Power of self-belief: Growth mindset fosters cognitive development via mesocortical functional coactivation and dynamic reconfiguration

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Abstract

Growth mindset is known for its positive impact on learning, problem-solving, and achievement by fostering the belief that one's abilities can be improved through continuous effort. Theories attributed the promotive effect to its optimization on cognitive and motivational processes, while relevant evidence remained scattered. Although recent studies identified pathways related to growth mindset, we still lack a comprehensive model linking its impacts on cognitive process, brain system dynamics and long-term outcomes. Here, we showed that the growth mindset promoted the development of working memory (WM) through dynamic coordination of the cortico-striatal system and tested its longitudinal effects on decisive processes over three years.

Behaviorally, growth mindset improves WM outcomes via accelerating the latent evidence accumulation process, as revealed by the computational modeling on trial-by-trial WM decisive response. Developmental neuroimaging further revealed that the coactivation of the striatum-cingulo-opercular and fronto-parietal systems plays a significant role in such long-term WM improvements. By leveraging Hidden Markov Modeling on cortico-striatal dynamics, we identified two distinct brain states that explain the relationship between the growth mindset and behavioral improvements. The enhanced while flexible cortico-striatal activity mediated the long-term optimization of growth mindset on the evidence accumulation process in WM. Our findings revealed the optimization of growth mindset on cortico-striatal latent dynamics and, for the first time, established a longitudinal model linking the impact of the growth mindset on neural orchestration to cognitive processes and behavioral outcomes.

Introduction

Growth mindset is known as the belief that one's attributes and skills are malleable and improvable through continuous efforts. Individuals who endorse a growth mindset often demonstrate better performance in a spectrum of cognitive tasks and academic achievement (C. Dweck & Yeager, 2019; Schroder et al., 2017; David S. Yeager et al., 2019). The benefits of endorsing a growth mindset have been found spanning a large range of age groups from childhood to adulthood (Sarrasin et al., 2018a), with most prominent effect in children's math learning and executive functions (Chen et al., 2022; Moser et al., 2011; Wang et al., 2021; David S. Yeager et al., 2019). In contrast to the recent questions towards cognitive training in children, interventions of growth mindset have been recognized to have stable and long-lasting benefits in children (Chen et al., 2022; Ganesan et al., 2024; David S. Yeager et al., 2019). These benefits

could be attributed to changes in motivational processes in goal-directed tasks, as well as more flexible and efficient allocation of neurocognitive resources in executive control (Mangels et al., 2006; Schroder et al., 2014a). Despite decades of research and application in education, our understanding of the underlying developmental neurocognitive mechanisms still remains in its infancy. Understanding the underlying mechanisms of growth mindset can inform the development of optimized interventions and utilize strategies in educational practice.

Both motivational and cognitive theories attempt to elucidate the effect of growth mindset. Theory of motivation hypothesized that the growth mindset is closely related to motivational processes (Ames & Archer, 1988; C. S. Dweck & Master, 2012; Xu et al., 2020). Behavioral models suggest that adopting a growth mindset fosters positive motivational changes in goal orientation and effort belief. This in turn helps children derive satisfaction from the process of learning and motivates them to invest their efforts required to achieve their goals (Blackwell et al., 2007; Xu et al., 2020; David S Yeager et al., 2016). Besides, recent experimental evidence points out the optimization of growth mindset on executive functions, especially attention and working memory. Rule based experiments, for instance, have linked growth mindset with more efficient allocation of attention and effortful coding of task-related stimuli, while suppressing irrelevant information (Mangels et al., 2006; Moser et al., 2011; Schroder et al., 2014b, 2017). However, different designs lead to varied results on the identified cognitive component related to growth mindset. Another concern is that experimental research with small sample size and lack of tests of longitudinal effect is questioned for its generalization performance. The current study utilized a well-designed WM task in healthy children sample with longitudinal design over three years. Stand on solid behavioral evidence, underlying neurocognitive mechanisms were further

explored to test the theories of motivation and cognition in children development.

One fundamental question is understanding how brain systems and networks are nuancedly organized to enable the merits of growth mindset not only for immediate tasks, but also for its long-term outcomes. Several neuroimaging studies have begun to illustrate the importance of the cortico-striatal systems, especially the coordination of dorsal striatum and cingulo-opercular regions. Specifically, activation in the dorsal anterior cingulate cortex (dACC) and striatum is associated with the benefits of growth mindset on cognitive control, likely reflecting sustaining error monitoring and reducing interference from irrelevant stimuli (Chen et al., 2022; Mangels et al., 2006; Moser et al., 2011; Schroder et al., 2017). Moreover, recent studies demonstrate that growth mindset is associated greater functional connectivity of striatum with frontal and cingulo-opercular regions during rest and math task (Chen et al., 2022; Myers et al., 2016). Interestingly, these regions are not just linked to motivation but also involved in higher cognitive control, in order to maintain goal-directed information and suppress irrelevant one (Arulpragasam et al., 2018; Jiang et al., 2015; Yee et al., 2021), namely motivation-cognition interplay. It is thus critical to understand how the striatum and cortical systems are organized to account for the effects of growth mindset on WM performance. Based on above empirical observations, we hypothesize that functional coordination between the striatum and cingulo-opercular network (CON) would play an important role in mediating the effects of growth mindset on WM performance. Given that growth mindset has been linked to long-term improvement in academic performance even in the following semesters in school-aged children (Blackwell et al., 2007; Good et al., 2003; David S. Yeager et al., 2019), we further hypothesize that the striatum and CON systems would serve as a precursor to predict longitudinal improvement in WM processing.

In parallel, we aim to clarify whether the growth mindset contributes to one specific cognitive process. Beyond the conventional measures including accuracy and reaction times, recent advances in computational modeling of trial-by-trial decisive responses enable us to unravel latent computational components in WM processing. Based on the sequential-sampling theory, the n-back task, analogous to speeded decision-making with continuous information updating, can be modeled as an evidence accumulation process in which effective information is derived from moment-to-moment noisy inputs until reaching a threshold to execute a choice (Pedersen et al., 2023; Ratcliff et al., 2016). By applying the Hierarchical Drift Diffusion Model (HDDM) model, this process can be decomposed into several computational parameters pertaining to latent process. Of these parameters, 'drift rate' refers to the speed of accumulating good quality information, reflecting the efficiency to extract evidence for decisive response from continuous inputs (Ratcliff et al., 2016). As such, the HDDM allows us to decipher which latent processes during WM would be most augmented by growth mindset.

The efficiency of dynamic evidence accumulation during WM could be attributed to flexible allocation of neurocognitive resources among large-scale functional brain networks. Such allocation of neural resources has been thought to regulate internal energy supply in an attempt to support information updating (Barulli & Stern, 2013; Hermans et al., 2014) and exhibit a tight link with drift rate (T. Liu et al., 2022; Taghia et al., 2018). Recent advances in dynamical network modeling such as hidden Markov modeling (HMM) have been validated to identify dynamic assembly of multiple brain regions at each time point, outperforming traditional sliding-window approaches (Chang & Glover, 2010; Hutchison et al., 2013). Moreover, this approach

can provide brain state dynamics including occurrence and transitions, thus ideal to probe dynamic functional organization of the cortico-striatal system during WM. We thus hypothesize that dynamic organization of the cortico-striatal system would be crucial to account for coactivation of these systems and its links to the benefits of growth mindset on WM.

To test above hypotheses, we leveraged functional magnetic resonance imaging (fMRI), in conjunction with computational modeling of trial-by-trial decisive responses during N-back task, to investigate the effects of growth mindset on longitudinal WM development in 454 school-aged children (8-15 years old) over three years (**Figure 1A**). Three WM loads were set to obtain task-invoked brain responses. To probe the longitudinal effects of growth mindset on WM development, children were invited back for follow-up measurements each year for growth mindset and WM assessments. A Bayesian hierarchical version of DDM was implemented to estimate latent dynamic decision parameters during WM processing. Brain-wide univariate activation and multiple regression were implemented to identify brain systems and networks linked to growth mindset. Meta-analytic coactivation and inverse reference decoding approaches were used to further examine the specific functions of our identified regions, temporal dynamics of which were then calculated by HMM to obtain latent brain states. Structural equation modeling was used to address how dynamics and coactivation of the cortico-striatal system contributed to the effects of growth mindset on WM development. As expected, we found that a growth mindset could lead to both across-sectional and longitudinal improvement in WM performance, particularly for drift rate under high task-demanding conditions. Such beneficial effects were associated with greater engagement and higher flexibility of the cortico-striatal systems involved in motivational and executive functioning.

Results

Growth mindset promoted WM d' and led to more efficient information processing over three years

We first examined the cross-sectional and longitudinal effects of growth mindset on children's WM performance. WM-loading manipulations and related developmental trajectories are provided in **Supplementary materials**. In the first year, growth mindset was positively correlated with WM d', especially under the 2-back condition (0-back: $r = 0.194$, $p < 0.001$; 1-back: $r = 0.134$, $p = 0.010$; 2-back: $r = 0.213$, $p < 0.001$; **Figure S3**). Linear mixed model analysis for longitudinal data with age and gender as covariates revealed the predictive effect of growth mindset on children's WM d' spanning over three years, with the strongest effect consistently showed up in the 2-back ($\beta = 0.123$, $t = 3.609$, $p = 0.001$) compared to 0- and 1-back conditions ($\beta < 0.120$, $t < 3.104$, $p > 0.003$; **Figure 1G & S4, Table S9**). Multiple comparisons were corrected for the above analyses. Notably, we did not observe any reliable age-related effect on children's growth mindset over development ($\beta = 0.367$, $t = 1.436$, $p = 0.151$).

HDDM was further implemented to unravel the benefits of the growth mindset on the latent cognitive components across three years with model comparisons to select the best-fitting model (**Figure 1C & S5, Table S2**). Among all three free parameters, the drift rate (v) emerged to be positively predicted by growth mindset at the first year (0-back: $r = 0.128$, $p = 0.014$; 1-back: $r = 0.170$, $p = 0.002$; 2-back: $r = 0.190$, $p < 0.001$; **Figure 1I**) and over three years (0-back: $\beta = 0.059$, $t = 2.359$, $p = 0.020$; 1-back: $\beta = 0.091$, $t = 3.987$, $p < 0.001$; 2-back: $\beta = 0.087$, $t = 3.853$, $p < 0.001$; **Figure 1J, Table S10**). Both age and gender were controlled, and multiple comparisons were corrected. These results indicate that the beneficial effects of the growth

mindset on children's WM ability are consistently stronger in high-demand conditions spanning over three years, which stems from more efficient latent evidence accumulation during information updating in WM.

Growth mindset was associated with enhanced activity in WM-related cortico-striatal systems

Next, we aimed to identify the neural substrates underlying the benefits of growth mindset on WM performance over development. To this end, we conducted whole-brain multiple regression analysis for WM-related neural activity maps, with the growth mindset as a covariate of interest at the first visit (Year-1) while controlling for age and gender. For the contrast of 2- with 0-back condition, we observed significant clusters in the dorsal striatum, cingulo-opercular, and frontoparietal regions (**Figure 2A & B, Table S11**). As suggested by the meta-analytic maps, these regions play an important role in executive functions (**Figure 2C**). In line with our hypothesis, we observed that growth mindset at the first visit was positively associated with greater activation in the dorsal striatum during WM, especially localized to the dorsolateral caudate nucleus **(Figure 2B)**. Enhanced activity of cortical regions including the dorsal anterior cingulate cortex (dACC) and right anterior insula (aIns) were also found to be associated with growth mindset, which are core nodes of the CON. We also observed positive correlations with growth mindset in various regions within the fronto-parietal network (FPN), such as the inferior parietal sulcus (IPS), dorsolateral prefrontal cortex (dlPFC), and frontal eye field (FEF). Additionally, there was an opposite correlation with growth mindset in the posterior cingulate cortex (PCC) and bilateral parahippocampus (PHC), which are core regions of the default mode network (DMN). These regions found aligned with the well-recognized triple network model of cognitive control (Cai et al., 2021; Menon, 2011), as confirmed by meta-analysis (**Table S13**).

We also observed a similar pattern in the 2-back versus 1-back contrast, but there were no significant effects for the contrast between 1-back and 0-back.

Beyond the above isolated neural responses, we then applied meta-analytic methods to compare the current results with the cortico-striatal systems from previous literature. With the above dorsal striatum as seed, we first obtained a meta-coactivation map (**blue in Figure 2C & 2D**) and compared it with our current mindset-induced map (see **Methods**). These two maps were highly overlapped, indicating that the cortical coactivation of dACC, aIns, IPS, dlPFC, FEF is frequently observed with the specific dorsal striatum subregion **(Figure 2D; Table S14)**. The meta-analytic decoding approach then revealed a wide overlap of executive function terms between the meta-coactivation map of dorsal striatum and current mindset-induced map. Both growth mindset-induced neural response and dorsal striatum meta-coactivation were primarily associated with terms of task demand and cognitive control, as presented in **Figure 2C**. Though it was more prominent in the meta-coactivation map, both maps also showed relevance with motivation, including “gain”, “reward”, “monetary” and “incentive”.

Together, these results indicate that the growth mindset is associated with greater WM-related activation in the dorsal striatum, and its coactivation with fronto-parietal and cingulo-opercular regions is critical for motivational and executive functioning.

Growth mindset led to more efficient information processing in WM via enhanced coactivation in striatum-CON and FPN

To investigate the relationship between brain activity associated with WM, growth mindset, WM performance, and decision-making processes from a network perspective, we centered our analysis on the striatum, CON, FPN, and DMN regions defined by an independent meta-analysis (**Figure 3A & S6**). Task-invoked activity in these regions was correlated with growth mindset,

behavioral outcomes, and HDDM components separately while controlling for age and gender as covariates of no interest (**Table S15-16**). The drift rate, a key latent process underlying evidence accumulation for WM-related decision-making, was found to be highly correlated with activity in the striatum, CON, and FPN. As we hypothesized, the coactivation of dorsal striatum and CON was positively correlated with growth mindset (striatum: $r = 0.150$, aIns $r = 0.167$, dACC: $r = 0.201$; all $p < 0.01$ corrected) and predicted faster drift rate (caudate $r = 0.201$, aIns $r = 0.232$, dACC $r = 0.172$; all $p < 0.004$ corrected). Additionally, activity in the FPN regions, including dlPFC, FEF, and IPS, was found to be associated with both growth mindset (dlPFC $r = 0.207$, FEF $r = 0.181$, IPS $r = 0.253$, all $p < 0.004$ corrected) and drift rate (dlPFC: $r = 0.124$, FEF $r = 0.218$, IPS $r = 0.223$, all $p < 0.03$ corrected). Among DMN regions, activation in the vmPFC, PCC, and HPC/PHC only showed negative correlations with drift rate (vmPFC $r = -0.224$, PCC $r = -0.151$; HPC/PHC: $r = -0.157$, all $p < 0.01$ corrected), while no association was found in AG ($r = -0.096$, $p = 0.10$). In summary, these results suggest that children held a growth mindset exhibited greater activity in the dorsal striatum and CON, along with the FPN regions, which were predictive of better WM performance and faster drift rates.

To test our hypothesis about how holding a growth mindset improves WM performance and drift rate through functional engagement in the cortico-striatal system, we conducted several mediation analyses using structural equation modeling (SEM). We examined both cross-sectional and longitudinal mediatory effects of the striatum-CON, while also tested the mediatory role of FPN as indicated by above findings. It showed that the coactivation of both the striatum-CON system and FPN mediated the relationship between growth mindset and WM performance (d') at first visit (indirect Est. = 0.039, 95% CI = [0.014, 0.077]; **Figure 3C, D & E; Table S17**). A similar mediatory effect was found in the FPN regions (indirect Est. = 0.043, 95%

CI = [0.015, 0.085]). The coactivation of striatum-CON and FPN also mediated the beneficial effects of growth mindset on drift rate at first visit (striatum-CON: indirect Est. = 0.035, 95% CI = [0.011, 0.075]; FPN: indirect Est. = 0.047, 95% CI = [0.019, 0.089]) **(Figure 3D**; **Table S18**).

More importantly, for the question at issue, we further investigated whether and how coactivation of the striatum-CON and FPN systems at first visit predicts the longitudinal benefits of growth mindset on WM performance and latent dynamic processing after one or two years in children. Although we did not find any direct effect of growth mindset on longitudinal WM performance (d': r = 0.015, RTs: r = 0.033, all p > 0.69), the task-invoked dACC response at the first visit (r = 0.191, p = 0.019) was positively associated with growth mindset, and its response further predicted faster RTs (r = -0.193, p = 0.018) and higher drift rate (r = 0.199, p = 0.014) at Year-2 or Year-3 (on average 1.65 years later), even after controlling for the baseline performance. Such associations only emerged in the dACC response (**Table S19 & S20**). Though task-invoked responses in FPN regions at first visit were associated with faster RTs in longitudinal WM assessment (FEF: r = -0.284, p < 0.001; IPS: r = -0.257, p = 0.002), growth mindset no longer predicted their activity in the longitudinal subgroup (FEF: r = 0.101, p = 0.219; IPS: r =0.148, p = 0.070). Indeed, activity within FPN regions at the first visit showed no association with a growth mindset in the longitudinal assessment. Further mediation analyses for longitudinal data revealed that task-invoked response in the striatum-CON system at the first visit could account for the indirect association between growth mindset and longitudinal improvement in WM performance at Year-2 or Year-3 (indirect Est. = 0.034, 95% CI = [0.005, 0.090]; **Table S21**). Parallel analyses revealed that striatum-CON coactivation could also account for the indirect association between growth mindset and longitudinal improvement in drift rate at Year-2 or Year-3 (indirect Est. = 0.043, 95% CI = [0.008, 0.104]; **Figure 3E; Table**

S22). These results indicate that the striatum-CON systems played a mediatory role in supporting longitudinal improvement in WM performance in youths, especially for the speed of latent evidence accumulation.

Growth mindset supported longitudinal WM improvement via orchestrating temporal dynamics of the coactive and idle brain states

Given the critical role of striatal-CON and frontoparietal coactivation in mediating the benefits of growth mindset on both cross-sectional and longitudinal WM performance observed above, we further investigated how these large-scale cortico-striatal regions are nuancedly organized to support WM processing and then account for longitudinal WM outcomes.

We began by extracting the BOLD time series from 11 specific brain regions to implement the HMM model (**Figure 4A & B**). This led to the identification of eight distinct latent brain states, each with unique temporal and spatial characteristics. By evaluating the likelihood of each state occurring at any given time, we were able to determine the dominant state at each time point (**Figure 4C**). These eight brain states effectively differentiate between the three different workloads of working memory tasks, highlighting the robustness of our model (**Figure 4D, E, S7-9**).

Two of the identified states, states 2 and 3, exhibited notably different temporal and spatial distributions. State 2 was associated with the highest frequency in the 2-back condition and displayed an enhanced coactive spatial pattern across all regions. In contrast, state 3 was more prevalent in low workload conditions and indicated a globally low-activate spatial pattern. Compared to the common state 1, states 2 and 3 showcased distinct brain dynamics supporting high- and low-demand conditions, respectively.

Moreover, we observed a strong correlation between the frequency of states 2 and 3, the growth

mindset, and 2-back performance (**Figure 4F**; **Table S23**). This suggests a potential influence of the growth mindset on the dynamics of latent brain states, particularly in relation to the coactive and idle states.

In order to understand the temporal dynamics of the two dominant states, we calculated their temporal stability across blocks and flexibility within each block for each WM workload (**Figure 5A**; See Methods for details). Temporal stability measures the correlation between blocks within each condition. It shows how stable the latent state is for each condition as it fluctuates among blocks during the task. On the other hand, temporal flexibility summarizes the variances of state within each block for each workload, depicting how one state flexibly responds to target and non-target stimuli under a certain demand level.

Compared to other states (***Table S24-25***), we found that growth mindset and WM performance were specifically correlated with the flexibility and stability of states 2 and 3 under the 2-back condition (***Figure 5B***). While the flexibility of state 1 was only associated with WM d' (r = 0.142, p = 0.036), the flexibility of state 2 strongly correlated with the growth mindset (r = 0.191, p = 0.006), WM d' (r = 0.253, p < 0.001), and drift rate (r = 0.218, p = 0.001). The same was found for the stability of state 3: more stable state 3 temporal dynamics across blocks under 2-back condition was correlated with children's growth mindset (r = 0.161, p = 0.040), WM d' (r = 0.306, p < 0.001), and drift rate (r = 0.283, p < 0.001). These extensive relationships were only found for state 2 and 3. Furthermore, the following mediation models revealed that the promotive effect of growth mindset on drift rate in the first visit could be partly explained by the flexibility of state 2 (indirect Est. = 0.037, 95% CI = [0.012, 0.076]; **Figure 5C**) and stability of state 3 (indirect Est. = 0.042, 95% CI = [0.016, 0.086]; ***Figure 5D***).

Finally, we tested the sequential mediatory role of striatum-CON coactivation and state 2

flexibility in the effect of growth mindset on cross-sectional and longitudinal WM improvement (***Figure 5E-F***). The chain mediation model shows that the growth mindset led to higher drift rate under 2-back condition via the coactivation of the striatum-CON system and the subsequent high flexibility of the coactive state 2 (indirect Est. = 0.018, 95% CI = [0.006, 0.040]). This model extensively explained the longitudinal effect of growth mindset in a subgroup of 155 children with measurements at Year-2 or Year 3 (indirect Est. = 0.013, 95% CI = [0.001, 0.041]): mindset-related enhanced striatum-CON response led to more flexible state 2 dynamics, which predicted higher future 2-back drift rate.

Discussion

This longitudinal study established a longitudinal model linking the subtle modulation of growth mindset on cortico-striatal dynamics with its impacts on cognitive processing. Behaviorally, we observed longitudinal improvements of WM performance in children with growth mindset. This was found to be related with faster evidence accumulation during moment-by-moment information updating, which could persist over three years in young children. These beneficial effects were associated with enhanced activity in the dorsal striatum, cingulo-opercular and fronto-parietal networks. Furthermore, the decoding results revealed that the mindset-induced cortico-striatal activation showed prominent relevance with both motivation and executive functioning. Growth mindset also impacted the latent brain dynamics of the cortico-striatal system, resulting in more flexible coordination during task and more stable idle state across blocks of the same condition. The coactivation of the striatum-CON, as hypothesized, induced higher temporal flexibility of the whole cortico-striatal system, mediated the short- and long-term optimization of growth mindset on WM information processing.

One of our major findings consists of both cross-sectional and longitudinal benefits of growth mindset on children's WM development, which is consistent with previous evidence showing growth mindset predicts a steady increase in mathematics grades over two years (Blackwell et al., 2007). The observed longitudinal effect was consistent across different age groups and remained evident over three years, even after accounting for age-related effects. The most significant positive impact of growth mindset was seen when children were faced with high-demand conditions (i.e. 2-back), as indicated by measures like d-prime and drift rate. This suggests that growth mindset motivates more effortful tasks, as growth mindset interventions can increase challenge-seeking behavior and higher enrollment in advanced math courses (Rege et al., 2020; David Scott Yeager & Dweck, 2012). Likewise, at-risk students tend to benefit more from interventions since they face more challenges and demand more cognitive resources dealing with schoolwork (Sarrasin et al., 2018b; David S Yeager et al., 2016). According to HDDM, higher drift rates indicate higher efficiency of evidence accumulation from low-level perceptual inputs. This optimized information processing caused by growth mindset is further attributed to the motivational modulation of attention control (Moser et al., 2011; Schroder et al., 2017) and encoding (Mangels et al., 2006) of goal-congruent information. By allocating greater attention to task-relevant stimuli before response, growth mindset leads to adaptive behavior in cognitive control tasks with distractors (Schroder et al., 2014a). Thus, it is likely that the beneficial effect of growth mindset is supported by intrinsic motivation along with more efficient unitization of on-task information processing and allocation of cognitive resources to achieve goal-directed tasks.

At the brain activation level, we identified that growth mindset was associated with higher WM-related activation in core regions of the striatal, cingulo-opercular, and fronto-parietal networks.

A similar pattern of results has been seen in the process of intrinsic motivation facilitating high workload performance in WM tasks (Di Domenico & Ryan, 2017; Satterthwaite et al., 2012). Specifically, we identified the dorsolateral caudate nucleus in the dorsal striatum as a potential modulatory target associated with growth mindset in WM tasks. This subregion is critical for children's learning abilities and predicts future learning performance (Peters and Crone, 2017), and it supports goal-directed and motivation-related cognitive control tasks through co-activation with dACC and anterior insula (Arulpragasam et al., 2018; Hedden & Gabrieli, 2010; Pauli et al., 2016). The enhanced involvement of this system, as the coactivation of striatum-CON, was found to mediate both the short- and long-term benefits of growth mindset. This is compatible to the previous detection of mindset-related potentials localized to ACC and aIns (Mangels et al., 2006; Moser et al., 2011) and cortico-striatal coupling (Chen et al., 2022; Myers et al., 2016). As indicated by decoded functional terms, while mindset-related neural response is associated with cognitive control and arithmetic capacity, the striatum-associated system is involved more in the motivational process. This is in line with the role of the dorsal striatum and cingulo-opercular regions in estimating subjective value and modulating goal-directed control (Arulpragasam et al., 2018; Yee et al., 2021). Growth mindset may enhance engagement of the dorsal striatum in high-demanding conditions, leading to more rapid updating of information in the face of challenges and facilitating adaptive behavior (Dahlin et al., 2008; Kühn et al., 2013). Additionally, through the enhanced engagement of dorsal striatum, growth mindset may increase the subjective value of effortful tasks, resulting in greater engagement of subsequent cortical processing (Arulpragasam et al., 2018; Krebs et al., 2012; A. Westbrook et al., 2020). Our findings support previous theories that growth mindset induces adaptive behavior through higher motivation

towards efforts and suggest that growth mindset may promote long-term adaptive adjustment in children through regulating the responses in the dorsal striatum and cingulo-opercular regions.

The latent brain dynamics of cortico-striatal system, coordinated with enhanced responses in striatum-CON, mediated the short- and long-term effects of growth mindset on WM outcomes. The cortico-striatal system fluctuates with task demands, and our HMM results revealed two opposite brain states representing the coactive and idle phases of the cortico-striatal dynamics in the WM task, respectively. These two distinct states aligned with the two crucial roles of cortico-striatal system: The coactive state occurred more frequently during higher workload conditions, assisting with the high cognitive demands to allocate attention to goal-related stimuli and allowing for more efficient information processing. In contrast, the idle state showed a higher frequency in low-demand conditions, during which the entire cortico-striatal system was less involved in the task to reserve cognitive resources. The higher stability of this idle state across blocks of the same workload implies low frequent and stable attentional lapses during sustained attention, which minimizes its inevitable influences (Adam et al., 2015; Bindra, 1978). A more stable idle state thus partly mediated the benefits of growth mindset to WM performance. On the other hand, the high temporal flexibility of the coactive state indicates that, although the cortico-striatal system remained highly involved throughout each high-demand block, it still fluctuated with real-time demand to keep updating and filtering information. According to the gating theory, such temporal flexibility may reflect the filtering mechanism of cortico-striatal circuit, as it acts as a gate to select input information from stimuli streams to cortical WM (Chatham et al., 2014; Chatham & Badre, 2015), with external stimuli being evaluated by striatum, and weighted information initiating cortical cognitive process (Pasupathy & Miller, 2005; Andrew Westbrook et al., 2021). The maturation of this fine-tuning circuit in adolescents results in better future

performance (Darki & Klingberg, 2015; Ullman et al., 2014; Willinger et al., 2021). In contrast, failures of adequate control over impulsive urges were associated with abnormal interactions between cingulo-opercular and dorsal striatum (Zhukovsky et al., 2020).

The enhanced neural response in striatum-CON allows for such high flexibility. The dual-network model proposes that the CON specifically provides set maintenance and keeps tonic alertness over a long-time scale compared with FPN (Dosenbach et al., 2008; Sadaghiani & D'Esposito, 2015). Furthermore, interacting with striatum, the CON also engages in attention allocation and behavior modulation in response to motivationally salience stimuli (Peters et al., 2016; Willinger et al., 2021). In comparison to the top-down modulation in FPN, the striatum-CON system supports bottom-up control, which mostly depends on the cortico-striatal interaction and initiates dACC activity (Jiang et al., 2015; Shulman et al., 2009). Mindset-related striatum-CON engagement thus qualified children with both sustained set-maintenance and enhanced bottom-up input control, resulting in higher efficiency of evidence accumulation. Based on these theories and evidence, we assume that the striatum-CON system serves to flexibly integrate motivational signals with sensory inputs to guide adaptive behavior, through which growth mindset achieves its long-term effect on future performance.

Several limitations should be warranted when interpreting our findings. First, though we recruited children from schools by the same standard, many other variables, such as motivation, intelligence, and general cognitive capabilities, should be taken into account in future studies. Second, the cortico-striatal functional circuitry is highly dependent on dopaminergic modulations. Future studies should account for dopaminergic projections from different subregions of caudate and other striatal regions with higher spatial resolution. Third, although we have identified key regions and pathways involved in WM in relation to growth mindset, the neurobiological

mechanisms of how growth mindset affects the maturation of large-scale functional brain networks and cognitive development of other domains should be further investigated.

In conclusion, our study demonstrates the pivotal role of the dynamic coordination of cortico-striatal system in the longitudinal benefits of growth mindset on children's cognitive computations. Growth mindset appears to provide a precursor by acting on core nodes of the cortico-striatal motivational and cognitive networks to promote evidence accumulation efficiency and performance outcomes in the future. Our findings suggest a computational neurocognitive account for how growth mindset promotes cognitive development via functional orchestration of distributed cortico-striatal coactivation, which can eventually inform further utilization of growth mindset in promoting learning and education programs.

Methods and materials

Participants

A total of 748 measurements in 454 school-aged children (ranging from 8 to 15 years old) were included in this study, which was derived from the Children School functions and Brain Development Project (CBD, Beijing Cohort). At their first visit, 375 children (mean age ± SD = 9.833±1.039) underwent fMRI scanning while they were performing the N-back task and completed the growth mindset assessment. The average interval between MRI scan and growth mindset assessment was around two months (63 ± 59 days). Children with excessive head motions (more than 1/3 frames with standardized DVARS >1.5 or frame displacement > 0.5) or incomplete scanning were excluded from further analyses **(Figure S1)**. A final sample of 306 children was included in the brain imaging analysis.

In the follow-up test, a subsample of 229 and 144 children were invited back to perform the WM

n-back task in the second and third year respectively **(Figure 1A and 1D)**. To investigate the neural substrates underlying the longitudinal effect of growth mindset on WM development, only children who had high-quality fMRI data at their first visit, along with completed follow-up WM tests, were considered. If children were retested in both the second and third years, the latter observation was selected to represent the longitudinal WM performance with a longer time lag, which resulted in 153 children for the longitudinal subset. Demographic information is summarized in **Table S1**. The written informed consent form was obtained from each child 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.

Growth mindset assessment

The Growth Mindset Scale (GMS) (adapted from Dweck, 2006) 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). Children aged 9 years old and above completed the questionnaire independently, and children under 9 completed the questionnaire with their parental or assessor's assistance. The final scores range from 0 to 60, with higher scores representing a higher growth mindset level.

N-back WM task

A classic numerical N-back task was used to assess participants' WM performance **(Figure 1B)**.

This task consisted of three conditions with three different workloads (i.e., 0-back, 1-back, and 2-back), and each condition consisted of 4 blocks. In each block, participants first viewed a 2-second cue that indicated the workload of this block (i.e., 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 judge whether the current item on the screen was "1" or not by a button press. In the 1-back condition, participants were asked to judge whether the current item was just the same as the previous one. In the 2-back condition, participants needed to judge whether the current item was the same as the one at two positions back. Stimuli were presented via E-Prime 2.0 (http://www.pstnet.com; Psychology Software Tools, Inc., Pittsburgh, PA). Both participants' response and reaction times (RTs) were recorded. We computed participants' behavioral performance based on their responses.

Behavioral performance

The behavioral performance was assessed by the discrimination ability of d-prime (d') based on the signal detection theory (Green & 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 the hit rate or false alarm rate was equal to 0 or 1, modified values 0.01 or 0.99 were used instead. This *d'* measurement was used to assess participants' WM performance together with RT in all analyses.

Behavioral statistical analysis

Behavioral measurements were analyzed with R (version 4.0.2, https://www.r-project.org, Platform: x86_64-apple-darwin17.0 (64-bit)). We used the linear mixed model to evaluate the effect of growth mindset across three years using the lme4 package in R (Bates et al., 2015). The linear mixed model allows us to test the fixed effects (group-level effect across longitudinal repeats or years in the current study) while controlling for random effects that vary across participants. We first compared models with age and gender as predictors to validate the developmental trajectory of each behavioral measurement. We then constructed a null model with only a fixed intercept and a random intercept to account for the repeated measurements. We further compared the null model with a gender model, a linear age effect model, and a quadratic age effect model. After determining the developmental trajectory for each behavioral measurement, we tested the effects of growth mindset on behavioral performance over age and gender. Models were fitted with the maximum likelihood (ML) estimation method. Model comparison was based on both Akaike Information Criterion (AIC) and Bayesian information criterion (BIC).

Mediation analysis

Before mediation analysis, we calculated the correlation coefficients of each ROI activation with mindset levels, WM performances, and HDDM parameters. After correcting for multiple

comparisons using FDR, networks with at least one region related to mindset and behavioral outcomes were sent for further mediation analysis. We conducted and statistically tested all mediation effects using Mplus 8.3 (Muthén & Muthén, 1998). Firstly, the structural equation models were constructed to examine whether the overall FPN and striatum-CON coactivation mediated the influence of growth mindset on current and future working memory performance separately. Based on the results from connectivity analysis, we constructed specific models to investigate how growth mindset influences current and future latent decision-making processes (drift rate) through cortico-striatal interaction and regional response in the insula. Because the effect of age and gender had already been controlled in each analysis of activation and connectivity, these two covariates were included in the equation of behavioral outcomes. The fitness of each model was assessed using a $\chi 2$ test, which showed no significance. In addition, the Root Mean Square Error of Approximation (RMSEA) was found to be below 0.08, the Standardized Root Mean Square Residual (SRMR) had an outcome value of less than 0.08, and the Comparative Fit Index (CFI) was above 0.90. For all models, a number of 5000 draws were done for bootstrap, and 95% confidence intervals were estimated. If the confidence interval did not include zero, the effect was considered significant.

HDDM for N-back task

The DDM describes decision-making as an evidence-accumulation process in which individuals continually accumulate effective evidence from the environment until they reach an internal threshold to make a final decision. Based on trail-by-trail RTs and accuracies, the DDM decomposes participants' decision-making performances into latent processes, which were indicated by three free parameters: drift rate (v), decision threshold (a), and non-decision time (t) (Wiecki et al., 2013). It is widely utilized in two-choice decision tasks but is also extendedly

implemented for one-choice tasks such as Go/no-Go tasks (Ratcliff et al., 2018; Zhang et al., 2016) and N-back tasks (L. Liu et al., 2022). In such paradigms, only trail-by-trail RTs for hits and false alarms were fitted for the DDM, while RTs of misses and correct rejections cannot be measured. For the current N-back task, the latent process is represented by participants accumulating evidence during a series of digit stimulus presentations to decide whether the current digit is the same as the digits that appear one or two points before in the sequence and then make the corresponding response. We estimated the DDM parameters by HDDM because it is more applicable to the case of relatively few trials and is able to estimate both group-level and individual-level parameters by drawing individual parameters from the group distribution. In this way, we can obtain group- and individual-level parameters for three workloads at three time points under the current paradigm. Note that models were estimated using all data with test timepoint and workloads were set as factors.

To exclude the effect of different incorporated parameters on the results, we fitted seven models with the same data, including models of a, v, t, av, at, vt, avt. For each model, Markov chain Monte Carlo (MCMC) sampling method was applied to generate 20,000 samples and discard the initial 2,000 samples as burn-in for performing Bayesian inference. We then compared the models based on the deviance information criterion (DIC) (Spiegelhalter et al., 2002). The model with the lowest DIC value was considered to have the best fit. Gelman-Rubin statistics were further employed to assess the convergence of the model. The r-hat values for each parameter were close to 1.0 and less than 1.1, indicating good convergence (Wiecki et al., 2013). Finally, the three individual-level parameters of the best-fit model (avt) were submitted to subsequent analyses (**Figure S5 & Table S2**).

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 from two sites. 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 WM task consisted of 232 volumes and lasted for 464s. Two different sites were included as a nuisance for fMRI data analyses.

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 for further analyses (n = 22).

General linear model (GLM) analysis

To identify WM-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 including 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 and white matter 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, and 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 children's growth mindset as a covariate of interest, gender and age as nuisances. Coefficients of the multiple regression maps 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/).

Meta-analytic coactivation and decoding

The meta-analytic coactivation map is a kind of meta-analog of functional connectivity map and is generated by the Neurosynth platform (http://neurosynth.org) based on the coordinates of seed regions. Our analysis is seeded in a 6-mm sphere centered on the coordinates of peak activity in the bilateral caudate nucleus identified by the multiple regression analysis for WM-related brain activity (2- versus 0-back contrast) with the growth mindset as a covariate of interest. The map reflects coactivation of brain regions across studies in the Neurosynth database and voxels with high Z values in the map are likely to be activated in similar studies as the seed voxels. The final coactivation mask only included clusters with more than 10 voxels satisfied Z > 3 ($p < 0.001$) in coactivation maps of both the left and right caudate nuclei. Subsequently, we overlapped the coactivation mask with the multiple regression results of growth mindset for comparison and visualization purposes. Mask of multiple comparisons only included continuous clusters with

more than 10 voxels passed the threshold of $p < 0.05$ corrected for multiple comparisons using FDR in the 2-back > 0-back contrast.

We then uploaded these two masks to the Image Decoder based on the Neurosynth database to identify the most related terms of brain response. The top 10 functional terms whose neural response showed the highest correlation with the current mask were presented. Because five terms were decoded in both masks, the final result presented 15 terms in total. Note that the redundant or anatomical terms were not included (e.g., “working memory” was presented, and “working” or “caudate” were removed).

Regions of interest (ROIs) analysis

ROIs of three functional brain networks were generated from meta-analysis images using the Neurosynth database. We searched for the meta-analysis maps related to terms “working memory” and “default mode”, and converted the maps to masks only including clusters with more than 10 voxels satisfied $Z > 3$ ($p < 0.001$). The whole-brain result and meta-analysis results were also overlapped for comparison and visualization.

Based on this criterion, we then picked the caudate nucleus for the striatum, anterior Insula (aIns), and dorsal anterior cingulate cortex (dACC) for the CON from the meta-analysis map of the term “working memory”. These regions in the striatum-CON system were responsible for motivational response during cognitive tasks as aforementioned. For the FPN, dorsal lateral prefrontal cortex (dlPFC), frontal eye field (FEF), and inferior parietal sulcus (IPS) were selected from the same map. Likewise, 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, the 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: caudate for striatum; aIns and dACC for CON; dlPFC, FEF, and IPS for FPN; vmPFC, AG, PCC, and HCP/PHC for DMN **(Figure 3A & S6)**. Parameter estimates from each ROI, and each participant was extracted from the individual-level contrast of 2-back with the 0-back condition using the MarsBaR (http://marsbar.sourceforge.net/) to characterize activation during the task in each ROI.

Hidden Markov Model (HMM)

We implemented the HMM to model the spatiotemporal brain dynamics within the mesolimbic and frontoparietal systems with which children meet the changing requirements and demands during the WM task. The HMM captured a set of distinct brain states from the multidimensional input signals extracted from 11 ROIs within striatum-CON and FPN. These brain states were determined using Gaussian distribution, taking into account the mean of each dimension and covariance among dimensions. The HMM-MAR toolbox (https://github.com/OHBA-analysis/HMM-MAR) was utilized to estimate the changing brain configurations underlying the data. To decide on the final number of states, we compared the models of 8, 10, and 12 states and selected the model whose output best aligned with our predefined workload changes. Through model comparison, we confirmed that the temporal features of 8-state outputs are sufficient to cover the neural dynamics of three workloads, while the others with higher than 8 states have inefficient states that were rarely active throughout the whole task. After deciding the final number of states, the Viterbi algorithm was used to obtain the maximum a posteriori probability path. As shown in **Figure 4**, the final temporospatial outputs included the decoded mostly likely sequence of hidden states, the frequency of occurrence for each state under each condition, the transition matrics among the 8 states, and the spatial features of each state within the predefined brain system. The temporospatial features were then correlated with behavioral

indices to select our interested states for further analysis, and the occurrence probability was used to calculate the temporal stability and flexibility of each state sequence.

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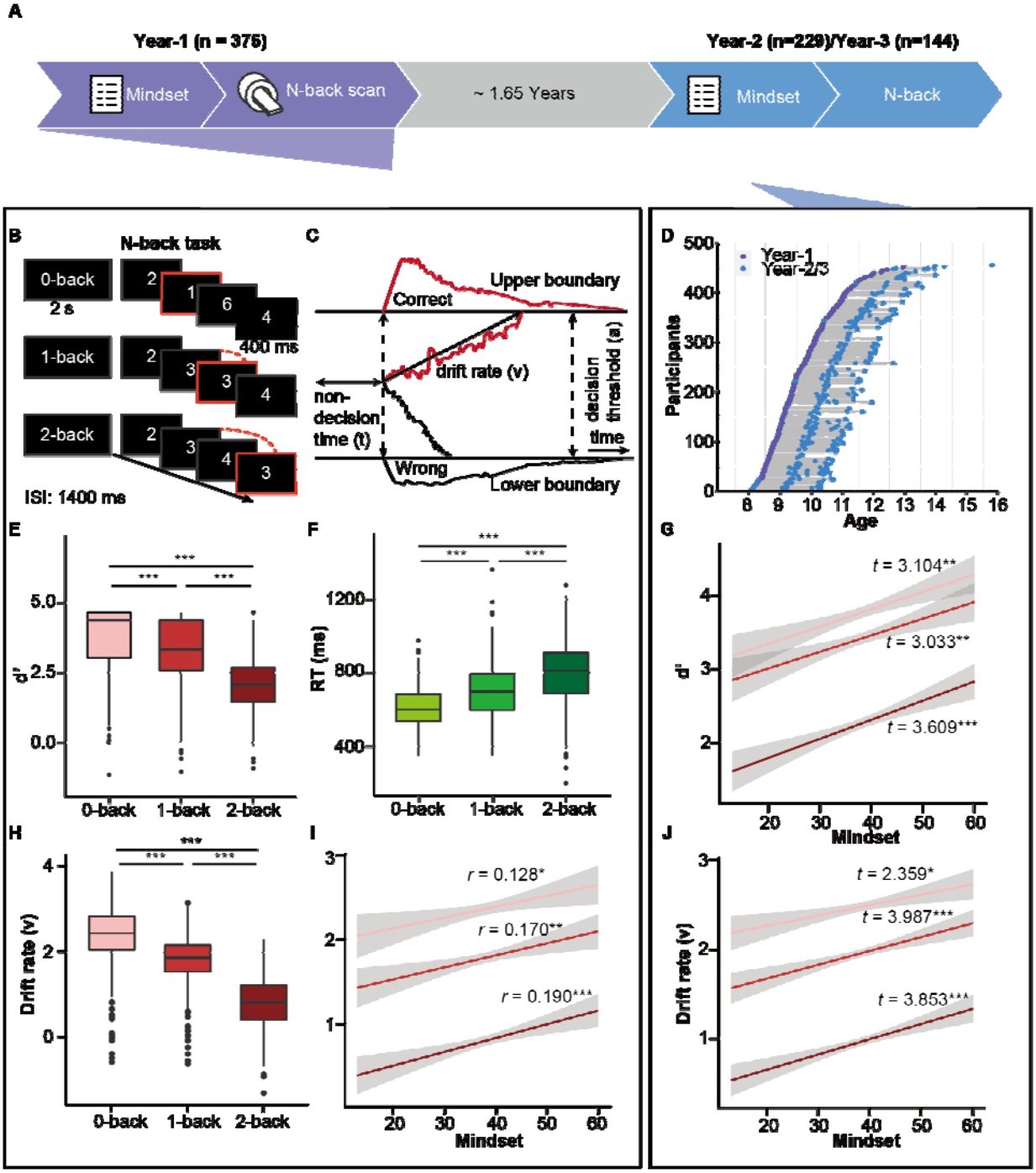

Figure 1. Growth mindset improved WM development spanning over three years in school-aged children. (A) *Longitudinal experimental design across three years, testing effects of growth mindset on WM development and its underlying neurocognitive substrates. Both behavioral and fMRI data were obtained in Year-1. A subsample of children was invited back for growth mindset*

and N-back tasks in Year-2 and/or Year-3. ***(B)*** *A schematic view of the numerical N-back task with three WM loads.* ***(C)*** *An illustration of the HDDM with three free parameters: drift rate (v) indicates the speed of evidence accumulation, decision threshold (a) is the boundary for the final choice, and non-decision time (t) reflects other processes like early stimulus encoding. The red and black lines represent the correct and incorrect decision paths, respectively.* ***(D)*** *Age distribution of children at each visit. Each dot represents one child at the time of tests. Dots of the same child are connected with lines.* ***(E-F)*** *Boxplots of discrimination indices (d') and reaction time (RTs) during WM in Year-1. The thick black line in each box represents the median, with the 25th and 75th percentiles.* ***(G)*** *Growth mindset predicts WM d' across three years ($N_{total\ observation} = 748$). Different shades of red represent WM workloads.* ***(H)*** *Boxplot of drift rate (v) in Year-1.* ***(I-J)*** *Growth mindset positively correlated with drift rate under three WM loads in Year-1, which further carried over across three years. Age and gender were controlled. Shading represents a 95% confidence interval (CI). Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, Bonferroni-corrected.*

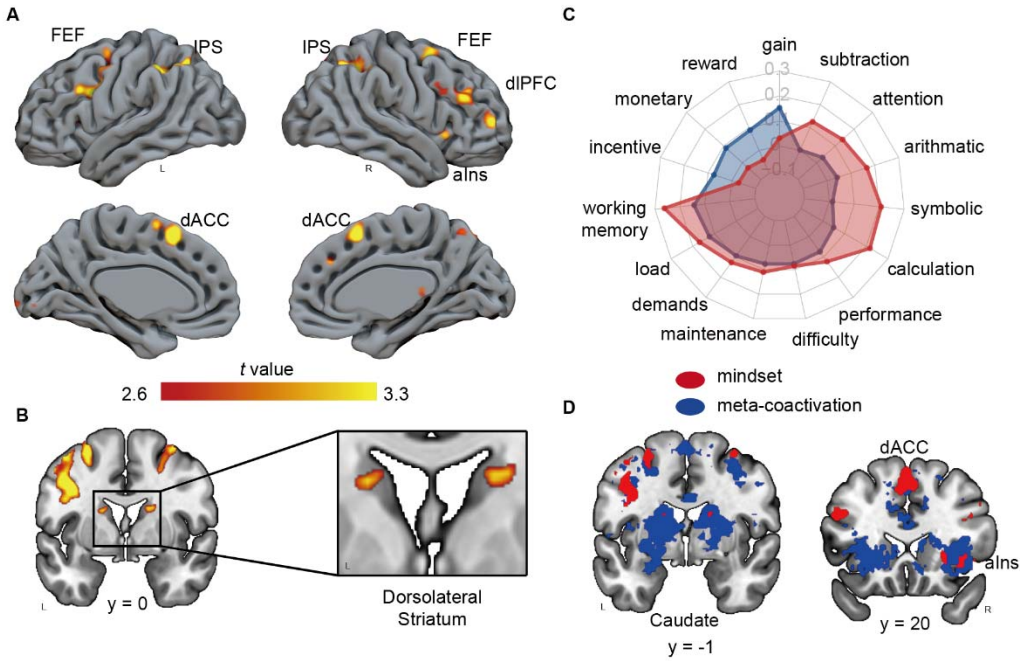

Figure 2. Brain systems associated with growth mindset under high WM task demands. (A, B) *Significant clusters from multiple regression analysis for the contrast map of 2- with a 0-back condition show positive correlations with growth mindset at the first visit. (**C**) Meta-analytic decoded terms showing highest correlation with neural response of growth mindset (red) and coactivation (blue) map with the dorsal dorsolateral caudate. Correlation (r) in the polar chart depicts the similarity between term-related neural response and decoded map. (**D**) Overlap of growth mindset-related regions (red) and meta-analytic coactivation of the dorsolateral caudate (blue). Notes: dlPFC: dorsal lateral prefrontal cortex, FEF: frontal eye field, aIns: anterior insula, IPS: inferior parietal sulcus, dACC: dorsal anterior cingulate cortex.*

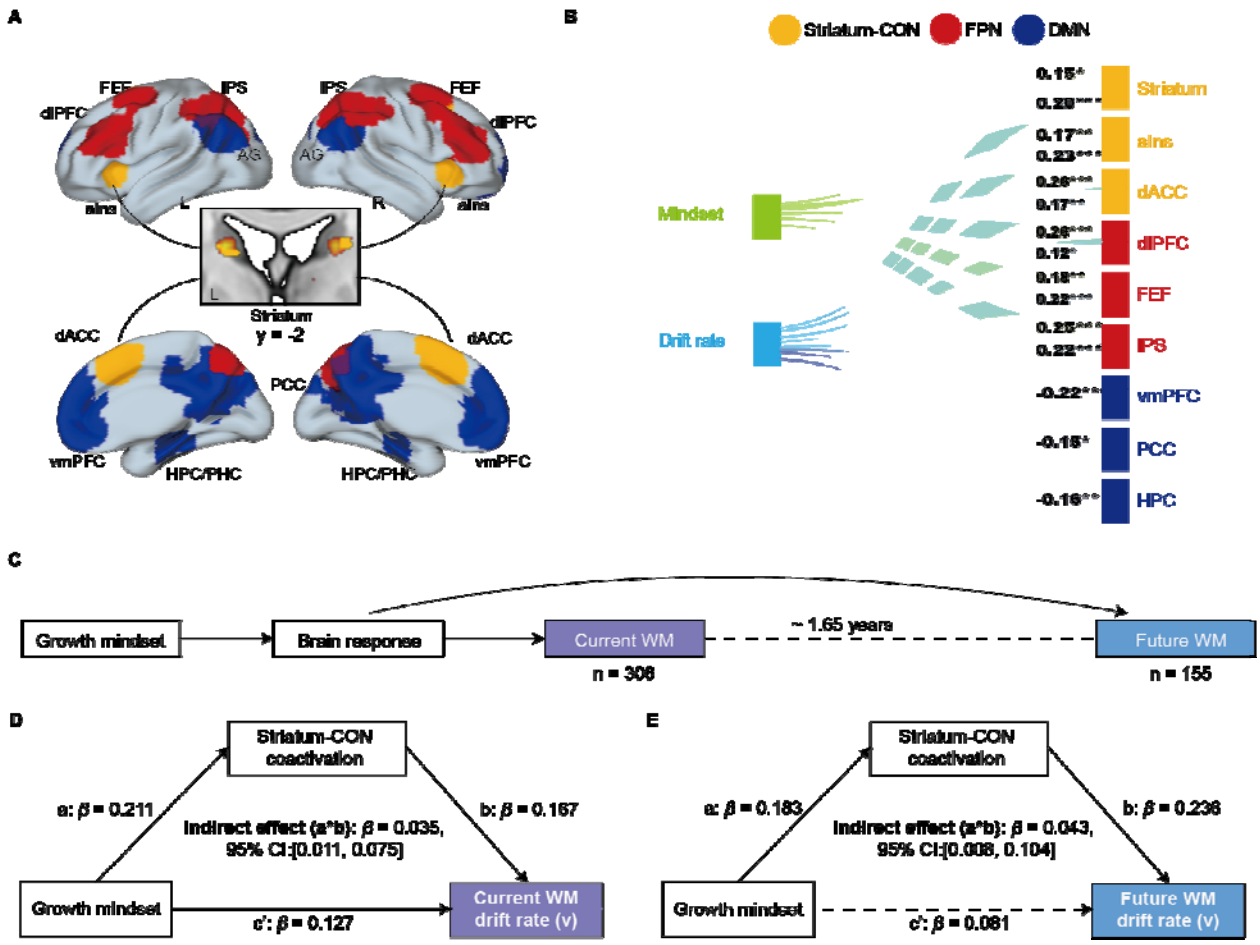

Figure 3. Growth mindset improves cross-sectional and longitudinal WM drift rates via striatal and CON network coactivation. (A) *ROIs are defined for striatum-CON (yellow), FPN (red), and DMN (blue). Regional response under 2-back compared to 0-back conditions were exacted from each ROI for further analysis.* ***(B)*** *Flow diagram of correlation of neural activity in each ROI with the mindset and drift rate at first visit. Both mindset and performance were positively correlated with the striatum-CON and FPN ROI activation. We used the drift rate in the 2-back condition regarding its high correlation with growth mindset compared to the 1-back condition. Age and gender were set as covariances, and all p values were corrected for multiple comparisons using FDR correction. ***p < 0.001, **p < 0.01, *p < 0.05, n.s.: no significance.* ***(C)*** *The framework of cross-sectional and longitudinal imaging data analysis. The mediatory*

role of mindset-related ROIs, as revealed by partial correlation, was examined in both current and future performance. The average length of intervals between the first and second tests (Year-2 or Year-3) is around 1.65 years. ***(D, E)*** *Mediation models of striatum-CON coactivation in the cross-sectional and longitudinal promotive effect of growth mindset on WM drift rate. Activation in the cortico-striatal system during the 2-back compared to the 0-back condition mediated the beneficial effect of the growth mindset on drift rate in the primary test. Furthermore, the mindset-related striatum-CON engagement also predicted a higher drift rate in the future task. Age and gender were set as covariates.*

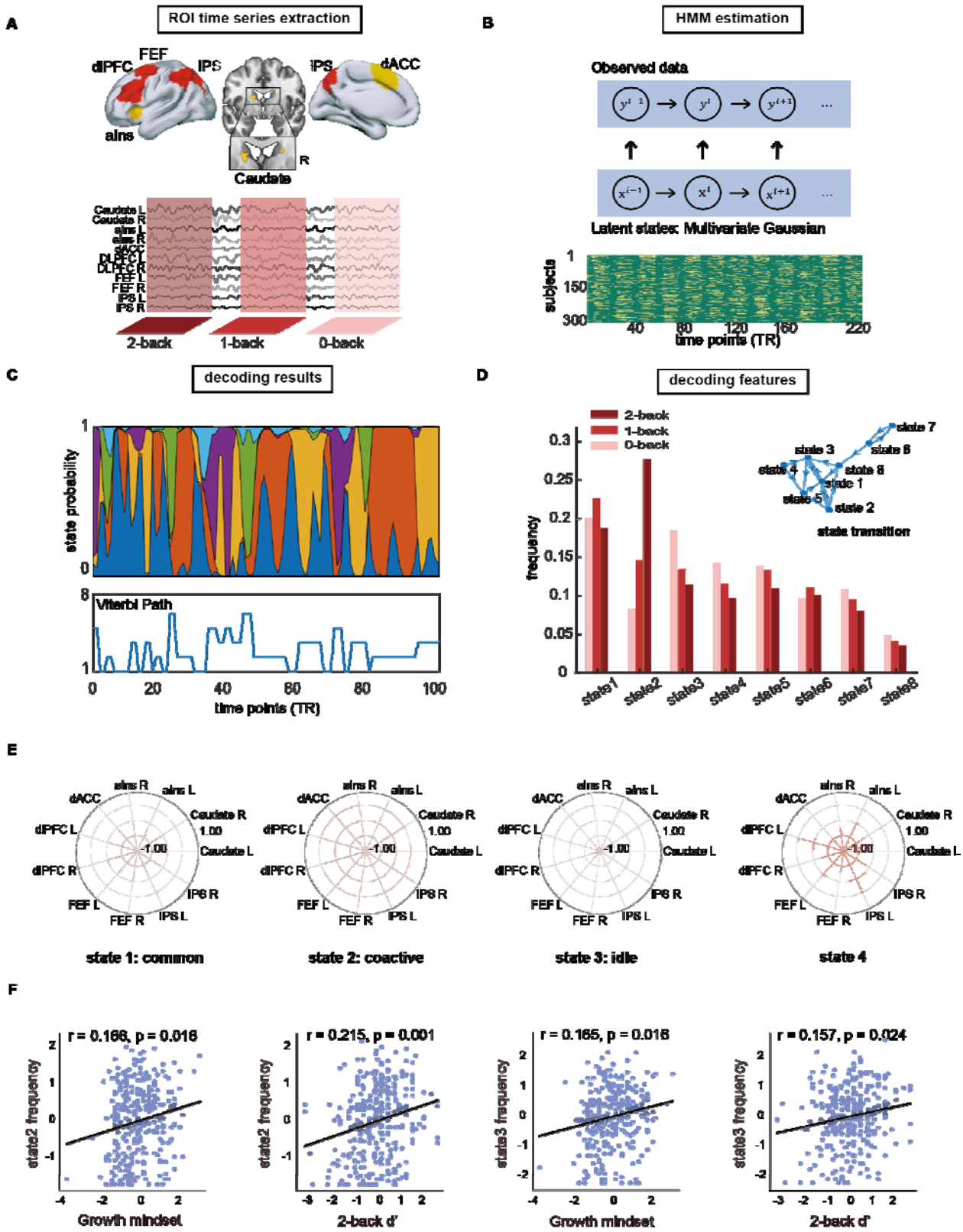

Figure 4. Spatiotemporal features of the hidden brain states under WM task. (A) The

*schematic plot of the time series extraction process. Time series from key nodes of the striatum-CON and FPN were extracted to estimate the hidden network dynamics under varied workloads. (**B**) The schematic diagram for HMM estimation. (**C**) The decoded state probability at each time point throughout the task. The Viterbi path depicts the most likely sequence of hidden states. (**D**) The frequency of each hidden state under each workload. (**E**) The spatial pattern of the first four states with the highest frequency throughout the task. The value of each area represents the relative activity magnitude referring to the mean value. (**F**) Regression plots between state frequency and behavioral indexes. Shading represents 95% CI. Each dot represents one subject's score on the first test.*

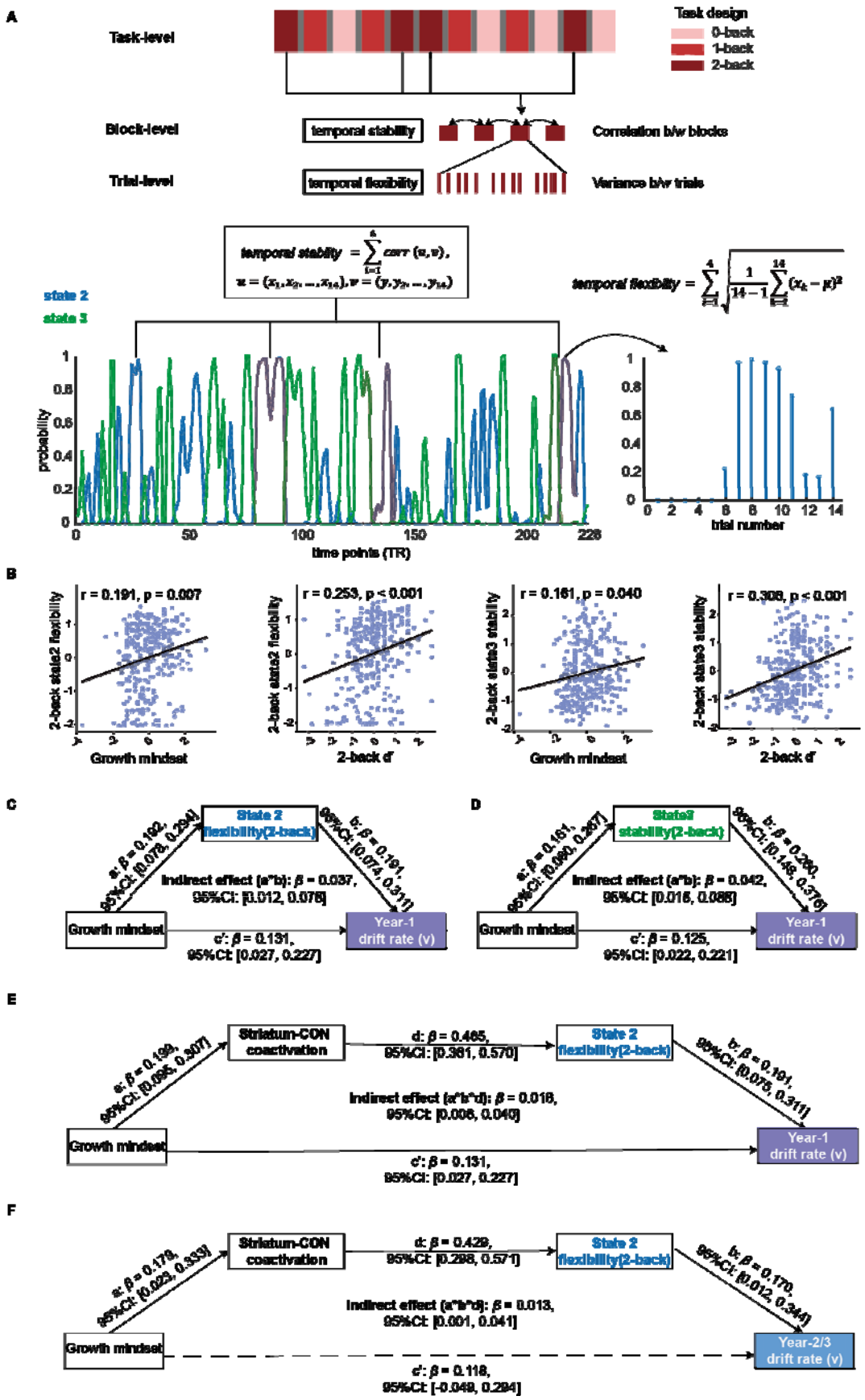
A
Task-level
Task design
0-back
1-back
2-back
Block-level
temporal stability
Correlation b/w blocks
Trial-level
temporal flexibility
Variance b/w trials
temporal stability = $\sum_{i=1}^{6} corr(u,v)$, $u = (x_1, x_2, \ldots, x_{14}), v = (y_1, y_2, \ldots, y_{14})$
temporal flexibility = $\sum_{i=1}^{4} \sqrt{\frac{1}{14-1}\sum_{k=1}^{14}(x_k-\mu)^2}$
state 2
state 3
probability
time points (TR)
trial number
B
r = 0.191, p = 0.007
2-back state2 flexibility
Growth mindset
r = 0.253, p < 0.001
2-back state2 flexibility
2-back d'
r = 0.161, p = 0.040
2-back state3 stability
Growth mindset
r = 0.308, p < 0.001
2-back state3 stability
2-back d'
C
State 2 flexibility(2-back)
a: β = 0.192, 95%CI: [0.078, 0.294]
b: β = 0.191, 95%CI: [0.074, 0.311]
Indirect effect (a*b): β = 0.037, 95%CI: [0.012, 0.076]
Growth mindset
c': β = 0.131, 95%CI: [0.027, 0.227]
Year-1 drift rate (v)
D
State2 stability(2-back)
a: β = 0.161, 95%CI: [0.060, 0.267]
b: β = 0.260, 95%CI: [0.148, 0.376]
Indirect effect (a*b): β = 0.042, 95%CI: [0.016, 0.086]
Growth mindset
c': β = 0.125, 95%CI: [0.022, 0.221]
Year-1 drift rate (v)
E
Striatum-CON coactivation
a: β = 0.199, 95%CI: [0.086, 0.307]
d: β = 0.465, 95%CI: [0.361, 0.570]
State 2 flexibility(2-back)
b: β = 0.191, 95%CI: [0.075, 0.311]
Indirect effect (a*b*d): β = 0.018, 95%CI: [0.006, 0.040]
Growth mindset
c': β = 0.131, 95%CI: [0.027, 0.227]
Year-1 drift rate (v)
F
Striatum-CON coactivation
a: β = 0.178, 95%CI: [0.023, 0.333]
d: β = 0.429, 95%CI: [0.298, 0.571]
State 2 flexibility(2-back)
b: β = 0.170, 95%CI: [0.012, 0.344]
Indirect effect (a*b*d): β = 0.013, 95%CI: [0.001, 0.041]
Growth mindset
c': β = 0.118, 95%CI: [-0.049, 0.294]
Year-2/3 drift rate (v)

Figure 5. Temporal flexibility and stability of states 2 and 3 supported the promotive effect of growth mindset on cross-sectional and longitudinal WM improvement. *(**A**) The calculation of temporal stability and flexibility with states 2 and 3 as examples. Blue lines: state 2 probability throughout WM task; Green lines: state 3 probability throughout WM task. (**B**) Regression plots between behavioral performances and state temporal dynamics. Shading represents 95% CI. Each dot represents one subject's score on the Year-1 test. (**C, D**) Mediation models of state 2 flexibility and state 3 stability under the promotive effect of growth mindset on 2-back WM drift rate at the Year-1 test. (**E, F**) Chain mediation models with striatum-CON coactivation and state 2 flexibility as sequential mediators.*