kent JD, Goncalves M, DuPre E, Snyder M, Oya H, Ghosh SS, Wright J, Durnez J, Poldrack RA, Gorgolewski KJ. 2019. fMRIPrep: a robust preprocessing pipeline for functional MRI. Nat Methods. 16:111–116.

Finc K, Bonna K, He X, Lydon-Staley DM, Kühn S, Duch W, Bassett DS. 2020. Dynamic reconfiguration of functional brain networks during working memory training. Nat Commun. 11:1–15.

Frank MJ, Loughry B, O'Reilly RC. 2001. Interactions between frontal cortex and basal ganglia in working memory: A computational model. Cogn Affect Behav Neurosci 2001 12. 1:137–160.

Gorgolewski K, Burns CD, Madison C, Clark D, Halchenko YO, Waskom ML, Ghosh SS. 2011. Nipype: A flexible, lightweight and extensible neuroimaging data processing framework in Python. Front Neuroinform. 5:13.

Green DM, Swets JA. 1966. SIGNAL DETECTION THEORY AND PSYCHOPHYSICS.

Hedden T, Gabrieli JDE. 2010. Shared and selective neural correlates of inhibition, facilitation, and shifting processes during executive control. Neuroimage. 51:421–431.

Jarbo K, Verstynen TD. 2015. Converging structural and functional connectivity of

orbitofrontal, dorsolateral prefrontal, and posterior parietal cortex in the human striatum. J Neurosci. 35:3865–3878.

Kühn S, Schmiedek F, Noack H, Wenger E, Bodammer NC, Lindenberger U, Lövden M. 2013. The dynamics of change in striatal activity following updating training. Hum Brain Mapp. 34:1530–1541.

Liljeholm M, O'Doherty JP. 2012. contributions of the striatum to learning, motivation, and performance: An associative account. Trends Cogn Sci.

Liu X, Eickhoff SB, Caspers S, Wu J, Genon S, Hoffstaedter F, Mars RB, Sommer IE, Eickhoff CR, Chen J, Jardri R, Reetz K, Dogan I, Aleman A, Kogler L, Gruber O, Caspers J, Mathys C, Patil KR. 2021. Functional parcellation of human and macaque striatum reveals human-specific connectivity in the dorsal caudate. Neuroimage. 235:118006.

Mangels JA, Butterfield B, Lamb J, Good C, Dweck CS. 2006. Why do beliefs about intelligence influence learning success? A social cognitive neuroscience model. Soc Cogn Affect Neurosci. 1:75–86.

Mason MF, Norton MI, Van Horn JD, Wegner DM, Grafton ST, Macrae CN. 2007. Wandering minds: The default network and stimulus-independent thought. Science (80-). 315:393–395.

Massar SAA, Libedinsky C, Weiyan C, Huettel SA, Chee MWL. 2015. Separate and overlapping brain areas encode subjective value during delay and effort discounting. Neuroimage. 120:104–113.

McLaren DG, Ries ML, Xu G, Johnson SC. 2012. A generalized form of context-dependent psychophysiological interactions (gPPI): A comparison to standard approaches. Neuroimage. 61:1277–1286.

McNab F, Klingberg T. 2008. Prefrontal cortex and basal ganglia control access to working memory. Nat Neurosci. 11:103–107.

Moser JS, Schroder HS, Heeter C, Moran TP, Lee YH. 2011. Mind your errors: Evidence for a neural mechanism linking growth mind-set to adaptive posterror adjustments. Psychol Sci.

Myers CA, Wang C, Black JM, Bugescu N, Hoeft F. 2016. The matter of motivation:

Striatal resting-state connectivity is dissociable between grit and growth mindset. Soc Cogn Affect Neurosci. 11:1521–1527.

Namkung H, Kim SH, Sawa A. 2017. The Insula: An Underestimated Brain Area in Clinical Neuroscience, Psychiatry, and Neurology. Trends Neurosci. 40:200–207.

Nee DE, Brown JW. 2013. Dissociable frontal-striatal and frontal-parietal networks involved in updating hierarchical contexts in working memory. Cereb Cortex. 23:2146–2158.

Ng B. 2018. The neuroscience of growth mindset and intrinsic motivation. Brain Sci.

Nir-Cohen G, Kessler Y, Egner T. 2020. Neural substrates of working memory updating. J Cogn Neurosci. 32:2285–2302.

Owen AM, McMillan KM, Laird AR, Bullmore E. 2005. N-back working memory paradigm: A meta-analysis of normative functional neuroimaging studies. Hum Brain Mapp. 25:46–59.

Qin P, Northoff G. 2011. How is our self related to midline regions and the default-mode network? Neuroimage. 57:1221–1233.

Rege M, Hanselman P, Solli IF, Dweck CS, Ludvigsen S, Bettinger E, Crosnoe R, Muller C, Walton G, Duckworth A, Yeager DS. 2020. How can we inspire nations of learners? An investigation of growth mindset and challenge-seeking in two countries. Am Psychol.

Sarrasin JB, Nenciovici L, Foisy LMB, Allaire-Duquette G, Riopel M, Masson S. 2018. Effects of teaching the concept of neuroplasticity to induce a growth mindset on motivation, achievement, and brain activity: A meta-analysis. Trends Neurosci Educ.

Satterthwaite TD, Ruparel K, Loughead J, Elliott MA, Gerraty RT, Calkins ME, Hakonarson H, Gur RC, Gur RE, Wolf DH. 2012. Being right is its own reward: Load and performance related ventral striatum activation to correct responses during a working memory task in youth. Neuroimage. 61:723–729.

Sayalı C, Badre D. 2019. Neural systems of cognitive demand avoidance. Neuropsychologia. 123:41–54.

Schroder HS, Fisher ME, Lin Y, Lo SL, Danovitch JH, Moser JS. 2017. Neural evidence for enhanced attention to mistakes among school-aged children with a growth mindset. Dev Cogn Neurosci. 24:42–50.

Schroder HS, Moran TP, Donnellan MB, Moser JS. 2014. Mindset induction effects on cognitive control: A neurobehavioral investigation. Biol Psychol. 103:27–37.

Seeley WW. 2019. The salience network: A neural system for perceiving and responding to homeostatic demands. J Neurosci.

Sidarus N, Palminteri S, Chambon V. 2019. Cost-benefit trade-offs in decision-making and learning. PLOS Comput Biol. 15:e1007326.

Taghia J, Cai W, Ryali S, Kochalka J, Nicholas J, Chen T, Menon V. 2018. Uncovering hidden brain state dynamics that regulate performance and decision-making during cognition. Nat Commun. 9:1–19.

Vatansever D, Manktelow A, Sahakian BJ, Menon DK, Stamatakis EA. 2018. Default Mode Network Engagement beyond Self-Referential Internal Mentation. Brain Connect. 8:245–253.

Wager TD, Barrett LF. 2017. From affect to control: Functional specialization of the insula in motivation and regulation. bioRxiv. 102368.

Wang D, Gan L, Wang C. 2021. The effect of growth mindset on reasoning ability in Chinese adolescents and young adults: the moderating role of self-esteem. Curr Psychol. 1–7.

Wang D, Yuan F, Wang Y. 2020. Growth mindset and academic achievement in Chinese adolescents: A moderated mediation model of reasoning ability and self-affirmation. Curr Psychol. 1–10.

Westbrook A, Frank MJ, Cools R. 2021. A mosaic of cost–benefit control over cortico-striatal circuitry. Trends Cogn Sci.

Westbrook A, van den Bosch R, Määttä JI, Hofmans L, Papadopetraki D, Cools R, Frank MJ. 2020. Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. Science (80-). 367:1362–1366.

Xu KM, Koorn P, de Koning B, Skuballa IT, Lin L, Henderikx M, Marsh HW, Sweller J, Paas F. 2020. A Growth Mindset Lowers Perceived Cognitive Load

and Improves Learning: Integrating Motivation to Cognitive Load. J Educ Psychol.

Yeager DS, Dweck CS. 2012. Mindsets That Promote Resilience: When Students Believe That Personal Characteristics Can Be Developed. Educ Psychol. 47:302–314.

Yeager DS, Romero C, Paunesku D, Hulleman CS, Schneider B, Hinojosa C, Lee HY, Brien JO, Flint K, Roberts A, Trott J, International ICF, Greene D, Walton GM, Dweck CS. 2016. Using design thinking to improve psychological interventions: The case of the growth mindset during the transition to high school. J Educ Psychol. 108:374–391.