

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

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23

24 **Abstract**

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

41

42 **Introduction**

43 To meet the challenges ahead, children develop positive inner beliefs that enable them
44 to continue their efforts without external support. The belief that human attributes and
45 skills are malleable and improvable is called growth mindset (Dweck and Yeager,
46 2019). It benefits cognitive control performance (Moser et al. 2011; Schroder et al.
47 2017) and further results in better academic achievements in school-aged children
48 (Claro et al., 2016; Good et al., 2003; Yeager et al., 2019). This merit covers a large
49 range of age groups from age 7 to adulthood (Sarrasin et al., 2018) and the effect
50 lasted for years (Blackwell et al., 2007). Such a substantial effect of growth mindset is
51 proposed to root in higher intrinsic motivation (Ng 2018; Xu et al. 2020) and
52 modulation of working memory processing (Mangels et al. 2006). Despite decades of
53 application and research in education, however, little is known about the underlying

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

56

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

72

73 Striatum and cortical networks are involved in the motivational process during
74 cognitive control. Since high-demand task with higher engagement of control systems
75 is inherently more costly, it need to be specifically motivated (Botvinick and Braver
76 2015; Sidarus et al. 2019). The striatum, especially the caudate nucleus, is involved in
77 the motivational process during cognitively demanding tasks through the evaluation
78 between benefit and cost (Westbrook et al. 2021). Higher activation of caudate
79 nucleus causes a higher willingness to conduct effortful working memory tasks
80 (Westbrook et al. 2020). This preference for high-demand tasks affects working
81 memory processing: the activation of caudate itself and its interaction with cortical
82 regions govern the updating of task-related information (McNab and Klingberg 2008;
83 Baier et al. 2010; Kühn et al. 2013). Though most studies focused on the coupling of

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

94

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

109

110 **Methods and materials**

111 **Participants**

112 A total number of 375 children (8-12 years old, $M \pm SD = 9.833 \pm 1.039$ years, 207
113 males and 168 females) (**Fig. 1D**) were recruited in the current study. The written
114 informed consent form was obtained from each participant and their caregivers or
115 legal guardians. The study procedures were approved by local ethics following the
116 standards of the Declaration of Helsinki. Participants had no obstacle in vision and
117 reported no history of neurological or psychiatric disorders and no current use of any
118 medication or recreational drugs. Participants with excessive head motions (more than
119 1/3 frames with standardized DVARS > 1.5 or frame displacement > 0.5), incomplete
120 scales or scanning were excluded from further analyses (**Fig. 1A**). A final sample of
121 306 children (8-12 years old, $M \pm SD = 9.869 \pm 1.024$ years, 163 males and 143 females)
122 were sent for imaging analysis.

123

124 **The measure of growth mindset**

125 The mindset was assessed using the Growth Mindset Scale (GMS) (Dweck 2006). It
126 consists of 20 items (e.g., No matter who you are, you always can change your
127 intelligence a lot), with 14 items about the individuals' theory of ability and 6 items
128 about the individuals' theory of personality (Chinese version used in Wang et al. 2020,
129 2021). Participants were asked to rate their agreement with each statement using a
130 4-point Likert-type scale (0 = Strongly Disagree, 1 = Disagree, 2 = Agree, 3 = Strongly
131 agree). The final score from 0 to 60 with higher scores represents higher growth
132 mindset level.

133

134 **N-back Task procedure**

135 A classic numerical n-back task was used to assess participants' working memory
136 performance. This task consisted of three conditions with different workloads (0-back,
137 1-back, and 2-back) and each condition consisted of 4 blocks. In each block, the
138 participants first viewed a 2-second cue that indicated the workload of this block

139 (0-back, 1-back, and 2-back). Followed by a sequence of 15 pseudorandom digits in
140 which each digit was presented for 400 milliseconds. In the 0-back condition,
141 participants were instructed to respond to the digit “1”. While in the 1-back condition,
142 participants were asked to respond to the digit which was just the same as the previous
143 one. In the 2-back condition, participants needed to respond to the digit which was the
144 same as the previous two. Stimuli were presented via E-Prime 2.0
145 (<http://www.psnet.com>; Psychology Software Tools, Inc., Pittsburgh, PA). Both
146 participants’ response and reaction time (RT) were recorded, then we calculated
147 participants’ accuracy based on their responses. The accuracy and RT were used as
148 indicators of individual working memory performance.

149

150 **Behavioral data analysis**

151 The accuracy was assessed by d' based on the signal detection theory (Green and Swets
152 1966). All trials for each participant were assigned into the following categories: (1)
153 hits: responses to targets; (2) misses: no response to targets; (3) false alarms: responses
154 to non-targets; (4) correct rejections: no response to non-targets. The hit rate and false
155 alarm rate were defined as follows:

$$\text{hit rate} = \frac{\text{hits}}{\text{hits} + \text{misses}}$$
$$\text{false alarm rate} = \frac{\text{false alarms}}{\text{false alarms} + \text{correct rejections}}$$

156

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

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

159

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

164

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

170

171 **Image data acquisition**

172 Data were acquired using the same type of 3.0T scanner (Magnetom Prisma syngo MR
173 D13D, Erlangen, Germany) with a 64-channel head coil. High-resolution anatomical
174 images were acquired by a three-dimensional sagittal T1-weighted
175 magnetization-prepared rapid gradient echo (MPRAGE) sequence (TR = 2530 ms, TE
176 = 2.98 ms, TI = 1100ms, flip angle = 7°, voxel size 0.5 x 0.5 x 1.0 mm³, matrix size =
177 256 × 224, FOV = 256 x 224 mm², brand width = 240 Hz/Px, 192 slices with 1 mm
178 thickness). Functional images with 33 axial slices (3.5 mm thick, 0.7 mm skip) parallel
179 to the anterior and posterior commissural line (AC-PC) were acquired using a
180 T2*-sensitive echo-planar imaging (EPI) sequence (TR = 2000ms, TE = 30ms, flip
181 angle = 90°, voxel size = 3.5 x 3.5 x 3.5 mm³, FOV = 224 x 224 mm²). The whole
182 n-back task consisted of 232 volumes and lasted for 464s.

183

184 **Image data preprocessing**

185 Brain images were preprocessed with the fMRIPrep 1.4.1 (Esteban et al. 2019) pipeline
186 implemented in Nipype 1.2.0 (Gorgolewski et al. 2011). The first 4 volumes of n-back
187 task were discarded for signal stability and adaptation of participants. For each
188 participant, the following preprocessing procedures were conducted. First, each T1w
189 volume was skull-stripped and a BOLD reference was estimated. Slice time correction
190 was then performed and all slices were realigned in time to the middle of each TR using
191 3dTshift from AFNI. Motion correction was done using mcflirt (FSL) and 6
192 head-motion parameters (three rotations, three translations) were estimated. The EPI
193 data was corrected for susceptibility distortions based on a field map and co-registered
194 to the anatomical reference using boundary-based registration with nine degrees of

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

200

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

213

214 **General linear model (GLM) analysis**

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

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

225

226 Relevant contrast parameter estimate images were initially generated at the
227 individual-subject level, then submitted to group-level analyses by treating participants
228 as a random variable. Contrast images of 2-back > 0-back, 2-back > 1-back, and 1-back >
229 0-back were submitted to separate multiple regression analyses with participants’
230 growth mindset as a covariate of interest, gender and age as nuisances. Coefficients of
231 the multiple regression were tested using one-sample t-test. Significant clusters were
232 determined at a voxel level false discovery rate (FDR) correction ($pFDR < 0.05$) on the
233 whole brain. For visualization of results, significant clusters were displayed using Surf
234 Ice (<https://www.nitrc.org/projects/surface/>) and MRIcroGL
235 (<https://www.nitrc.org/projects/microgl/>).

236

237 **Regions of interest (ROIs) analysis**

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

245

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

252 hippocampus/parahippocampus (HCP/PHC) was also included based on the result of
253 whole-brain multiple regression. Finally, ROIs generated from the original
254 meta-analysis maps include: dlPFC, FEF, and IPS nucleus for FPN; aInsula and ACC
255 for SN; vmPFC, AG, PCC, and HCP/PHC for DMN (Fig. S1A & B). Parameter
256 estimates from each ROI and each participant were extracted from the individual-level
257 2-back > 0-back contrast using MarsBaR (<http://marsbar.sourceforge.net/>) to
258 characterize activation during the task in each ROI.

259

260 **Functional connectivity analysis**

261 To assess the effect of cortico-striatal interaction, connectivity between bilateral
262 caudate and whole cortical regions was calculated using the generalized
263 psychophysiological interaction (gPPI) method (McLaren et al. 2012). The bilateral
264 caudate seed was defined as the group-level significant clusters after FDR correction
265 in the 2-back > 0-back contrast, which is located in the dorsolateral caudate. The gPPI
266 approach assessed task-dependent functional connectivity of the seed region with all
267 voxels within global gray matter. Specifically, the mean time series of voxels within
268 the seed region were extracted and subsequently deconvolved to uncover neural
269 activity (physiological variable). The estimated neural activities were then multiplied
270 with task design vectors (0-back, 1-back, 2-back; psychological variable) and
271 convolved with a canonical HRF to form the PPI regressors of interest. Besides,
272 physiological/psychological variables, as well as signals within CSF and WM were
273 also included in individual GLM to account for potential confounds and remove the
274 effects of common driving inputs on brain connectivity. Individual-level contrast
275 images of gPPI effects were then submitted to second-level multiple regression
276 analyses with participants' growth mindset as a covariate of interest while gender and
277 age as nuisances. The significance threshold was determined by Monte Carlo
278 Simulation using 3dClustSim in AFNI (Cox et al. 2017) at a height threshold of $p <$
279 0.001, and an extent threshold of $p < 0.05$. Parameter estimates were extracted from
280 significant clusters using the same method noted above.

281

282 **Mediation analysis**

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

289

290 **Results**

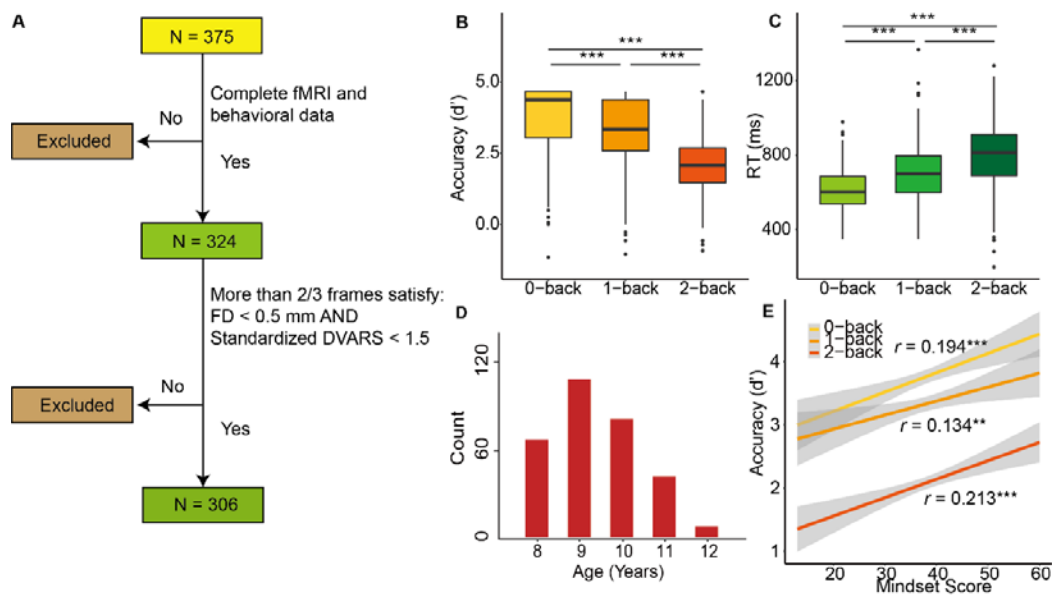
291 **Growth mindset predicts higher working memory performance in young children**

292 We first verified the effectiveness of our workload manipulation. We conducted
293 repeated-measures analysis of variance (ANOVA) on accuracy and RT respectively
294 with workloads as within-subject factors. Both accuracy and RT showed robust main
295 effects (Accuracy: $F(1.94, 724.95) = 471.913, p < 0.001, \eta^2 = 0.308$; RT: $F(1.71,$
296 $624.61) = 325.855, p < 0.001, \eta^2 = 0.228$). Following separate pairwise comparisons
297 revealed lower accuracy in higher workload condition (paired t-test, two-sided: 1- and
298 0-back: $t(374) = -7.946$; 2- and 1-back: $t(374) = -23.075$, both $p < 0.001$,
299 Bonferroni-corrected; **Fig. 1B**). And participants responded slower while workload
300 increasing (paired t-test, two-sided: 1- and 0-back: $t(370) = 15.712$; 2- and 1-back:
301 $t(367) = 11.415$, both $p < 0.001$, Bonferroni-corrected; **Fig. 1C**). Furthermore, we
302 performed Pearson correlation between working memory performance and age, which
303 revealed improvement in both accuracy and RT in children from 8 to 12 years old (**Fig.**
304 **S2**). Improvements of RTs in all three workloads were roughly the same (0-back: $r =$
305 $-0.289, p < 0.001$; 1-back: $r = -0.281, p < 0.001$; 2-back: $r = -0.203, p < 0.001$), while
306 larger improvement in higher workload was observed in accuracy (0-back: $r = 0.078, p$
307 $= 0.131$; 1-back: $r = 0.159, p = 0.002 < 0.005$; 2-back: $r = 0.258, p < 0.001$).

308

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

312 accuracy under all three workloads (0-back: $r = 0.194, p < 0.001$; 1-back: $r = 0.134, p =$
 313 $0.009 < 0.01$; 2-back: $r = 0.213, p < 0.001$), while RT also showed the same pattern but
 314 no significance was found (0-back: $r = -0.007, p = 0.892$; 1-back: $r = -0.042, p = 0.419$;
 315 2-back: $r = 0.010, p = 0.846$) (**Fig. S3**). Age and mindset score showed no interaction
 316 effect in all workloads. Moreover, we conducted correlation analyses to test whether
 317 mindset also developed as children grew up. This analysis revealed no significant
 318 correlation ($r = 0.018, p = 0.730$), indicating that mindset is a relatively stable trait from
 319 8 to 12 and its effect towards working memory is independent of development.



320

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

332 25th and 75th percentiles) above 75th percentile and below 25th percentile. **D.** Age
333 distribution of the final sample ($n = 306$). Participants' ages ranged from 8 to 12 years
334 old. **E.** Correlation between mindset and accuracy with age and gender as covariates (n
335 = 375). Accuracy was positively correlated with mindset score under all three
336 workloads. Shading represents 95% CI (confidence interval). Largest correlation was
337 observed under 2-back condition. *** $p < 0.001$, ** $p < 0.01$, Bonferroni-corrected.

338

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

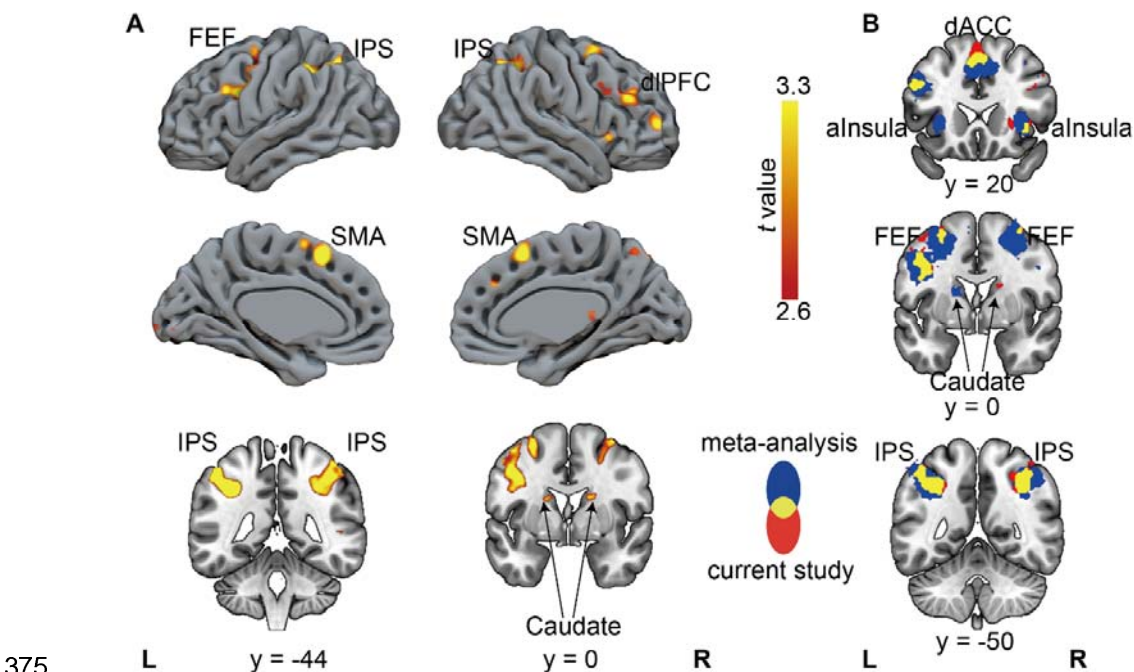
340 To investigate the neural bases of how growth mindset benefits working memory
341 performance, we applied whole-brain multiple regression analysis. Multiple regression
342 has been applied for 2-back > 0-back, 2-back > 1-back and 1-back > 0-back contrasts
343 (derived from first-level analysis) to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

345

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

362

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



375

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

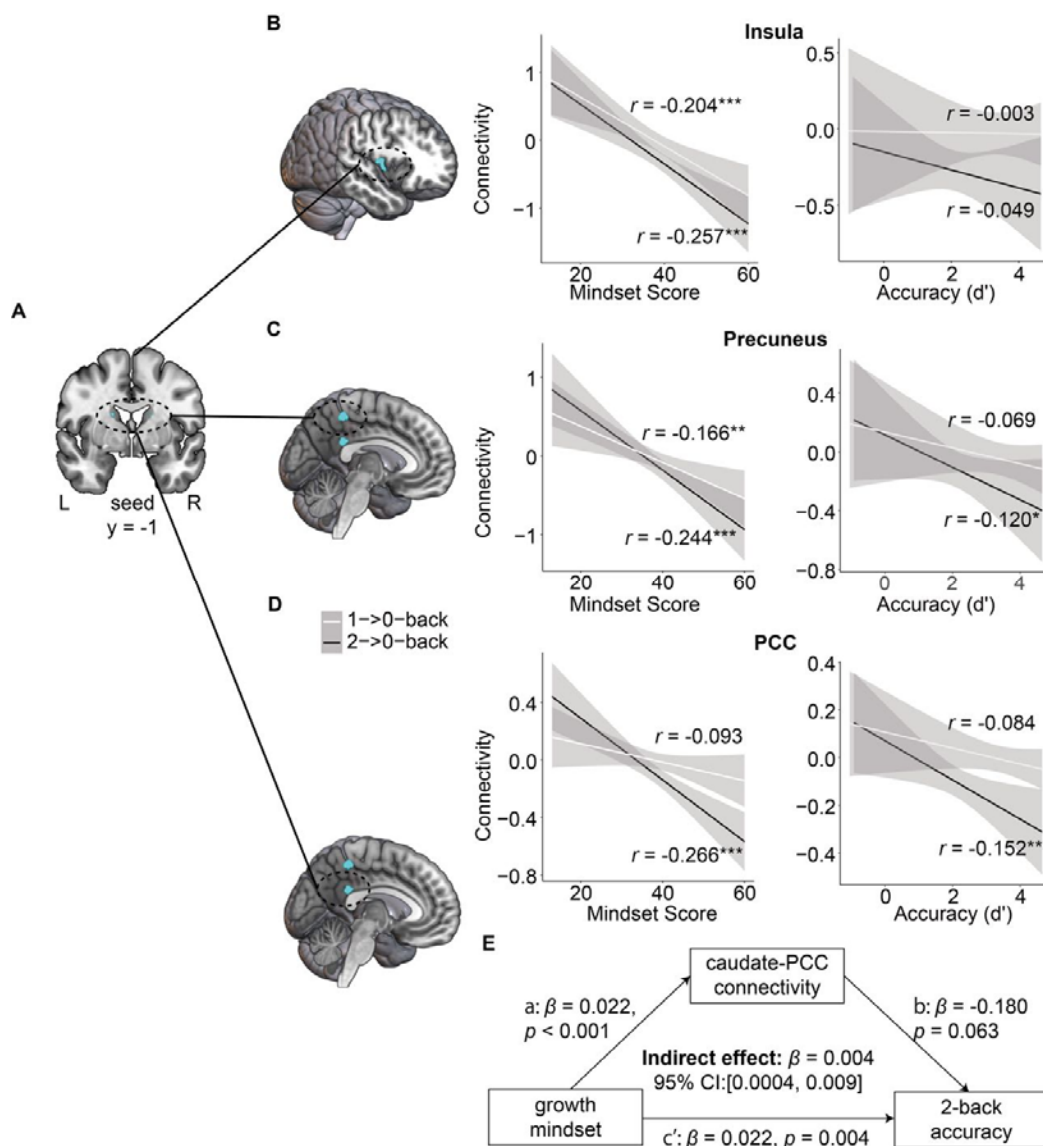
380 multiple comparison and meta-analysis result. Regions that linked to higher growth
381 mindset were highly overlapped with areas crucial for working memory task, especially
382 in fronto-parietal area. Blue: meta-analysis map of working memory with threshold of
383 $Z > 3$. Red: Whole-brain multiple comparison results of current study with $p < 0.05$
384 (corrected for multiple comparison using FDR). Yellow: overlap of meta-analysis
385 result and multiple regression results. Only clusters larger than 10 voxels were
386 presented. dlPFC: dorsal lateral prefrontal cortex, IPS: inferior parietal sulcus, SMA:
387 supplementary motor area.

388

389 **Growth mindset affects cortico-striatal connectivity**

390 We then tested how growth mindset modulates intrinsic cortico-striatal connectivity.
391 Bilateral caudate regions identified above were used as seed for functional
392 connectivity analysis (**Fig. 3A**; see Methods for details). Whole brain multiple
393 regression analysis of growth mindset was conducted for connectivity targets in
394 2->0-back and 1->0-back contrasts, with age and gender as covariates. Higher
395 growth mindset caused decoupling between caudate and cortical regions in 2->0-back
396 contrast. Interestingly, connectivity between caudate and PCC was predicted by
397 interaction between growth mindset and workload ($t(304) = 2.75, p = 0.006$) (**Fig. 3C**).
398 Only under high workload condition, growth mindset predicts lower intrinsic
399 connectivity (2->0-back: $r = -0.266, p < 0.001$; 1->0-back: $r = -0.093, p = 0.106$).
400 Compared with PCC, connectivity to precuneus and insula was not influenced by
401 workload, but only predicted by growth mindset (precuneus: 2-back>0-back: $r =$
402 $-0.244, p < 0.001$; 1->0-back: $r = -0.166, p = 0.004$; insula: 2->0-back: $r = -0.257, p <$
403 0.001 ; 1->0-back: $r = -0.204, p < 0.001$) (**Fig. 3B, D**). Connectivity between caudate
404 and PCC was also distinctive in its association with behavioral performance:
405 caudate-PCC connectivity negatively predicted accuracy in high workload condition
406 (2->0-back: $r = -0.152, p = 0.008$; 1->0-back: $r = -0.084, p = 0.146$) (**Fig. 3C**). By
407 comparison, caudate-precuneus connectivity showed weak correlation and
408 caudate-insula connectivity did not have such effect (precuneus: 2-back>0-back: $r =$
409 $-0.120, p = 0.036$; 1->0-back: $r = -0.069, p = 0.229$; insula: 2->0-back: $r = -0.049, p =$

410 0.398; 1->0-back: $r = -0.003$, $p = 0.953$) (**Fig. 3B, D**). We then tested mediation effect
 411 of caudate-PCC connectivity in the association between growth mindset and
 412 behavioral performance. Analysis showed that growth mindset affects working
 413 memory performance via caudate-PCC connectivity in high load condition (indirect
 414 Est. = 0.004, 95% CI = [0.0004, 0.009]) (**Fig. 3E**). These results revealed that growth
 415 mindset modulates cortico-striatal connectivity. Specially, caudate-PCC connectivity
 416 mediates the association between growth mindset and behavioral performance in high
 417 workload.



418

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

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

428

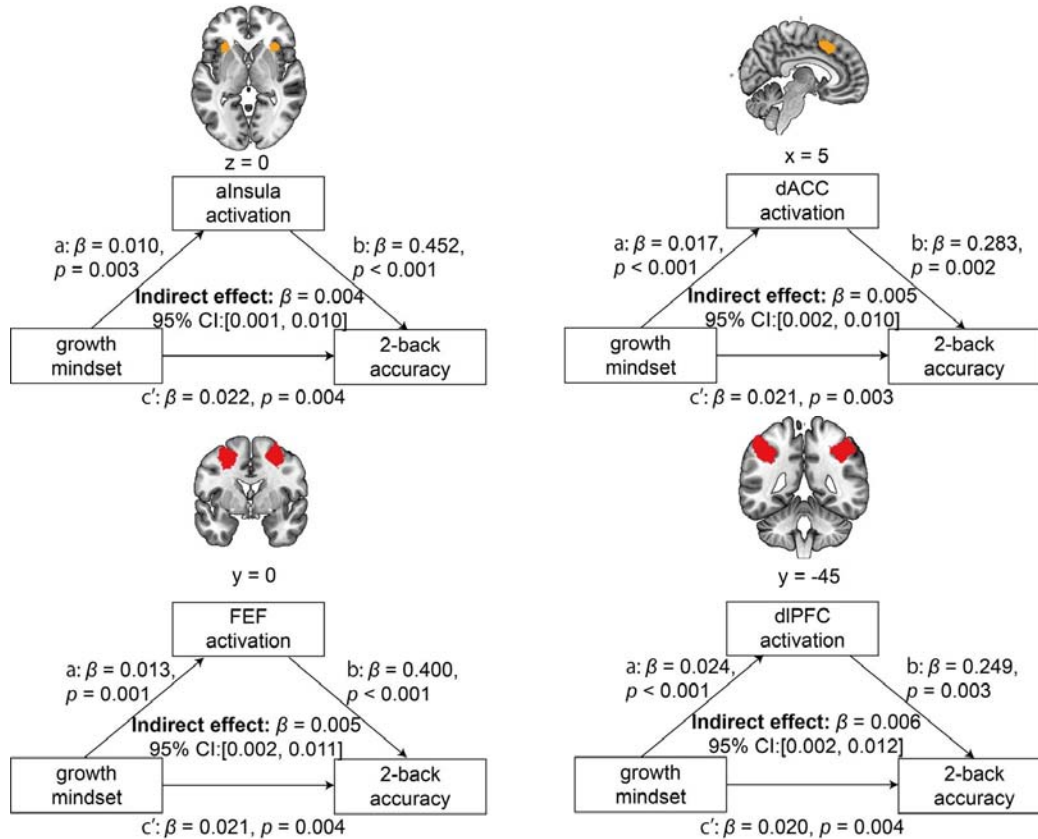
429 **Growth mindset predicts working memory performance via cortical network** 430 **activation**

431 To elucidate how cortical activation alone associates with growth mindset and
432 behavior in a network view, we focused our analysis on 9 core FPN, SN and DMN
433 regions based on meta-analysis map of working memory. As expected, each ROI from
434 FPN and SN showed positive activation while regions from DMN deactivated in two
435 contrasts (**Fig. S1D**). Overall activation of ROIs from FPN and SN was significantly
436 different from that of ROIs from DMN (paired t-test, two-sided: FPN-DMN: $t(305) =$
437 29.730 , $p < 0.001$; SN-DMN: $t(305) = 27.504$, $p < 0.001$; Bonferroni-corrected), and
438 FPN showed highest activation compared with SN (paired t-test, two-sided: $t(305) =$
439 2.634 , $p = 0.030$, Bonferroni-corrected; see **Table S4** for details).

440 Network response was also associated with both mindset and working memory
441 performance (**Fig. S4**): Activation strength of all FPN and SN regions was positively
442 correlated with mindset score and predicted higher accuracy. Among FPN regions,
443 strongest activation was evoked in IPS, which was associated with higher mindset score
444 ($r = 0.253$, $p < 0.001$) and accuracy ($r = 0.210$, $p < 0.001$). Both FEF and dlPFC had
445 similar but weaker effect (FEF and mindset score: $r = 0.181$, $p = 0.001$; FEF and
446 accuracy: $r = 0.246$, $p < 0.001$; dlPFC and mindset score: $r = 0.207$, $p < 0.001$; dlPFC
447 and accuracy: $r = 0.115$, $p = 0.046$). Neural response in SN regions also showed
448 correlation with both mindset score (dACC: $r = 0.201$, $p < 0.001$; aInsula: $r = 0.167$, p
449 $= 0.003$) and accuracy (dACC: $r = 0.209$, $p < 0.001$; aInsula: $r = 0.221$, $p < 0.001$). On
450 the contrary, only activation in HPC/PHC was negatively correlated with both mindset

451 score ($r = -0.117, p = 0.042$) and accuracy ($r = -0.217, p < 0.001$). Activation of PCC
452 and vmPFC only showed negative correlation with accuracy (PCC: $r = -0.143, p =$
453 0.012 ; vmPFC: $r = -0.227, p < 0.001$), while no association was found in AG. These
454 results implicated that neural response in network regions may serve as neural mediator
455 under the direct effect from growth mindset to behavioral performance.

456 To validate this assumption, we then investigated whether growth mindset benefits
457 working memory performance via neural response in FPN, SN and DMN regions. We
458 used the accuracy in 2-back condition regarding its high correlation with growth
459 mindset compared to 1-back condition. With age and gender set as nuisances, analysis
460 showed that activation in FEF and IPS from FPN mediated the relationship between
461 growth mindset and working memory accuracy (FEF: indirect Est. = 0.005, 95% CI =
462 [0.002, 0.011]; IPS: indirect Est. = 0.006, 95% CI = [0.002, 0.012]) (**Fig. 4**). Similar
463 mediation effect was also found in SN regions (aInsula: indirect Est. = 0.004, 95% CI =
464 [0.001, 0.010]; dACC: indirect Est. = 0.005, 95% CI = [0.002, 0.010]). In contrast,
465 mediation effects of all DMN regions showed no significance. These results indicate
466 that neural response in both FPN and SN regions played a mediatory role in the
467 promoting effect of growth mindset on working memory performance.



468

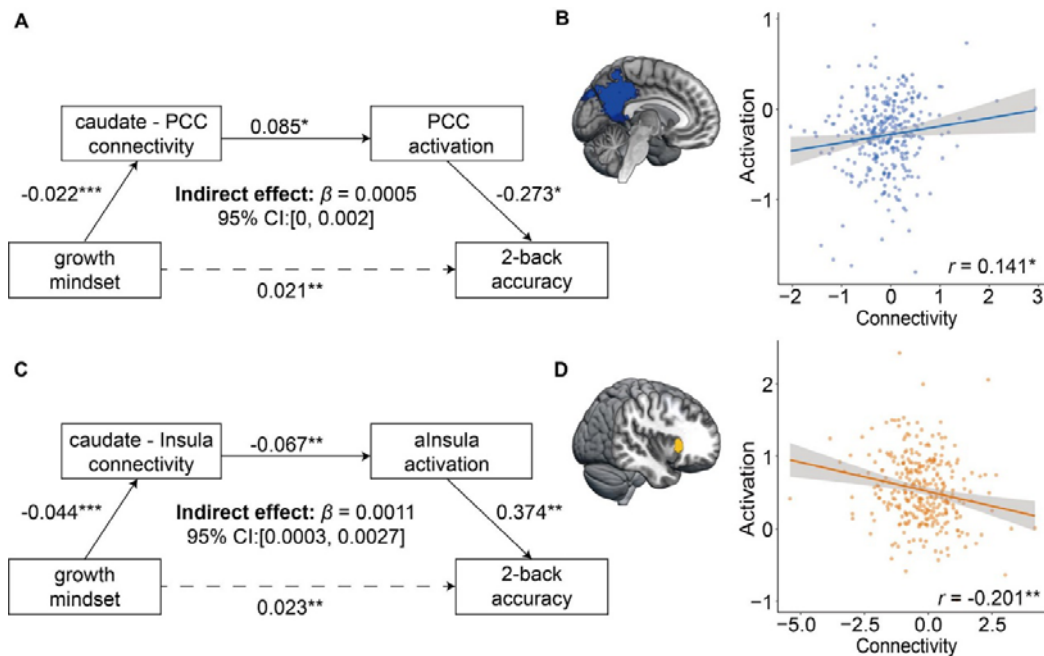
469 **Fig. 4.** Mediation models of ROIs. Activation of regions in SN (dACC and aInsula) and
 470 regions in FPN (FEF and IPS) from 2- > 0-back contrast showed a significant indirect
 471 effect in the association between mindset score and accuracy in 2-back task (n = 306).
 472 Age and gender were set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

475

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

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

484 contrast ($r = -0.201$, $p < 0.001$) (**Fig. 5D**). This caudate-cortical information
 485 processing may also serve in the effect of growth mindset to performance. Further
 486 chain mediation analysis supported this assumption: for processing in PCC, higher
 487 growth mindset level was linked to lower caudate-PCC connectivity, which then
 488 related to lower PCC response, and caused higher accuracy in 2-back condition
 489 (indirect Est. = 0.0005, 95% CI = [0, 0.002]) (**Fig. 5A**); for processing in insula, higher
 490 growth mindset level related to lower caudate-insula connectivity, but then caused
 491 higher aInsula response, and led to higher accuracy in 2-back condition (indirect Est.
 492 = 0.001, 95% CI = [0.0003, 0.003]) (**Fig. 5C**). Parallel analyses for low workload
 493 condition and precuneus region were also conducted but found no effects. Other
 494 alternative models showed null effects. These results further expanded the mediation
 495 effect through caudate-cortical interaction, and implicated that caudate-cortical gating
 496 affects cortical response in reaction to change in information processing.



497
 498 **Fig. 5.** Mediation models of connectivity and activation in PCC/insula. **A.**
 499 Caudate-PCC connectivity and activation in PCC showed a significant indirect effect in
 500 the association between mindset score and accuracy in 2-back condition. **B.**
 501 Representation of PCC ROI and correlation between caudate-PCC connectivity and
 502 PCC activation. **C, D.** same as **A, B**, but in insula region. Age and gender were set as

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

505

506

507 **Discussion**

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

521

522 **Growth mindset promotes working memory performance**

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

537 The neurocognitive mechanisms underlying this phenomenon are subsequently
538 discussed below.

539

540 **Growth mindset facilitates working memory via enhancing FPN and SN activity**

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

550 Similar to current results, increasing activation within FPN and SN was observed
551 under high cognitive demand (Dima et al. 2014), and predicted higher accuracy
552 (Taghia et al. 2018). The enhanced neural response in these cortical regions reflects
553 higher efficiency of information processing within working memory, but in distinct
554 ways. It has long been recognized that frontal and parietal regions are critical for
555 maintaining and adaptively updating information during working memory process
556 (Cohen et al., 1997; Roth et al., 2006). In detail, both FEF and IPS top-down control
557 attention towards target stimuli during cognitive demanding task (Bressler et al.,
558 2008), while also serving to maintain and update memory representations (Takahama
559 et al., 2010). Among frontal regions, FEF is considered to direct response and control
560 sensory systems regarding working memory content (Badre and Nee 2018). Posterior
561 regions such as IPS are especially involved in symbolic manipulation (Davis et al.,
562 2018) and number processing (Bugden et al., 2012). Higher involvement of
563 fronto-parietal regions in the demanding condition indicates more effortful updating
564 and maintenance, together with increased control over the sensory-motor system.
565 Distinct from FPN, anterior cingulate and insula cortex detect salience and regulate
566 access to attentional resources depending on task demand (Taghia et al. 2018). During

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

572

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

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

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

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

597 fronto-parietal activity (Nir-Cohen et al. 2020). Though this cortico-striatal interaction
598 is supported by evidence of coactivation and interventions (McNab and Klingberg
599 2008; Baier et al. 2010; Broadway et al. 2018), few studies directly tested this
600 coupling. One study observed increased frontostriatal coupling during high-level
601 context updates (Nee and Brown 2013), and another study observed little evidence of
602 input gating (Chatham et al. 2014). In contrast to the necessity to constrain
603 information from competing information in these studies, the high workload condition
604 in the current study calls for a lower level of gating but higher efficiency of updating.
605 Future studies comparing different contexts of working memory may clarify this
606 discrepancy. Thus, we proposed that decreased coupling predicted by growth mindset
607 reflects more input information and less controlled gating.

608

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

611 Changes in the input-gating process triggered higher involvement of insula while
612 higher deactivation in PCC. On one hand, rapid updating of working memory content
613 offers more task-related information in time and allows for a higher possibility of
614 accurate response. On the other hand, this expanded working memory content
615 includes both task stimuli and distractions, calling for more efficient processing in
616 cortical regions. For FPN and SN networks, higher engagement in high workload
617 indicates local assessing of information to guide appropriate behavior. As mentioned
618 above, aInsula is a major afferent cortical hub (Seeley 2019). Within the insula region,
619 related content is assessed to guide salience detection, attention shifting (Wager and
620 Barrett 2017) and update internal estimation (Namkung et al. 2017). As for PCC,
621 task-independent distractions and self-referential thinking are suppressed (Mason et al.
622 2007; Qin and Northoff 2011) to reserve cognitive resources and resist disturbance, as
623 reflected by deactivation in high workload. Taken together, caudate-striatal
624 connectivity and resultant cortical response jointly formed the neurocognitive model
625 by which growth mindset affects working memory performance in children.

626

627 **Limitations**

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

639

640 **Conclusions**

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

651

652 **CRedit authorship contribution statement**

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

660

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668

669 **Data and code availability statement**

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

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

675

676 **Declaration of competing interest**

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

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