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Children with ADHD recruit perceptual over meaningful memory

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Abstract: Memory is formed through two distinct forms: reactivation of perceptual traces and meaningful reconstruction into conceptual representations. How memory diverges across development remains unclear in humans. Here, we applied representational similarity analysis (RSA) to electroencephalography (EEG) data from 114 children with attention deficit/hyperactivity disorder (ADHD) and 109 typically developing (TD) children (aged 6–12 years) while they performed a recognition memory task. We revealed distinct neural mechanisms for perceptual memory and meaningful memory. Specifically, children with ADHD predominantly engaged in sensory reactivation in parietal–occipital regions, whereas TD children engaged prefrontal areas to support meaningful memory transformation. Deep neural networks (DNN) further revealed that memory transformation occurred during encoding through semanticization of images. Further, intersubject correlation (ISC) revealed differences in memory patterns between both groups of children, providing potential neurobiological evidence for impaired memory transformation in children with ADHD. Our findings reveal that children with ADHD recruit perceptual reactivation over meaningful memory, highlighting the critical role of semantic transformation in the developmental emergence of meaningful memory.

Keywords: EEG, RSA, ADHD, memory, development.

1. Introduction

Recognition memory is a crucial component of episodic memory, forming the foundation of human cognition and enabling the recollection of past experiences and identification of familiar events[1,2]. However, not all memories are acquired in the same way: some are retained through reactivation of perceptions, whereas others gain strength by forming meaningful connections with past events[3,4]. How the brain distinguishes between these two forms of acquisition, and which neural systems support them during development remain elusive.

Neuronal measurements and cellular imaging provide evidence that memory relies on the encoding and later reactivation of memory engrams[5,6]. Cognitive neuroscience translates this idea into large-scale measures of encoding-retrieval similarity (ERS)[7,8], which track whether retrieval reactivates prior neural patterns or transforms them into new representational formats[9-12]. This distinction suggests a functional division: perceptual memory may rely on direct reactivation of sensory traces, whereas meaningful memory may depend on transformation within higher-order systems.

Memory reactivation is well captured by the cortical reinstatement hypothesis[13-15], which reflects the reinstatement of encoding-related activity during retrieval. This process primarily involves the hippocampus[16,17] and lateral occipital cortex (LOC)[18,19], reflecting the sensory processing hierarchy within memory areas, including the ventral visual stream (VVS)[20,21]. In contrast, memory transformation has also been observed between encoding and retrieval[11,12]. This process involves the prefrontal cortex (PFC)[22-24], which interacts with the hippocampus to support the retrieval of memory[25,26], especially for abstract or semantic information[27-29]. Importantly, activity in these higher-order regions during memory retrieval reliably predicts memory success[30,31], suggesting a central role for representational transformation.

Much evidence underscores this distinction from a developmental perspective, confirming the continuous evolution of memory-related neural systems across childhood and adolescence[32,33]. Sensory and perceptual systems appear to reach maturity earlier, with the structure and function of visual cortical regions (such as LOC) stabilizing relatively

early[34,35]. In contrast, higher-order memory processes depend on frontoparietal systems that undergo more protracted development. In particular, the PFC continues to mature into late adolescence[36-39], supporting the gradual emergence of strategic encoding, organization, and retrieval processes. Consistent with this account, semantic strategy use during verbal recall gradually increases across childhood and adolescence[40], and this increase is associated with lateral PFC structure, consistent with the hypothesis that PFC pruning during development contributes to successful strategy use[41]. More broadly, developmental changes in frontoparietal regions associate with improvements in memory encoding and retrieval across childhood[42]. These findings suggest a developmental shift of memory-related neural processes: perceptual memory may depend on early-maturing sensory systems, whereas meaningful memory relies on later-developing prefrontal mechanisms. Children with developmental disorders, whose brains have delayed structural or functional maturation, may offer a unique opportunity to test this hypothesis.

Attention-deficit/hyperactivity disorder (ADHD) is a common neurodevelopmental disorder in childhood that is characterized by inappropriate patterns of inattentiveness, hyperactivity and/or impulsivity[43], and affects approximately 7.2% of children globally[44]. Children with ADHD mainly show delayed cortical[45] and functional[46] maturation of prefrontal regions. Substantial research evidence indicates that deficits in episodic memory in ADHD[47,48] are linked to the frontoparietal network associated with executive function and attentional control[49], including the PFC[50,51]. Given the critical role of the PFC in memory transformation, comparisons between children with ADHD and typically developing (TD) children during critical developmental stages can reveal the influence of the PFC on memory formation.

Intersubject correlation (ISC) provides a complementary approach for examining developmental differences in memory representations. Memories of the same images are not entirely idiosyncratic across individuals[52], indicating that some representational structures are shared. Such shared representations also support social interaction[53]; individuals following similar developmental trajectories exhibit more similar neural representations[54]. Therefore, higher ISC reflects greater similarity in the organization of memory representations across children and may index increasing representational stability during development[2]. Previous research identified a key stage in the development of

memory representations in TD children, around which representational patterns become more consistent across individuals[55]. We therefore hypothesize that children with ADHD would exhibit a different developmental pattern around this stage.

Here, we adopted a recognition memory task that included encoding and retrieval. Through representational similarity analysis (RSA)[56] of electrophysiological activities, we aimed to quantify ERS and relate it to memory performance in children with and without ADHD. Memory reactivation or transformation is calculated as the ERS difference between remembered and forgotten items[10]: Higher ERS for remembered than for forgotten items indexed reactivation; conversely, if the memory representation is transformed, the ERS for remembered items is lower than that for forgotten items, reflecting meaningful memory transformation. We hypothesize that perceptual memory involves reactivation in lower-level sensory regions, whereas meaningful memory involves transformation in higher-level (e.g., prefrontal) regions, and we anticipate that children with ADHD and TD children would differ in their relative reliance on these two processes. Representations at the category level were assessed to reveal how and when memory is represented. If transformation relies on semantic processing, we expected memory-related ERS differences to be stronger between rather than within categories. We further used a pretrained deep neural network (DNN) to assess the visual and semantic formats of these representations[57-59]. Finally, ISC analysis was applied to delineate the developmental patterns of memory representations across children.

2. Results

2.1 Behavioral performance and development

We recruited 238 children to complete a classic recognition memory task (Fig. 1a), comprising 126 children with ADHD and 112 TD children aged 6 to 12 years (Fig. 1b). During the encoding phase, participants were required to remember 60 images while performing an animal/nonanimal classification task. All participants completed the animal classification task with high accuracy (mean ± s.d.; 93 ± 4.7%) and a response time of 845 ± 101 ms. Subsequent analyses were restricted to trials that were correctly classified. In the retrieval phase, participants were instructed to classify 40 old (selected from encodings)

and 40 new (foil) images as old or new. The corrected recognition score *Pr* (hits − false alarms)[60] and the mean response time (RT) for correct trials were used to measure recognition performance. Trials with responses exceeding the mean RT ± 2.5 standard deviations within each participant were excluded (2.8%). Fifteen participants with poor performance ($Pr \leq 0$) were excluded from further analyses. In the remaining sample (N_{ADHD} = 114; N_{TD} = 109; detailed in Table 1), TD children had higher *Pr* than children with ADHD (0.70 vs. 0.63; $T_{221} = 3.030$, $P = 0.003$; Fig. 1c), while the RTs were faster for TD children than for children with ADHD (1107 vs. 1209 ms; $T_{221} = -3.820$, $P < 0.001$). Notably, no difference was observed in the number of remembered items (i.e., hits) between the two groups (77% vs. 79%; $T_{221} = 1.583$, $P = 0.115$). Memory performance (*Pr*) was significantly correlated with age in both groups (ADHD: $r = 0.335$, $P < 0.001$; TD: $r = 0.359$, $P < 0.001$; Fig. 1d). These behavioral results reflected the gradual development of memory among children, allowing us to identify differences in the neuronal features of memory function in typical versus abnormal developmental children.

2.2 Perceptual reactivation in children with ADHD

To investigate the neural mechanisms of memory, we assessed item-specific ERS across six regions of interest (ROIs) in the EEG data: the left frontal (LF), right frontal (RF), left middle (LM), right middle (RM), left parietal–occipital (LP), and right parietal–occipital (RP) regions. Specifically, item-specific power values were extracted across frequencies (1–30 Hz) and electrodes, and temporal correlations were calculated within each ROI using sliding windows (300 ms width with a 50-ms step; Fig. 1e). The item-specific ERS (ERS_{Item}; Fig. 1g) was defined by comparing the neural similarity within-item (ERS_{WI}) versus between-item (ERS_{BI}), i.e., ERS_{Item} = avg.(ERS_{WI}) − avg.(ERS_{BI}). We compared differences in ERS_{Item} between remembered and forgotten items (i.e., whether memory was successful in retrieval), as well as their interaction with age and memory performance.

In children with ADHD, we identified significant memory reactivation clusters in the bilateral parietal–occipital regions (LP: $T_{sum} = 300.34$, $N_{bin} = 125$, $P_{cluster} = 0.031$; Fig. 2a). To maintain methodological consistency (e.g., cluster size, channel count) with subsequent memory transformation effects, we performed all subsequent analyses using the LP, while the RP yielded the same results (RP: $T_{sum} = 522.89$, $N_{bin} = 206$, $P_{cluster} = 0.008$;

Supplementary Fig. 1). The clusters in the LP extended from short intervals of 300–600 ms during encoding and long intervals of 300–1250 ms during retrieval, suggesting that memory retrieval in children with ADHD relied on prolonged reinstatement of early sensory representations. Within this cluster, remembered items showed significantly higher ERS_{Item} than forgotten items ($T_{113} = 2.856$, $P = 0.005$, Cohen's $d = 0.267$; Fig. 2b, left). Specifically, the item-specific reactivation involved a positive ERS_{Item} in remembered items in older children, whereas no such effect was observed in forgotten items (Supplementary Fig. 2), reflecting that successful memory retrieval depended on reinstating encoding-related activity patterns in children with ADHD. Additionally, this reactivation effect was not observed in TD children ($T_{108} = 0.557$, $P = 0.579$, Cohen's $d = 0.053$; Supplementary Fig. 3).

Further analysis revealed that this effect was specific to within-item similarity: the memory effect emerged for ERS_{WI} ($T_{113} = 2.122$, $P = 0.036$, Cohen's $d = 0.199$; Fig. 2b, right), but not for ERS_{BI} ($T_{113} = -0.998$, $P = 0.320$, Cohen's $d = -0.093$). This finding revealed that reactivation was specific to the same items rather than reflecting common cognitive overlap across different items. ERS_{WI} and ERS_{BI} were significantly greater than zero for both remembered and forgotten items (all $T_{113} \geq 2.001$, $Ps \leq 0.048$), deriving from the presence of shared neural patterns across items, regardless of retrieval success.

To examine the spatial distribution across the whole brain, we averaged ERS_{Item} across poststimulus intervals during encoding and retrieval. Children with ADHD again showed reactivation effects primarily in bilateral parietal–occipital regions (Fig. 2c), with no significant effects in other ROIs (all $P_{cluster} \geq 0.062$; Supplementary Fig. 4). This finding suggested that reactivation was reliant on sensory representations over the visual regions. Notably, the magnitude of reactivation was unrelated to memory performance ($r = -0.003$, $P = 0.979$; Fig. 2d), which indicated that although reactivation occurred robustly, it did not result in better retrieval outcomes. These findings implied that children with ADHD might rely predominantly on perceptual reactivation to retrieve sensory representations mirroring encoding patterns but did not support efficient memory performance.

2.3 Meaningful transformation in TD children

For TD children, we identified a significant memory transformation cluster in the right

frontal (RF) region (T_{sum} = −210.72, N_{bin} = 89, $P_{cluster}$ = 0.047; Fig. 2e), spanning −150 to 950 ms during encoding and 200 to 400 ms during retrieval. This pattern indicated that memory transformation occurred rapidly, with retrieval-related representations being temporally compressed and involving abstract or semantic information from almost the whole encoding phase. Within this memory transformation cluster, remembered items had significantly lower ERS_{Item} than forgotten items (T_{108} = −3.028, P = 0.003, Cohen's d = −0.290; Fig. 2f, left). Specifically, meaningful transformation in item-specific representations resulted in near-zero ERS_{Item} for remembered items and positive ERS_{Item} for forgotten items (Supplementary Fig. 2), suggesting that TD children did not rely on reinstating the same encoding patterns but instead transformed them into different patterns according to their own experiences to facilitate memory.

The memory effect was specific to ERS_{WI} (T_{108} = −2.876, P = 0.005, Cohen's d = −0.275; Fig. 2f, right), with no effect on ERS_{BI} (T_{108} = 0.763, P = 0.447, Cohen's d = 0.073). This finding revealed significant differences in the contributions of ERS_{WI} and ERS_{BI}. Similarly, ERS_{WI} and ERS_{BI} were significantly greater than zero for both remembered and forgotten items (all $T_{108} \geq 3.591$, $Ps \leq 0.001$), indicating the presence of shared neural patterns across items, independent of memory success. Additionally, this memory transformation effect was absent in children with ADHD (T_{113} = 0.484, P = 0.629, Cohen's d = 0.045; Supplementary Fig. 3).

In contrast to ADHD, transformation was observed primarily over high-level cognitive regions of TD children after the stimuli appeared (forgotten > remembered), especially over the right frontal region (Fig. 2g; all $P_{cluster} \geq 0.073$ for the other regions in Supplementary Fig. 4). This overall pattern suggested that retrieval in TD children involves conceptual rather than purely sensory representations. Importantly, item-specific transformation in the right frontal region was negatively correlated with memory performance (r = −0.222, P = 0.021; Fig. 2h), and this correlation remained significant after controlling for age (ρ = −0.231, P = 0.016; Supplementary Fig. 5). These findings indicated that greater meaningful transformation predicted better memory performance, highlighting that TD children retrieved memories through flexible manipulation of information rather than reinstatement of sensory traces.

2.4 Development of memory reactivation and transformation

To examine differences in memory between children with ADHD and TD children, as well as their developmental patterns, we employed the average of significant clusters within specific ROIs as indices of reactivation or transformation. With respect to reactivation in the LP, children with ADHD had significantly greater values than zero (T_{113} = 2.856, P = 0.005, Cohen's d = 0.267; Fig. 2i, left), whereas TD children did not (T_{108} = 0.557, P = 0.579, Cohen's d = 0.053). However, this between-group difference was not significant (T_{221} = 1.647, P = 0.101, Cohen's d = 0.221), suggesting that reactivation was common in both groups, regardless of developmental abnormalities. Notably, reactivation remained relatively stable across development in children with ADHD (r = −0.036, P = 0.707, Fig. 2i, right) but decreased marginally in TD children (r = −0.183, P = 0.057).

With respect to meaningful memory transformation in the RF, TD children exhibited significantly lower ERS_{Item} than zero (T_{108} = −3.028, P = 0.003, Cohen's d = −0.290; Fig. 2j, left), whereas children with ADHD did not (T_{113} = 0.484, P = 0.629, Cohen's d = 0.045). This between-group difference was significant (T_{221} = 2.473, P = 0.014, Cohen's d = 0.331), highlighting that memory transformation was a skill specific to TD children. We next tested whether individual item-specific memory transformation levels depended on age and found that the transformation effect was not significantly correlated with age in both groups (*Ps* ≥ 0.262; Supplementary Fig. 6). As an exploratory descriptive analysis, we additionally divided participants by median age and revealed that older children with ADHD (MD = 8.288 years) showed marginally greater transformation (T_{112} = 1.956, P = 0.053, Cohen's d = 0.366; Fig. 2j, right), approaching the levels of younger TD children (T_{110} = 0.759, P = 0.449, Cohen's d = 0.144). This exploratory pattern suggested that, despite the absence of significant memory transformation in children with ADHD, these memory effects might still exhibit developmental trends with age. In contrast, there was no significant difference between the low- and high-age subgroups of TD children (MD = 8.545 years; T_{107} = 0.135, P = 0.892, Cohen's d = 0.026), with values for younger (T_{54} = −2.267, P = 0.027, Cohen's d = −0.306) and older children (T_{53} = −2.034, P = 0.047, Cohen's d = −0.277) significantly smaller than 0.

A multiple linear regression model was conducted to examine the age-dependent

contributions of LP reactivation and RF transformation to *Pr*. In TD children, RF transformation significantly predicted *Pr* (β = 0.232, P = 0.004, 95% CI [0.076, 0.387]), and this predictive effect decreased significantly with increasing age (β = −0.163, P = 0.040, 95% CI [−0.318, −0.008]). Simple-slope analyses further showed that the association between RF transformation and *Pr* was strongest in younger TD children and was no longer significant in older children. In contrast, LP reactivation did not significantly predict *Pr* (β = 0.036, P = 0.640, 95% CI [−0.117, 0.189]), and its predictive effect did not vary significantly with age (β = −0.017, P = 0.812, 95% CI [−0.160, 0.126]). In children with ADHD, neither LP reactivation nor RF transformation significantly predicted *Pr* ($Ps \geq$ 0.549), and none of the associations were significantly moderated by age ($Ps \geq 0.514$).

Together, these results suggested that 6–12-year-old TD children had acquired transformation abilities during early childhood and maintained them throughout development, and this transformation has an age-dependent predictive effect on memory performance. Conversely, children with ADHD acquired transformation skills more gradually, reaching transformation levels comparable to those of younger TD children only at older ages, and no similar age-dependent behavioral-neurological associations were observed—providing potential neurobiological evidence for memory developmental abnormalities associated with ADHD.

2.5 Representational contents of memory reactivation and transformation

To reveal the representational contents of reactivation and transformation, we subdivided between-item ERS into within-category (ERS_{WC}) and between-category (ERS_{BC}) according to the image category (animal/nonanimal), representing whether the item came from the same category in encoding and retrieval (Fig. 3a). Compared to the image representation space, the distances between animals and nonanimals (between-category) were farther than those between animals and animals (within-category) in the semantic representation space. Therefore, we hypothesized that between-category items had greater differences (Rem vs. Forg) than within-category items in terms of semantic representations instead of image representations. We expected greater representational differences in ERS_{BC} than in ERS_{WC} ($ERS_{BC} \neq ERS_{WC}$) if reactivation/transformation relied on semantic

abstraction. Conversely, ERS_{WC} would show similar representational differences to ERS_{BC} ($ERS_{BC} \approx ERS_{WC}$) if reactivation/transformation relied on image representations (Fig. 3b).

In children with ADHD, neither ERS_{WC} ($T_{113} = -0.370$, $P = 0.712$, Cohen's $d = -0.035$) nor ERS_{BC} ($T_{113} = 1.245$, $P = 0.216$, Cohen's $d = 0.117$) showed significant reactivation effects in the LP (Fig. 3c). These findings indicated that memory reactivation in ADHD depended primarily on the reinstatement of low-level visual representations in the parietal–occipital region, without engaging semantic processing, which was consistent with the repetition of perceptual traces.

In contrast, in TD children, meaningful transformation emerged specifically in ERS_{BC} within the RF ($T_{108} = 1.998$, $P = 0.048$, Cohen's $d = 0.191$), with no such effect for ERS_{WC} ($T_{108} = -0.046$, $P = 0.963$, Cohen's $d = -0.004$; Fig. 3d). Notably, ERS_{WC} and ERS_{BC} were both derived from ERS_{BI} (i.e., the subtrahend in the above memory effect: $ERS_{WI} - ERS_{BI}$), such that more positive ERS_{WC} or ERS_{BC} values in such instances indicated greater transformation. Whole-brain analysis further revealed significant ERS_{BC} transformation in bilateral frontal regions (LF: $T_{108} = 2.260$, $P = 0.026$, Cohen's $d = 0.216$; RF: $T_{108} = 2.565$, $P = 0.012$, Cohen's $d = 0.246$; Fig. 3e), whereas ERS_{WC} was absent ($Ps \geq 0.175$). Moreover, in the RF, ERS_{BC} transformation was significantly greater than ERS_{WC} ($T_{108} = 2.332$, $P = 0.022$, Cohen's $d = 0.223$). These findings suggested that recognition in TD children involved memory transformation of semantic information within high-level cognitive regions. Such reliance on transformation highlighted a developmental advantage in flexibly reconstructing representations to support recognition memory.

2.6 Memory is transformed during encoding in TD children

Next, we examined whether meaningful memory transformation occurred during encoding or retrieval by comparing the representational similarity between items (Fig. 4a). Specifically, we assessed the similarity between each item and all other items within the same memory phase, i.e., encoding (EES) and retrieval (RRS), and tested the generalization (remembered > forgotten) and differentiation (forgotten > remembered) of memory representations across items. Here, memory differentiation reflects representational transformation between different memory items.

In TD children, significant effects on memory differentiation emerged in EES. In the

LP, remembered items showed lower similarity to other items than forgotten items (T_{sum} = −9.065, N_{bin} = 4, $P_{cluster}$ < 0.001, −100–50 ms, EES_{Rem} = 0.019, EES_{Forg} = 0.029; Fig. 4b), which indicated that more representational transformations occurred between items that were subsequently remembered than those that were subsequently forgotten. Notably, the apparent early onset was likely attributable to the sliding-window approach, as the first window averaged activity from 0–300 ms post-stimulus. A similar effect was observed in the RF (T_{sum} = −9.525, N_{bin} = 4, $P_{cluster}$ < 0.001, 150–300 ms, EES_{Rem} = 0.026, EES_{Forg} = 0.042). Interestingly, category analyses further revealed that differentiation in LP was not significantly different between within- and between-category items (T_{108} = 1.669, P = 0.098, Cohen's d = 0.160; Supplementary Fig. 7), whereas the RF tended towards greater differentiation for between-category items than for within-category items (T_{108} = 1.925, P = 0.057, Cohen's d = 0.184), consistent with semantic modulation.

Together, these results suggest that memory-related differentiation during encoding involved distinct representational formats across regions: differentiation in the LP was primarily associated with sensory/visual information, whereas differentiation in the RF showed evidence of higher-level semantic modulation. Notably, no differentiation effects were observed in RRS, indicating that memory transformation in TD children had already occurred during encoding. Additionally, this encoding differentiation effect was absent in children with ADHD (Supplementary Fig. 7).

2.7 DNN reveals representational formats of reactivation and transformation

To further investigate representational formats in the LP and RF and their associations with memory, we compared the neural representations of items observed during encoding with representations in individual layers of the AlexNet DNN (Fig. 4c). AlexNet consists of five convolutional layers and three fully connected layers. Visual information is initially processed on a pixel-by-pixel basis in the first convolutional layer (conv1), then propagated to downstream layers, and finally assigned semantic labels in the output layer (fc8). We compared the neural-DNN correspondences for remembered and forgotten items at all time points and applied cluster-based permutation tests for multiple comparisons across time points.

During the memory encoding (EES-DNN) in TD children, we identified a significant cluster between 600 and 800 ms in layer fc8, in which the representation for remembered items was significantly lower than that for forgotten items ($T_{sum} = -12.024$, $N_{bin} = 5$, $P_{cluster} = 0.038$; Fig. 4d), and this cluster was located within the encoding time window showing the memory transformation effect. To better capture ROI-specific differences in the memory specificity of neural-DNN correspondences, we conducted post hoc tests for specific time windows showing the reactivation effect (300–600 ms) and the transformation effect (0–1000 ms). In the LP region of children with ADHD, we found that the neural representation of memory reactivation was associated with the early convolutional layers, which may reflect low-level, pixel-based visual information. By contrast, in the RF region of TD children, the neural representation of memory transformation was associated with the final fully connected layers, which may be related to higher-level semantic labels (Supplementary Fig. 8).

Notably, within this exploratory analysis, interpretation of effects based on individual layers should not be overemphasised. Nevertheless, the overall pattern of separable representational formats of reactivation and transformation in different groups of children may provide new insights into underlying memory strategies and how they are deployed during the encoding process.

2.8 ISC reveals differences in memory development across children

We adopted a model-free approach to reveal differences in memory representations across participants. Specifically, we calculated correlations across all participants and constructed intersubject RSMs. The average ISC between each child and all the other children was used as a measure of group differences. The intersubject RSM derived from the memory-related regions (LP of ADHD / RF of TD) was subsequently tested against four age-based developmental models: nearest neighbor, divergence, key stage, and convergence (Fig. 1f). For the key-stage model, we systematically adjusted candidate key ages (sliding key ages with 0.1-year steps) to determine the best fit for children with ADHD and TD.

Analysis of the average ISC revealed TD children showed significantly greater-than-zero ISC in the LP region ($T_{108} = 3.089$, $P = 0.003$, Cohen's $d = 0.296$; Fig. 4e), but not in the RF region ($T_{108} = 0.317$, $P = 0.752$, Cohen's $d = 0.030$), with a significant difference

determined between the two regions (T_{108} = 2.442, P = 0.016, Cohen's d = 0.234). In contrast, neither the LP nor the RF region showed a significant value greater than zero in children with ADHD ($Ps \geq 0.118$). These findings suggested that TD children shared a common memory representational structure, whereas such shared representations were almost absent in children with ADHD. The reduced average ISC in the RF of TD children might be attributed to their increased representational transformation, which yielded more individualized semantic representations and consequently reduced the intersubject similarity.

Among the four developmental models, the key-stage model showed the strongest correspondence with the intersubject RSMs in both groups (ADHD: ρ = 0.022, P = 0.046; TD: ρ = 0.016, P = 0.080, one-tailed permutation test; Fig. 4f), whereas the remaining models showed no significant correlations ($Ps > 0.444$). The time window for the ISC analysis was focused on significant ERS clusters. Further analysis of the key-stage models for these two groups of children revealed group differences in the key age: the key age was younger for TD children, whereas it was older for children with ADHD (Fig. 4g). In the LP (T_{221} = −574.017, $P < 0.001$, Cohen's d = −77.225; Fig. 4h) or RF (T_{221} = −10.987, $P <$ 0.001, Cohen's d = −1.478) regions, the developmental differences between the two groups of children were statistically significant. These findings indicated age-related differences in the organization of memory representations between children with ADHD and TD children, providing potentially neurobiological evidence for impaired or delayed meaningful memory transformation.

3. Discussion

Recognition memory can be acquired in two neural mechanisms: perceptual memory and meaningful memory. The key distinction lies in whether stored representations are simply reinstated or reconstructed into new conceptual connections. By comparing ERS between TD children and those with ADHD who exhibit delayed prefrontal maturation[45], this study revealed region-specific mechanisms: children with ADHD showed greater reliance on perceptual reactivation over visual regions; whereas TD children showed greater engagement of representational transformation over prefrontal regions, likely reflecting the flexible reconstruction of perceptual traces into semantic representations—a hallmark of

meaningful memory. Reactivation and transformation can occur simultaneously in distinct brain regions[10], yet their developmental patterns remain unclear. Here, we provide the first evidence of these two processes in children aged 6–12 years, and reveal a dynamic evolution from reactivation to transformation regulated by the prefrontal system. Furthermore, intersubject similarity revealed differences in memory development across children, providing neurobiological evidence for their impaired or potentially delayed recognition memory.

Specifically, over the parietal–occipital region, children with ADHD exhibited stronger and more age-stable reactivation. During the recognition of visual images, memory retrieval is completely dependent on matching sensory input with the encoding context, i.e., processing previously encoded sensory information within visual regions[18-21]. This ability is consistent with the feature of perceptual memory, characterized by the vivid reinstatement of perceptual details. This persistent dependence on reactivation may explain why children with ADHD can recognize perceptual details but struggle to integrate or generalize information[61]. In contrast, memory retrieval in TD children showed weaker reliance on reactivation, which further decreased with age. This shift likely reflects an adaptive change in the strategic balance between perceptual memory (reactivation) and meaningful memory (transformation), as TD children increasingly encode information through abstraction and semantic integration rather than purely through sensory processing. Additionally, the reduced dependence on reactivation in TD children may also arise from memory differentiation effects occurring in encoding, specifically the representation transformation between memory items.

The TD children exhibited stronger memory transformation in frontal regions, supporting the notion of dynamic adaptation between perceptual and meaningful memory. This transformation is supported by the maturation of the prefrontal–hippocampal system[25,26], which enables flexible integration of perceptual and semantic information. The spatial dissociation between perceptual and meaningful memory in the parietal–occipital and frontal regions corresponds to the memory models proposed in previous studies[62,63]. These models propose that posterior hippocampal regions encode fine perceptual details in concert with posterior neocortical areas, whereas anterior regions encode abstract, schematic features and interact with the anterior medial prefrontal cortex. The impaired

transformation observed in children with ADHD fits this framework, reflecting the atypical development of the prefrontal circuitry. This finding is consistent with prior neuroimaging evidence of delayed prefrontal maturation associated with executive and attentional control deficits in individuals with ADHD[45,46,49]. This impaired transformation also explains why ADHD involves associative learning deficits[64]. Notably, this impairment is not permanent damage but a developmental delay: older children with ADHD exhibit representational profiles comparable to those of younger TD children.

This memory framework provides a theoretical basis for distinguishing perceptual and meaningful memory, which serve as different forms of neural dynamics. Perceptual memory reinstates perceptual traces, recovering surface-level details with limited flexibility, whereas meaningful memory reflects a shift in neural representations between encoding and retrieval that may enable semantic reconstruction. Through this "semanticization" process, richly detailed event memories are progressively reduced to schematic generalizations, resulting in the loss of fine perceptual detail during long-term consolidation[12,65,66]. Category-level analysis revealed that TD children showed stronger representational transformations between different categories, which were associated with better memory performance. Representational similarity analysis highlights how objects can be organized along multiple dimensions (e.g., life, shape, color, and function), yet semantic dimensions often capture category structure most effectively[67]. For instance, distinctions between animal and nonanimal images are more robustly represented in semantic than in perceptual space[68,69]. Thus, stronger between-category similarity supports the idea that memory transformation occurs through semanticization, and more pronounced semantic representation patterns predict better subsequent memory[8].

Interestingly, stronger between-category transformations also emerge between different items within encoding (EES) but not retrieval, indicating that memory-related representational differentiation, including semantic differentiation, is already evident during encoding. Analysis based on DNN further revealed a correspondence between the neural representations in RF of TD children during encoding and the semantic/label representations in DNN, tentatively suggesting a memory effect influenced by negative matching between neural and DNN representations. This negative matching between related items has previously been described as "repulsion" of memory representations[70-72].

Notably, although the transformation in RF is sensitive to higher-level semantic information, reduced ERS in frontal regions is not process-specific and may also reflect differences in executive control, task state, decision-related processing, or the temporal organization of frontal engagement across memory phases. The present findings should therefore be interpreted as evidence for a change in representational organization with semantic modulation, rather than as a unique neural signature of semantic transformation. These encoding-related differences may shape the mnemonic representations subsequently accessed during retrieval and thereby contribute to the reduced encoding-retrieval similarity observed for remembered items. These findings explicitly reveal how and when memory representations are transformed. This prefrontal-driven transformation from visual to semantic codes supports meaningful memory reconstruction and the formation of new conceptual links across experiences.

ISC provided a complementary perspective on memory representation patterns across populations. In this study, TD children and children with ADHD differed in the extent to which representational structures were shared across individuals. Compared with TD children, children with ADHD showed no reliable intersubject similarities, which may reflect greater heterogeneity in the memory representations. This interpretation is consistent with previous findings that ADHD is associated with reduced intersubject neural synchrony and less stable neural response patterns across individuals[73,74]. Nevertheless, intersubject similarity may be influenced by multiple sources of individual variability, including behavioral performance, cognitive strategy, and functional organization. This issue may be particularly relevant to higher-order prefrontal regions, where representations are more strongly shaped by individual experience and semantic knowledge and therefore tend to exhibit greater intersubject heterogeneity[75,76]. Analysis of developmental models further suggested that intersubject similarity is neither static nor uniformly related to age, but instead exhibits region-specific age-related patterns. This finding complements previous conclusions that intersubject similarity can either increase or decrease with age depending on the brain region and representational content[77-79]. The different key-stage patterns observed between the TD and ADHD groups are more conservatively interpreted as group differences in the age-related consistency of memory representations, rather than as direct markers of neural maturation. Since the present data are cross-sectional, these

findings cannot distinguish developmental delay from an atypical developmental trajectory. However, they complement the individual-level ERS results, suggesting that the two groups differ not only in representational processes within individuals, but also in the intersubject consistency and age-related organization of these representational patterns.

Our findings hold broader implications for memory theory. They suggest that recognition—often viewed as a simple process driven by external cues—is not purely perceptual but instead depends on the developmental capacity to flexibly transform representations. This phenomenon reframes recognition as a dynamic interplay between reactivation and transformation, with the latter marking progress towards meaningful memory. Crucially, prefrontal transformations predicted better memory performance in TD children, highlighting their functional role in supporting semantic reconstruction. This finding aligns with evidence showing that developmental changes in the prefrontal region shape strategy use in memory: tasks requiring strategic encoding engage the executive functions of the frontal cortex[80]. Compared with shallow encoding, deep semantic encoding elicits stronger age-related prefrontal activation[81]. Encouraging children to adopt semantic strategies could therefore enhance prefrontal engagement, optimize encoding, and promote meaningful memory formation[33,82]. More broadly, these findings highlight the potential for representational patterns of neurophysiological signals, such as memory transformation, to serve as diagnostic markers for typical and atypical populations.

Several limitations should be acknowledged. First, although EEG provides excellent temporal resolution, its limited spatial precision constrains the ability to localize the underlying neural mechanisms. Future work combining EEG with fMRI or using magnetoencephalography (MEG) could more accurately map the circuits supporting reactivation and transformation. The use of OPM-MEG, in which the sensor arrays can be adapted to the smaller head size of the children, might offer an opportunity for better localization of the effects[83,84]. Second, the cross-sectional design precludes the ability to distinguish developmental delays from atypical trajectories. Longitudinal studies will be essential to trace how these mechanisms evolve within individuals over time.

In summary, our study identifies two complementary mechanisms that support recognition memory in childhood: perceptual memory supported by reactivating sensory

traces, and meaningful memory supported by semantic transformation that reshapes representations. The TD children rely on the transformation early in development, whereas children with ADHD exhibit developmental delays, prolonging their dependence on reactivation. These findings extend theories of memory by reframing recognition as a dynamic balance between perceptual and meaningful memory. Moreover, this study revealed the role of prefrontal regions in meaningful memory, clarified the basis for memory divergence in children with ADHD and revealed the potential for modulating this process through targeted interventions.

4. Materials and Methods

4.1 Participants

In this study, a total of 238 children (6–12 years old) were recruited, comprising 126 children with ADHD and 112 TD children. Fifteen participants were excluded from all analyses because of poor memory performance. The final sample included 114 children with ADHD (31 females; 8.39 ± 1.32 years old) and 109 TD children (40 females; 8.62 ± 1.37 years old). The age of the participants was normally distributed (ADHD: $P = 0.161$; TD: $P = 0.267$; Kolmogorov-Smirnov test; Fig. 1b), and no differences were observed between these two groups in terms of age ($T_{221} = 1.279$, $P = 0.202$) or gender ($\chi^2 = 2.319$, $P = 0.128$). Children with ADHD were recruited from the clinics of local children's hospitals, and healthy controls (i.e., TD children) were recruited from local schools. All participants were right-handed, had normal or corrected-to-normal vision, and had full-scale intelligence quotients (IQs) above 80, as measured by the Wechsler Intelligence Scale for Chinese Children-Revised (WISCC-R). The IQs of children with ADHD were lower than those of TD children ($T_{221} = 4.263$, $P < 0.001$). Informed consent was obtained from all participants and their parents via the Declaration of Helsinki, following the protocols approved by the local ethics committee.

The diagnosis of ADHD was based on the K-SADS (Kiddie-Schedule for Affective Disorders and Schizophrenia) and DSM-V (Diagnostic and Statistical Manual of Mental Disorders, 5th edition) criteria through a semistructured interview with qualified psychiatrists, and symptom severity was measured using the SNAP-IV (Swanson, Nolan,

and Pelham rating scales, 4th edition) parental rating scale. Children diagnosed with ADHD satisfied all the criteria outlined in the DSM-V and SNAP-IV assessment scales, whereas TD children did not. Compared with TD children, those with ADHD had significantly higher SNAP inattention ($T_{221} = 23.124$, $P < 0.001$) and SNAP hyperactivity scores ($T_{221} = 22.868$, $P < 0.001$). None of the participants in this study received psychostimulant medication prior to the experiment, and all of them met the following criteria: no comorbidities such as schizophrenia, autism spectrum disorders, mood disorders, epilepsy, or tic disorders; no history of head trauma; and no organic, neurologic, or other serious diseases.

4.2 Experimental stimuli and task

Participants completed a recognition memory task (Fig. 1a) that was applied to investigate recognition memory with paediatric samples[55]. The materials included animal and nonanimal images from the Snodgrass and Vanderwart image set[85]. These images were preprocessed into white line drawings on a black background and normalized for physical attributes such as size, background, contrast, and brightness.

The experimental task consisted of encoding and retrieval phases with 1-minute intervals, which lasted approximately 10 minutes in total. In the encoding phase, participants were presented with 60 animal/nonanimal images (half each category) and were instructed to define them as animal/nonanimal by pressing keys. Each trial started with a stimulus image presentation for 1000 ms, followed by an interstimulus interval (ISI) of 1500 ms. Then, following a retrieval phase, where participants were presented with old (40; selected from encodings) and new (40; foil) images and were instructed to press keys to indicate their memory discrimination (i.e., old or new). Each trial started with a fixation cross of 250 ms, followed by a black screen for 500 ms; the stimulus image was then presented for 500 ms, and finally, the ISI was presented for 3000 ms.

The stimulus images were presented using E-Prime 2.0 software (Psychological Software Tools, Pittsburgh, PA, USA), and all the images were presented on a black background. The participants were seated 90 cm away from the screen, and the viewing angle of the images was 3.18° × 3.18°. To minimize artefacts caused by blinking and eye movements, participants were also asked to fixate a white cross on the screen during the

experiment and to blink during key-press responses. To implement the representational similarity analyses across participants, each participant saw the same stimulus items, but the presentation order was randomized. To ensure comprehension, participants underwent a practice before the formal experiment.

4.3 EEG recording and preprocessing

EEG data were recorded using a 21-channel amplifier (Stellate System Inc., CA, USA) according to the standard 10-20 system. All scalp electrodes were referenced to CPz and sampled at 500 Hz, and all interelectrode impedance was maintained below 5 kΩ during recording.

EEG data were preprocessed using EEGLAB[86] in MATLAB (MathWorks, MA, USA). The EEG data were bandpass filtered between 0.01 and 40 Hz, and rereferenced to the global average[87]. Bad channels were removed with the following criteria: continuous flat over 5 s; more than 4 standard deviations of line noise relative to their signal; and correlation with the estimates of nearby channels less than 0.8. Artefact subspace reconstruction (ASR) was implemented to remove data portions containing artefacts[88]. Additional data portions were removed if more than 25% of the channels had a power greater than 7 standard deviations. Independent component analysis (ICA) was performed to correct eye artefacts[89], and the ICA matrix was applied to the full-length data prior to the removal of artefacts by ASR. Components with a probability of eye artefacts greater than 0.6 were removed using the ICLabel plugin[90].

The processed EEG data were segmented from −500 to 1500 ms relative to the onset of each image. If more than 10 channels had amplitudes exceeding ± 100 μV or if the joint probability of local/global thresholds exceeded 3 standard deviations, the epoch was rejected using the TBT plugin [91]; otherwise, the epoch was retained and only the channels of that epoch were interpolated. The previously removed channels were interpolated using spherical splines, and 97 ± 5.0% of the epochs were retained for subsequent analysis.

4.4 Time-frequency analysis for RSA

To avoid edge artefacts in the spectral decomposition, we first mirrored each epoch by appending the flipped data to the beginning (from −2.5 to −0.5 s) and end (from 1.5 to 3.5

s) of each epoch. Next, we applied a Morlet wavelet transform to the epochs from −500 to 1500 ms, with Morlet wavelets ranging from 1 to 30 Hz (in 1 Hz steps) and linear intervals of 3 to 15 cycles. The average spectral power was normalized (*Z* score) with the prestimulus baseline of −500 to −200 ms before stimulus onset. We averaged the data in 300-ms time windows, sliding in 50-ms steps. Each window was assigned to its midpoint (e.g., the first window spanned from −500 to −200 ms and was labelled as −350 ms), resulting in a total of 35 distinct windows within the range of −500 to 1500 ms. Additionally, we divided all the channels into six ROIs (LF, RF, LM, RM, LP, and RP) and used the channels from each ROI as spatial features. For each trial, n (channels) × 30 (frequencies) × 35 (time steps) values were generated, which were used for subsequent analysis. We also explored memory effects (remembered − forgotten) on time-frequency features during encoding and retrieval in different ROIs (Supplementary Fig. 9).

4.5 Representational similarity analysis

To investigate the neural similarity within the encoding or retrieval phases, we used representational similarity analysis (RSA) on items that appeared in both memory phases (i.e., 40 old items). Since directly calculating the neural similarity of a specific item between participants (i.e., first-level pattern similarity) may be affected by potential differences in potential, we calculated the pattern similarity when participants processed the same set of stimuli (i.e., second-level pattern similarity)[53,92]. For items that were removed because of data artefacts (3% of all items), we interpolated using the corresponding group average item (item average of all participants). We estimated the pattern similarity between different items using Spearman correlation and constructed a 40 × 40 individual representational similarity matrix (RSM) for each participant, where the diagonal represents the similarity between each item and itself (Fig. 1e). Specifically, we used the power distribution of specific items across channels and frequencies (e.g., 4 electrodes × 30 frequencies in LF) as features for similarity estimation. These features were concatenated into a 4 × 30 one-dimensional vector and correlated with features from the same and all different items. This analysis was repeated separately for all time steps and memory phases (encoding/retrieval) for each participant.

4.6 Intersubject correlation analysis

To explore the developmental trajectories related to memory representation and better capture patterns of memory representations across individuals, we used a model-free approach[54,93] within the same memory phase. We calculated the intersubject correlation (ISC) between each pair of individual RSMs, resulting in an intersubject RSM. The obtained matrix was transformed using the Fisher *r*-to-*z* before further analysis. Intersubject RSM was obtained separately for children with ADHD and TD children, after which we tested whether it corresponded to one of the different developmental models (Fig. 1f). All developmental models were constructed using the actual age of the participants as a measure of maturity. There are four main methods for estimating maturity similarity, each of which evaluates different hypotheses about how memory representations develop with age:

(1) Nearest neighbor: Children with similar maturity have more similar memory representations (metric: sample maximum minus absolute of paired differences). (2) Divergence: Younger children have more similar memory representations (metric: sample maximum minus paired average). (3) Key stage: Children with maturity closer to the key age have more similar memory representations (metric: sample maximum minus absolute difference between pairs and key age, with key age constructed by sliding 0.1-year steps between the minimum and maximum ages). (4) Convergence: Older children have more similar memory representations (metric: paired average).

4.7 Encoding-Retrieval Similarity

We investigate item-specific neural similarity between encoding and retrieval (ERS) to reveal the representation reactivation or transformation of memory. In this analysis, a 40 × 40 ERS matrix (Fig. 1g) was constructed, in which the diagonal represents the similarity between the same items across encoding and retrieval, and the off-diagonal represents the similarity between different items, capturing item-specific representations and common cognitive processes across different items, respectively. Before further analysis, the ERS matrix was also transformed using the Fisher *r*-to-*z*. The item-specific ERS (ERS_{Item}) was calculated using the average of all items with the same memory performance (remembered/forgotten) in encoding and retrieval (within-item, ERS_{WI}, diagonal elements) minus the average of that item in encoding with all other items in retrieval (between-item,

ERS_{BI}, off-diagonal elements in the row direction), i.e., ERS_{Item} = avg.(ERS_{WI}) – avg.(ERS_{BI}). Additionally, we considered the off-diagonal elements in the column direction, as well as the off-diagonal elements in both the row and column directions (Supplementary Fig. 10). We investigated the relationships between neural representations across all time steps during encoding and retrieval, generating matrices of encoding time × retrieval time. We revealed the reactivation and transformation of temporal representations by comparing the ERS_{Item} of remembered and forgotten items at each time step.

To further reveal the representational patterns of reactivation and transformation, we classified the similarity between specific items in encoding and all other items in retrieval (i.e., between-item) into two categories according to image category (animal/nonanimal). Within-category (ERS_{WC}) refers to items from the same category (animal & animal or nonanimal & nonanimal) in encoding and retrieval, whereas between-category (ERS_{BC}) refers to items from different categories (animal & nonanimal or nonanimal & animal) in encoding and retrieval (Fig. 3a). The ERS_{WC} and ERS_{BC} were measured by calculating the average difference between remembered and forgotten items. Compared with image representations, the ERS between different categories was more pronounced in semantic representations. This distinction allowed us to test whether memory effects reflected semantic-level differences, with stronger representational differences expected in ERS_{BC} than in ERS_{WC} if reactivation or transformation relied on semantic abstraction (Fig. 3b). Off-diagonal elements in the column direction, and in both the row and column directions, were also considered (Supplementary Fig. 11).

4.8 Between-item similarity (EES/RRS)

We calculated the pairwise similarity of items within the same memory phase (EES/RRS) for the between-item similarity analysis (Fig. 4a). We used the symmetric individual RSMs constructed from the time-frequency features as described above. Subsequent analyses were based on the lower diagonal of these RSMs, which were Fisher *r*-to-*z* transformed prior to analysis. For each time step, we investigated whether there were differences in the pairwise similarity between remembered and forgotten items. In the subject-level analysis, we performed paired-sample *T* tests for the mean of items with the same memory performance for each participant. In the group-level analysis, we tested whether the *T*

values of each participant consistently deviated from zero. In the time series of group-level effects, we searched for temporal clusters formed by adjacent times and estimated their statistical significance using cluster-based permutation statistics.

4.9 Deep neural network (DNN) models

We applied a pre-trained convolutional neural network "AlexNet[94]" to classify the images featured in the experiment. AlexNet comprises five convolutional layers and three fully connected layers (Fig. 4c), and was trained on 1.2 million high-resolution images labelled with 1000 categories. Image information was initially processed on a pixel-by-pixel basis in the first convolutional layer, then propagated unidirectionally to downstream layers, with semantic labelling ultimately assigned at the output layer (softmax). We averaged the values across the spatial dimension[95] for each convolutional layer of every image, thereby obtaining a single value corresponding to each feature (image × feature). Based on estimated pairwise correlation coefficients derived from internal feature activation values, we generated eight 40 × 40 symmetric, layer-specific RSMs, which were then Fisher *r*-to-*z* transformed for further analysis.

The RSMs generated by DNN correspond to the individual neural RSMs obtained through EES analysis and were applied equally across different ROIs, thereby enabling a direct comparison of the representational structures between neural features and AlexNet. For all time points in the encoding phase, we obtained 35 EES matrices (image × image) for each participant and for each ROI. To maintain consistency with the item-specific approach used in ERS analysis, we calculated image-specific alignment between neural features and each DNN layer. For each image, we extracted the vector of similarity values with all other images (vector of length N−1, i.e., a row or column of matrix) from the neural and DNN matrices. These vectors capture the geometric relationships between this image and all other images. We then calculated the Spearman correlation coefficients between the vectors from neural and DNN matrices for each time point and network layer, yielding a value of the item-specific similarity between the neural and the DNN representations. The statistical procedure was similar to the ERS analysis: we first performed *T* tests on the values of remembered and forgotten items to examine whether similarity at different time points differed according to memory performance. In the group-level analysis, we tested

whether these *T*-values differed significantly from zero across all participants. We then identified adjacent significant ($P < 0.05$) time points in group-level *T*-tests and corrected for multiple comparisons between adjacent time points using permutation tests, in which the order of the image-specific similarity vectors in the neural matrices was randomized prior to comparison with image-specific vectors from a single DNN layer matrix.

4.10 Statistical analysis

To test whether similarity between encoding and retrieval could support memory reactivation and transformation, we first computed ERS at the subject-level. Paired-sample *T* tests were used to compare ERS for remembered versus forgotten items, yielding subject-specific *T* value maps with the encoding × retrieval time for subsequent group analysis. At the group level, one-sample *T* tests were used to assess whether the mean *T* values differed from zero, and significant clusters ($P < 0.05$) were identified by summing adjacent time points into empirical clusters. Post hoc two-sample(independent-samples) *T* tests were then used to examine group differences between children with ADHD and TD children. Multiple-comparison correction was implemented using cluster-based permutation tests[96]. For each RSA, 1,000 permutations were performed in which memory labels (remember/forget) were randomly shuffled while preserving size. Group-level significance was assessed by identifying empirical clusters in the time (EES/RRS) or time × time (ERS) maps, summing all *T* values within each cluster, and ranking the observed cluster against the permutation distribution in the same direction (positive or negative). The *P* value was defined as the rank of the observed cluster divided by the permutation count (P = rank/1000).

To link ERS effects to development and behavior, we constructed regression models relating ERS values of significant clusters to age and memory performance. ERS values were Fisher *r*-to-*z* transformed to yield normalized scores. Linear, quadratic, and cubic regression models[97] were tested, and the best-fitting model (Supplementary Table 1) was selected on the basis of Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). To control for shared variance, partial correlations were also computed for item-specific ERS while accounting for the interaction between age and memory performance.

To further examine the age-dependent contributions of LP reactivation and RF transformation to *Pr*, separate multiple regression models were fitted for the TD and ADHD groups, with *Pr* predicted by age, LP reactivation, RF transformation, and the interactions of age with each neural measure. All continuous variables were standardised before model fitting. The following linear regression model was fitted separately for each group: $Pr \sim \text{Age} \times \text{reactivation} + \text{Age} \times \text{transformation} + \varepsilon$.

For intersubject correlation analysis, we calculated Spearman correlations between intersubject RSMs and developmental models. The model with the highest correlation was taken as the best fit. Intersubject correlation was repeated 1,000 times with shuffled maturity labels to construct null distributions, and a false discovery rate (FDR = 0.05) was used for multiple-comparison correction. Key ages were identified by sliding the ages in the key-stage model, indicating the emergence of shared memory representations. To assess group-level differences in the distributions of key ages, we performed a leave-one-subject-out procedure separately for children with ADHD and TD children.

5. References

1 Tulving, E. Episodic memory: From mind to brain. *Annu. Rev. Psychol.* **53**, 1–25 (2002).

2 Ghetti, S. & Bunge, S. A. Neural changes underlying the development of episodic memory during middle childhood. *Dev. Cogn. Neurosci.* **2**, 381–395 (2012).

3 Mayer, R. E. Rote versus meaningful learning. *Theory Pract.* **41**, 226–232 (2002).

4 Karpicke, J. D. Retrieval-based learning: active retrieval promotes meaningful learning. *Curr. Dir. Psychol.* **21**, 157–163 (2012).

5 Josselyn, S. A. & Tonegawa, S. Memory engrams: recalling the past and imagining the future. *Science* **367**, eaaw4325 (2020).

6 Jung, J. H. *et al.* Examining the engram encoding specificity hypothesis in mice. *Neuron* **111**, 1830–1845 (2023).

7 Pacheco Estefan, D. *et al.* Coordinated representational reinstatement in the human hippocampus and lateral temporal cortex during episodic memory retrieval. *Nat. Commun.* **10**, 2255 (2019).

8 Liu, J. *et al.* Transformative neural representations support long-term episodic memory. *Sci. Adv.* **7**, eabg9715 (2021).

9 Favila, S. E., Lee, H. & Kuhl, B. A. Transforming the concept of memory reactivation. *Trends Neurosci.* **43**, 939–950 (2020).

10 Rau, E. M. *et al.* Reinstatement and transformation of memory traces for recognition. *Sci. Adv.* **11**, eadp9336 (2025).

11 Xiao, X. *et al.* Transformed neural pattern reinstatement during episodic memory retrieval. *J. Neurosci.* **37**, 2986–2998 (2017).

12 Dudai, Y., Karni, A. & Born, J. The consolidation and transformation of memory. *Neuron* **88**, 20–32 (2015).

13 Johnson, J. D. & Rugg, M. D. Recollection and the reinstatement of encoding-related cortical activity. *Cereb. Cortex* **17**, 2507–2515 (2007).

14 Bosch, S. E., Jehee, J. F., Fernández, G. & Doeller, C. F. Reinstatement of associative memories in early visual cortex is signaled by the hippocampus. *J. Neurosci.* **34**, 7493–7500 (2014).

15 Danker, J. F. & Anderson, J. R. The ghosts of brain states past: remembering reactivates the brain regions engaged during encoding. *Psychol. Bull.* **136**, 87 (2010).

16 Ritchey, M., Wing, E. A., LaBar, K. S. & Cabeza, R. Neural similarity between encoding and retrieval is related to memory via hippocampal interactions. *Cereb. Cortex* **23**, 2818–2828 (2013).

17 Staresina, B. P. *et al.* Hippocampal pattern completion is linked to gamma power increases and alpha power decreases during recollection. *eLife* **5**, e17397 (2016).

18 Bone, M. B., Ahmad, F. & Buchsbaum, B. R. Feature-specific neural reactivation during episodic memory. *Nat. Commun.* **11**, 1945 (2020).

19 Guo, D. & Yang, J. Reactivation of schema representation in lateral occipital cortex supports successful memory encoding. *Cereb. Cortex* **33**, 5968–5980 (2023).

20 Güçlü, U. & Van Gerven, M. A. Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. *J. Neurosci.* **35**, 10005–10014 (2015).

21 Kuzovkin, I. *et al.* Activations of deep convolutional neural networks are aligned with gamma band activity of human visual cortex. *Commun. Biol.* **1**, 107 (2018).
22 Buckner, R. L. & Wheeler, M. E. The cognitive neuroscience of remembering. *Nat. Rev. Neurosci.* **2**, 624–634 (2001).
23 Fletcher, P. C. & Henson, R. N. A. Frontal lobes and human memory: insights from functional neuroimaging. *Brain* **124**, 849–881 (2001).
24 Umeda, S. *et al.* Functional network in the prefrontal cortex during episodic memory retrieval. *NeuroImage* **26**, 932–940 (2005).
25 Cohen, M. X. Hippocampal-prefrontal connectivity predicts midfrontal oscillations and long-term memory performance. *Curr. Biol.* **21**, 1900–1905 (2011).
26 Eichenbaum, H. Prefrontal-hippocampal interactions in episodic memory. *Nat. Rev. Neurosci.* **18**, 547–558 (2017).
27 Wagner, A. D., Paré-Blagoev, E. J., Clark, J. & Poldrack, R. A. Recovering meaning: left prefrontal cortex guides controlled semantic retrieval. *Neuron* **31**, 329–338 (2001).
28 Thompson-Schill, S. L. Neuroimaging studies of semantic memory: inferring "how" from "where". *Neuropsychologia* **41**, 280–292 (2003).
29 Blumenfeld, R. S. & Ranganath, C. Prefrontal cortex and long-term memory encoding: an integrative review of findings from neuropsychology and neuroimaging. *Neuroscientist* **13**, 280–291 (2007).
30 Morici, J. F., Weisstaub, N. V. & Zold, C. L. Hippocampal-medial prefrontal cortex network dynamics predict performance during retrieval in a context-guided object memory task. *Proc. Natl. Acad. Sci. U. S. A.* **119**, e2203024119 (2022).
31 Ofen, N. *et al.* Development of the declarative memory system in the human brain. *Nat. Neurosci.* **10**, 1198–1205 (2007).
32 Golarai, G. *et al.* Differential development of high-level visual cortex correlates with category-specific recognition memory. *Nat. Neurosci.* **10**, 512–522 (2007).
33 Ghetti, S., DeMaster, D. M., Yonelinas, A. P. & Bunge, S. A. Developmental differences in medial temporal lobe function during memory encoding. *J. Neurosci.* **30**, 9548–9556 (2010).
34 Sowell, E. R., Trauner, D. A., Gamst, A. & Jernigan, T. L. Development of cortical and subcortical brain structures in childhood and adolescence: a structural MRI study. *Dev. Med. Child Neurol.* **44**, 4–16 (2002).
35 Lenroot, R. K. & Giedd, J. N. Brain development in children and adolescents: insights from anatomical magnetic resonance imaging. *Neurosci. Biobehav. Rev.* **30**, 718–729 (2006).
36 Giedd, J. N. *et al.* Brain development during childhood and adolescence: a longitudinal MRI study. *Nat. Neurosci.* **2**, 861–863 (1999).
37 Sowell, E. R. *et al.* Mapping cortical change across the human life span. *Nat. Neurosci.* **6**, 309–315 (2003).
38 Gogtay, N. *et al.* Dynamic mapping of human cortical development during childhood through early adulthood. *Proc. Natl. Acad. Sci. U. S. A.* **101**, 8174–8179 (2004).
39 Sowell, E. R. *et al.* Longitudinal mapping of cortical thickness and brain growth in normal children. *J. Neurosci.* **24**, 8223–8231 (2004).
40 Yu, Q. *et al.* Age-associated increase in mnemonic strategy use is linked to prefrontal cortex development. *NeuroImage* **181**, 162–169 (2018).

41 Petanjek, Z. *et al.* Extraordinary neoteny of synaptic spines in the human prefrontal cortex. *Proc. Natl. Acad. Sci. U. S. A.* **108**, 13281–13286 (2011).
42 Ghetti, S. & Fandakova, Y. Neural development of memory and metamemory in childhood and adolescence: toward an integrative model of the development of episodic recollection. *Annu. Rev. Dev. Psychol.* **2**, 365–388 (2020).
43 American Psychiatric Association. *Diagnostic and statistical manual of mental disorders*. (APA Publishing, 1994).
44 Thomas, R., Sanders, S., Doust, J., Beller, E. & Glasziou, P. Prevalence of attention-deficit/hyperactivity disorder: a systematic review and meta-analysis. *Pediatrics* **135**, e994–e1001 (2015).
45 Shaw, P. *et al.* Attention-deficit/hyperactivity disorder is characterized by a delay in cortical maturation. *Proc. Natl. Acad. Sci. U. S. A.* **104**, 19649–19654 (2007).
46 Sripada, C. *et al.* Disrupted network architecture of the resting brain in attention-deficit/hyperactivity disorder. *Hum. Brain Mapp.* **35**, 4693–4705 (2014).
47 Øie, M. & Rund, B. R. Neuropsychological deficits in adolescent-onset schizophrenia compared with attention deficit hyperactivity disorder. *Am. J. Psychiat.* **156**, 1216–1222 (1999).
48 Krauel, K. *et al.* Impact of emotional salience on episodic memory in attention-deficit/hyperactivity disorder: a functional magnetic resonance imaging study. *Biol. Psychiatry* **61**, 1370–1379 (2007).
49 Koirala, S. *et al.* Neurobiology of attention-deficit hyperactivity disorder: historical challenges and emerging frontiers. *Nat. Rev. Neurosci.* **25**, 759–775 (2024).
50 Rubia, K. *et al.* Hypofrontality in attention deficit hyperactivity disorder during higher-order motor control: a study with functional MRI. *Am. J. Psychiat.* **156**, 891–896 (1999).
51 Dosenbach, N. U. *et al.* Distinct brain networks for adaptive and stable task control in humans. *Proc. Natl. Acad. Sci. U. S. A.* **104**, 11073–11078 (2007).
52 Isola, P., Xiao, J., Torralba, A. & Oliva, A. in *CVPR 2011*. 145–152 (IEEE).
53 Chen, J. *et al.* Shared memories reveal shared structure in neural activity across individuals. *Nat. Neurosci.* **20**, 115–125 (2017).
54 Finn, E. S. *et al.* Idiosynchrony: from shared responses to individual differences during naturalistic neuroimaging. *NeuroImage* **215**, 116828 (2020).
55 Li, Y. *et al.* Intersubject neural similarity reveals the development trajectory of recognition memory in children. *Dev. Cogn. Neurosci.* **73**, 101553 (2025).
56 Kriegeskorte, N., Mur, M. & Bandettini, P. A. Representational similarity analysis–connecting the branches of systems neuroscience. *Front. Syst. Neurosci.* **2**, 4 (2008).
57 Liu, J. *et al.* Stable maintenance of multiple representational formats in human visual short-term memory. *Proc. Natl. Acad. Sci. U. S. A.* **117**, 32329-32339 (2020).
58 Davis, S. W. *et al.* Visual and semantic representations predict subsequent memory in perceptual and conceptual memory tests. *Cereb. Cortex* **31**, 974-992 (2021).
59 Heinen, R., Bierbrauer, A., Wolf, O. T. & Axmacher, N. Representational formats of human memory traces. *Brain Struct. Funct.* **229**, 513-529 (2024).
60 Snodgrass, J. G. & Corwin, J. Pragmatics of measuring recognition memory: applications to dementia and amnesia. *J. Exp. Psychol. Gen.* **117**, 34–50 (1988).

61 Panagiotidi, M., Overton, P. G. & Stafford, T. Multisensory integration and ADHD-like traits: evidence for an abnormal temporal integration window in ADHD. *Acta Psychol.* **181**, 10–17 (2017).

62 Robin, J. & Moscovitch, M. Details, gist and schema: hippocampal-neocortical interactions underlying recent and remote episodic and spatial memory. *Curr. Opin. Behav. Sci.* **17**, 114–123 (2017).

63 Sekeres, M. J., Winocur, G. & Moscovitch, M. The hippocampus and related neocortical structures in memory transformation. *Neurosci. Lett.* **680**, 39–53 (2018).

64 Huang-Pollock, C. L., Maddox, W. T. & Tam, H. Rule-based and information-integration perceptual category learning in children with attention-deficit/hyperactivity disorder. *Neuropsychology* **28**, 594–604 (2014).

65 McClelland, J. L., McNaughton, B. L. & O'Reilly, R. C. Why there are complementary learning systems in the hippocampus and neocortex: insights from the successes and failures of connectionist models of learning and memory. *Psychol. Rev.* **102**, 419–457 (1995).

66 Lifanov, J., Linde-Domingo, J. & Wimber, M. Feature-specific reaction times reveal a semanticisation of memories over time and with repeated remembering. *Nat. Commun.* **12**, 3177 (2021).

67 Hebart, M. N., Zheng, C. Y., Pereira, F. & Baker, C. I. Revealing the multidimensional mental representations of natural objects underlying human similarity judgements. *Nat. Hum. Behav.* **4**, 1173–1185 (2020).

68 Huth, A. G., Nishimoto, S., Vu, A. T. & Gallant, J. L. A continuous semantic space describes the representation of thousands of object and action categories across the human brain. *Neuron* **76**, 1210–1224 (2012).

69 Carlson, T. A., Ritchie, J. B., Kriegeskorte, N., Durvasula, S. & Ma, J. Reaction time for object categorization is predicted by representational distance. *J. Cogn. Neurosci.* **26**, 132–142 (2014).

70 Chanales, A. J., Oza, A., Favila, S. E. & Kuhl, B. A. Overlap among spatial memories triggers repulsion of hippocampal representations. *Curr. Biol.* **27**, 2307–2317. e2305 (2017).

71 Schlichting, M. L., Mumford, J. A. & Preston, A. R. Learning-related representational changes reveal dissociable integration and separation signatures in the hippocampus and prefrontal cortex. *Nat. Commun.* **6**, 8151 (2015).

72 Kunz, L. *et al.* Hippocampal theta phases organize the reactivation of large-scale electrophysiological representations during goal-directed navigation. *Sci. Adv.* **5**, eaav8192 (2019).

73 Salmi, J. *et al.* ADHD desynchronizes brain activity during watching a distracted multi-talker conversation. *NeuroImage* **216**, 116352 (2020).

74 Gao, Z. *et al.* Reduced temporal and spatial stability of neural activity patterns predict cognitive control deficits in children with ADHD. *Nat. Commun.* **16**, 2346 (2025).

75 Mueller, S. *et al.* Individual variability in functional connectivity architecture of the human brain. *Neuron* **77**, 586–595 (2013).

76 Xiao, X. *et al.* Individual-specific and shared representations during episodic memory encoding and retrieval. *NeuroImage* **217**, 116909 (2020).

77 Moraczewski, D., Chen, G. & Redcay, E. Inter-subject synchrony as an index of functional specialization in early childhood. *Sci. Rep.* **8**, 2252 (2018).

78 Cohen, S. S., Tottenham, N. & Baldassano, C. Developmental changes in story-evoked responses in the neocortex and hippocampus. *eLife* **11**, e69430 (2022).
79 Petroni, A. *et al.* The variability of neural responses to naturalistic videos change with age and sex. *eNeuro* **5**, ENEURO. 0244-0217.2017 (2018).
80 Ofen, N. The development of neural correlates for memory formation. *Neurosci. Biobehav. Rev.* **36**, 1708–1717 (2012).
81 McAuley, T., Brahmbhatt, S. & Barch, D. M. Performance on an episodic encoding task yields further insight into functional brain development. *NeuroImage* **34**, 815–826 (2007).
82 Craik, F. I. & Tulving, E. Depth of processing and the retention of words in episodic memory. *J. Exp. Psychol. Gen.* **104**, 268–294 (1975).
83 Hill, R. M. *et al.* Multi-channel whole-head OPM-MEG: Helmet design and a comparison with a conventional system. *NeuroImage* **219**, 116995 (2020).
84 Rier, L. *et al.* Tracking the neurodevelopmental trajectory of beta band oscillations with optically pumped magnetometer-based magnetoencephalography. *eLife* **13**, RP94561 (2024).
85 Snodgrass, J. G. & Vanderwart, M. A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity. *J. Exp. Psychol. Hum. Learn.* **6**, 174–215 (1980).
86 Delorme, A. & Makeig, S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neurosci. Methods* **134**, 9–21 (2004).
87 Bentin, S., Allison, T., Puce, A., Perez, E. & McCarthy, G. Electrophysiological studies of face perception in humans. *J. Cogn. Neurosci.* **8**, 551–565 (1996).
88 Mullen, T. R. *et al.* Real-time neuroimaging and cognitive monitoring using wearable dry EEG. *IEEE Trans. Biomed. Eng.* **62**, 2553–2567 (2015).
89 Jung, T. P. *et al.* Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. *Clin. Neurophysiol.* **111**, 1745–1758 (2000).
90 Pion-Tonachini, L., Kreutz-Delgado, K. & Makeig, S. ICLabel: an automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage* **198**, 181–197 (2019).
91 Ben-Shachar, M. S. TBT: Reject and interpolate channels on a trial-by-trial basis. *Zenodo* https://doi.org/10.5281/zenodo.1241518 (2018).
92 Sheng, J. *et al.* Intersubject similarity in neural representations underlies shared episodic memory content. *Proc. Natl. Acad. Sci. U. S. A.* **120**, e2308951120 (2023).
93 Camacho, M. C. *et al.* Large-scale encoding of emotion concepts becomes increasingly similar between individuals from childhood to adolescence. *Nat. Neurosci.* **26**, 1256–1266 (2023).
94 Krizhevsky, A., Sutskever, I. & Hinton, G. E. ImageNet classification with deep convolutional neural networks. *Commun. ACM* **60**, 84–90 (2017).
95 Lindh, D., Sligte, I. G., Assecondi, S., Shapiro, K. L. & Charest, I. Conscious perception of natural images is constrained by category-related visual features. *Nat. Commun.* **10**, 4106 (2019).
96 Maris, E. & Oostenveld, R. Nonparametric statistical testing of EEG-and MEG-data. *J. Neurosci. Methods* **164**, 177–190 (2007).

97 Ferguson, H. J., Brunsdon, V. E. A. & Bradford, E. E. F. The developmental trajectories of executive function from adolescence to old age. *Sci. Rep.* **11**, 1382 (2021).

Data and code availability

All data and code used in this study are available at the Open Science Framework (https://osf.io/mqzga).

Author contributions

Y.L., C.W., X.D. and Y.S. designed research; C.W., Q.Z., and H.M. performed research; Y.L. analyzed data; Y.L. wrote the paper. All authors reviewed the manuscript and approved the final version.

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Competing interests

The authors declare no competing interests.

Ethics statement

This work was approved by the Ethics Committee of the Children's Hospital of Changzhou in accordance with the Declaration of Helsinki (1991). Informed consent was obtained from all subjects involved in the study.

Figures and Tables

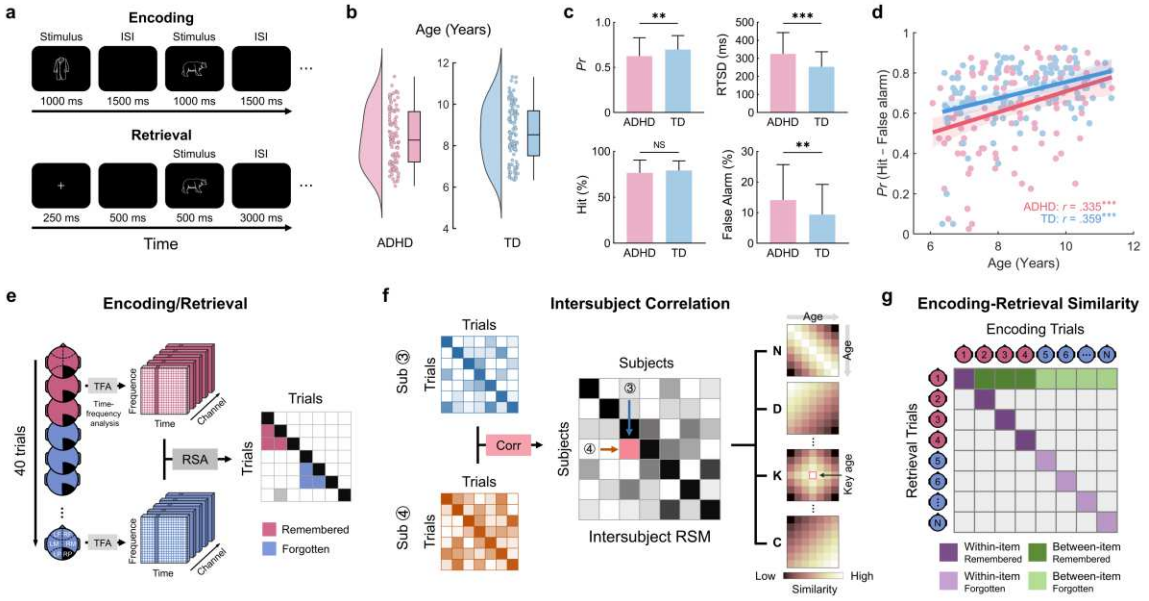


Fig. 1. Experimental paradigms, sample distribution, behavioral performance and the pipeline of representational similarity analysis. (a) Participants completed a recognition memory task including encoding (classifying animals/nonanimals) and retrieval (identifying old/new) phases. **(b)** Age distribution of ADHD (8.39 ± 1.32 years) and TD children (8.62 ± 1.37 years). **(c)** Recognition performance was poorer in ADHD than in TD children, which was attributed to false alarms of new items (*Pr*: hits – false alarms; RTSD: standard deviation of response time; Hit: hit rate of old items; False Alarm: false alarm rate of new items). **(d)** Correlations between memory performance (*Pr*) and age in ADHD or TD children. **(e)** Schematic of the individual representational similarity matrix. Item-specific time-frequency features were extracted from the raw EEG data. The power values across frequencies and electrodes were then extracted across distinct time windows and ROIs. The pairwise similarity matrices were constructed using RSA, reflecting the paired representation similarity between different items. **(f)** Schematic of intersubject correlation (ISC). ISC was constructed by calculating the similarity between each pair of individuals (Intersubject RSM) and fitted to four development models to track memory representational trajectories. N, nearest neighbor; D, divergence; K, key stage; C, convergence. **(g)** Schematic of encoding-retrieval similarity (ERS). Similarities within the same items (ERS_{WI}, diagonal) and between different items (ERS_{BI}, off-diagonal) were quantified. Item-specific ERS were defined as ERS_{Item} = avg.(ERS_{WI}) − avg.(ERS_{BI}). Differences between remembered and forgotten items were used to determine whether memory benefited from reactivation (remembered > forgotten) or transformation (forgotten > remembered).

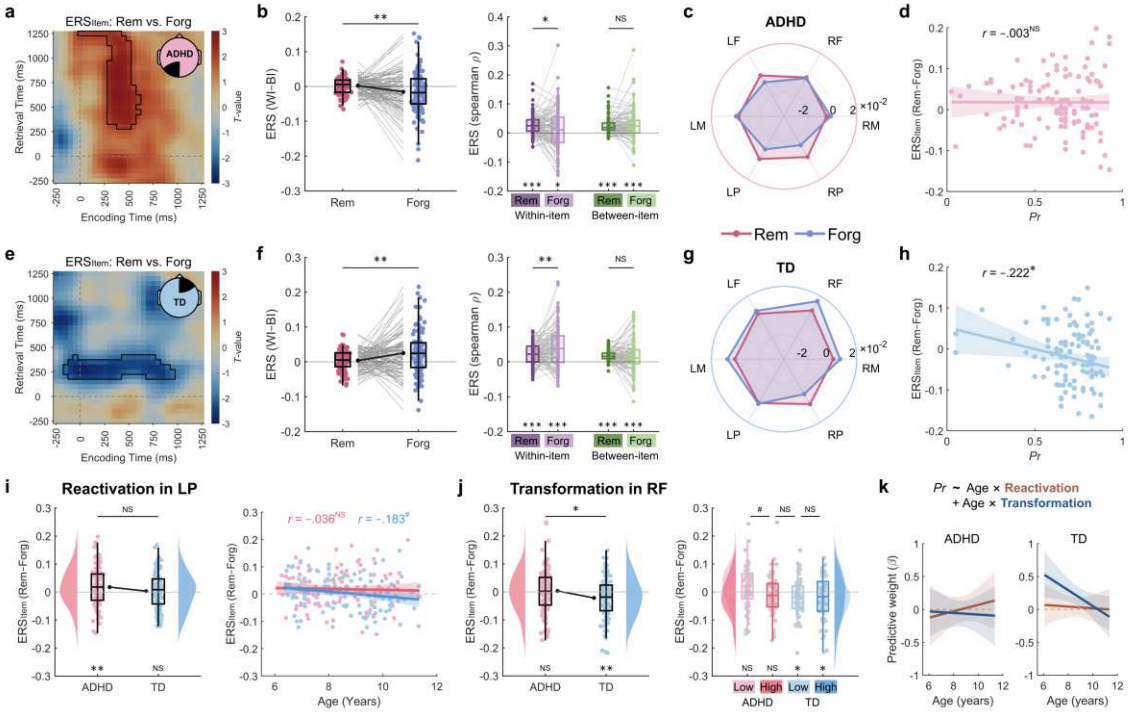


Fig. 2. Memory reactivation in ADHD and transformation in TD children. (a) Temporal dynamics of item-specific ERS during encoding and retrieval. Children with ADHD showed significant reactivation clusters in the LP (remembered > forgotten). Color indicates *T* values; black outline indicates significant clusters after cluster-based multiple comparisons correction. **(b)** ERS values in the LP for each child with ADHD, averaged across significant clusters. Left: remembered vs. forgotten (WI – BI; i.e., ERS_{Item}). Right: within-item (WI) vs. between-item (BI). **(c)** Reactivation effects across six ROIs in ADHD, averaged across poststimulus intervals. **(d)** No correlation was detected between reactivation and memory performance (*Pr*) in ADHD. **(e)** TD children showed significant transformation clusters in the RF (forgotten > remembered). **(f)** ERS values in the RF for each TD child, averaged across significant clusters. **(g)** Transformation effects across six ROIs in TD. **(h)** Significant correlation between transformation and memory performance in TD. **(i)** Developmental effects of reactivation in the LP. Left, individual reactivation values. Right, correlation between reactivation and age in both groups. **(j)** Developmental effects of transformation in the RF. Left, individual transformation values. Right, subgroup contrasts by median split. Transformation increased with age in the ADHD group but remained stable in the TD group. Colors indicate age subgroups. **(k)** Age-dependent shifts in the predictive weights of reactivation (brown) and transformation (blue) for *Pr* in the multiple linear regression model for both groups of children. Bottom * indicates significance for the one-sample *T* test; Line * indicates significance for the paired-sample or two-sample *T* test; $*P < 0.05$; $**P < 0.01$; $***P < 0.001$; # $P < 0.08$; NS, not significant.

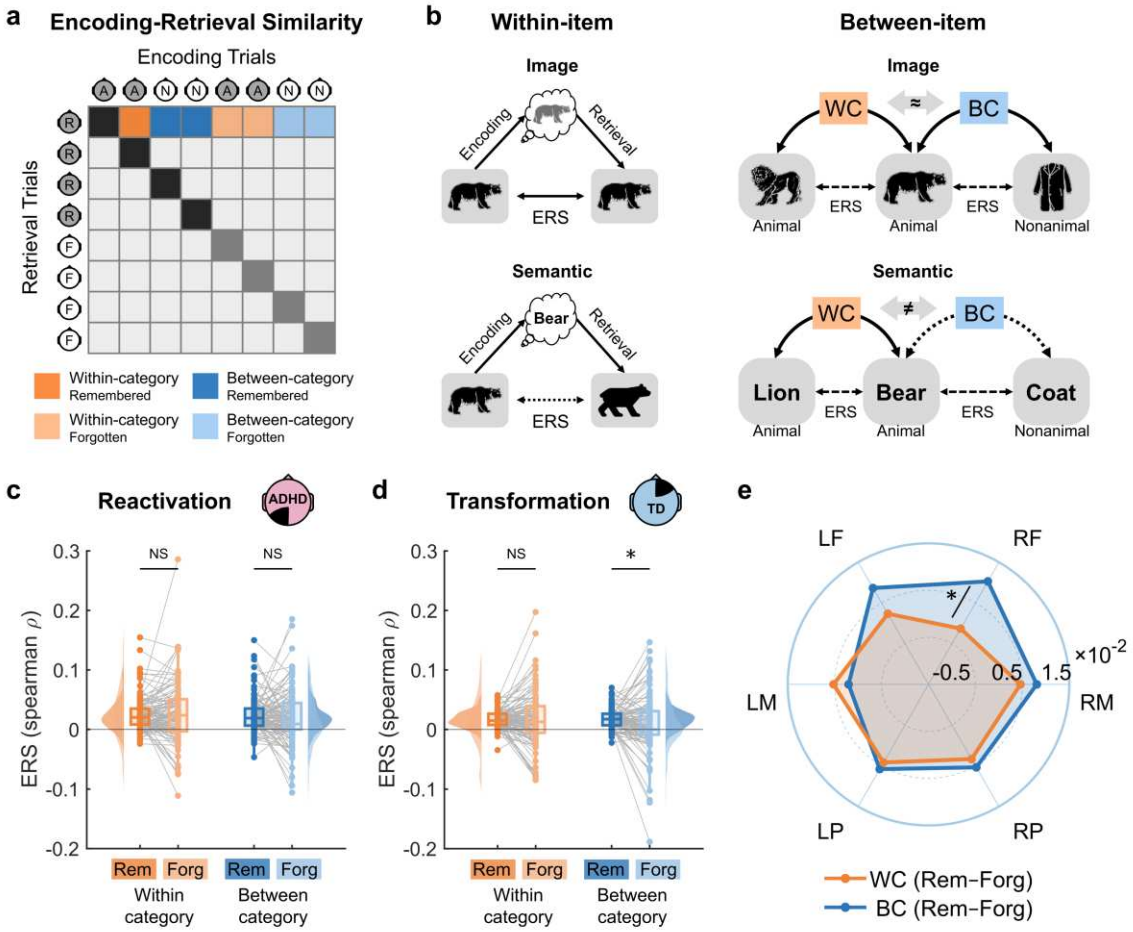


Fig. 3. Representational contents of memory reactivation and transformation. (a) The similarity between different items is depicted on the off-diagonal of the ERS matrix. Within-category (ERS_{WC}, orange) indicates items from the same category, and between-category (ERS_{BC}, blue) indicates items from different categories. A, animals; N, nonanimals; R, remembered; F, forgotten. **(b)** Memory patterns may be reactivated or transformed through images or semantics. If reactivation or transformation relies on images, $ERS_{BC} \approx ERS_{WC}$; if it relies on semantics, $ERS_{BC} \neq ERS_{WC}$. **(c)** Memory reactivation reflects image processes, with similar memory reactivation differences observed in ERS_{BC} and ERS_{WC}. **(d)** Memory transformation reflects semantic modulation, with more memory transformation differences observed in ERS_{BC} than in ERS_{WC}. **(e)** Memory transformation differences (Rem − Forg) across six ROIs in TD, averaged across poststimulus intervals. Line * indicates significance for the paired-sample *T* test; $*P < 0.05$; NS, not significant.

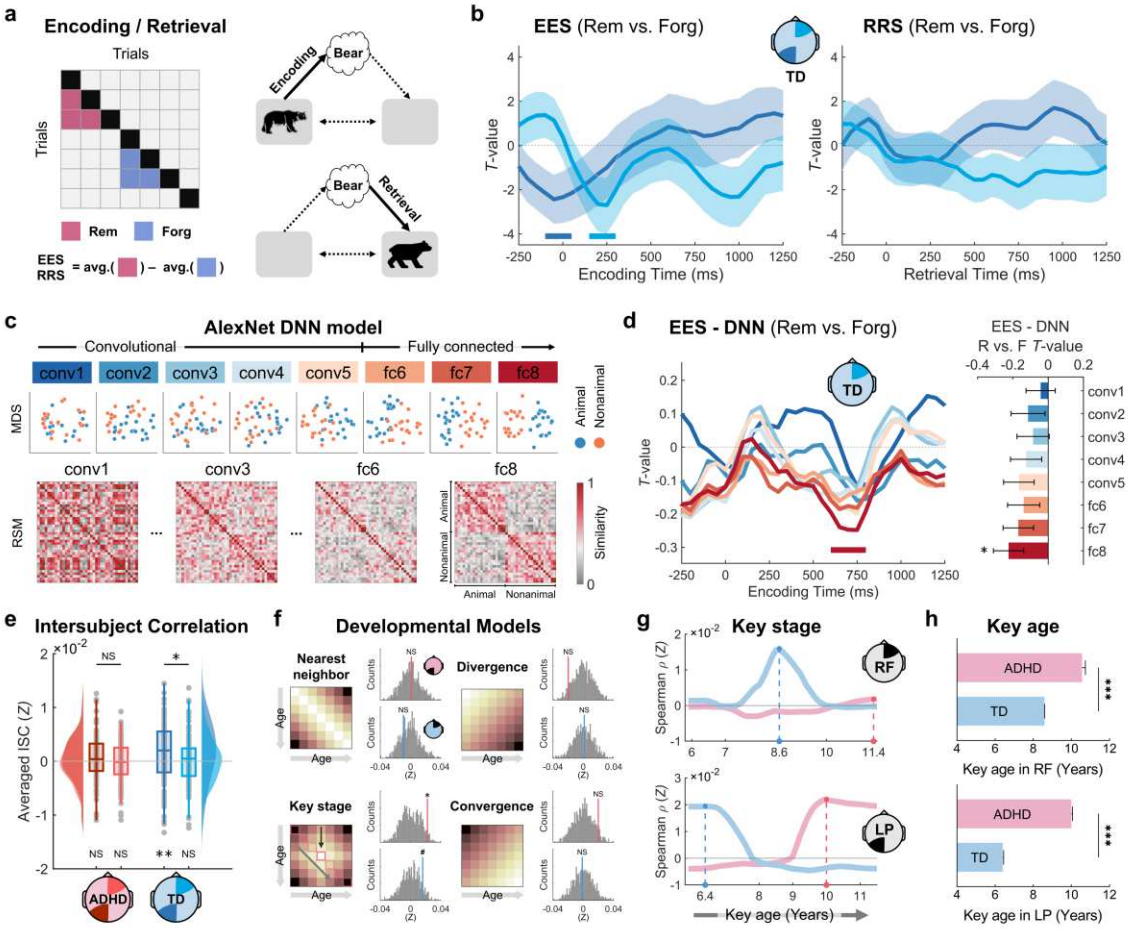


Fig. 4. Memory transformation formats and intersubject correlation (ISC). (a) Between-item similarity within encoding (EES) or retrieval (RRS) phases was used to test when memory transformation occurs. **(b)** Memory differentiation effects (forgotten > remembered) across ROIs during encoding (left) and retrieval (right). Colored curves indicate *T* values across time; Colored horizontal bars indicate significant clusters after multiple-comparison correction. **(c)** Schematic diagram of a DNN model (AlexNet). Top: multidimensional scaling (MDS) plots of stimulus images. Bottom: partial RSM of stimulus images sorted by category. Both illustrate that the clustering of represented categories (animals/non-animals) is more pronounced in the higher than in the lower DNN layers. **(d)** Comparison of neural RSMs from EES of TD children with those from each DNN layer. Left: time-resolved analysis of the EES-DNN correspondence for remembered and forgotten items. Colored horizontal bars indicate significant clusters after multiple-comparison correction. Right: Transformation shows significant EES-DNN correspondences at higher layers (fc8), averaged across significant clusters. **(e)** Distribution of average ISC in children with ADHD and TD children. Children with ADHD have similar ISC in the LP (dark red) and RF (light red) regions, whereas TD children have higher ISC in the LP (dark blue) than in the RF (light blue) region. **(f)** Model fits between ISC and four developmental models (LP for ADHD; RF for TD), with the key-stage model providing the best fit. Grey bars indicate permutation-based null distributions; Colored lines indicate observed model fits. **(g)** Fitting coefficients of key-stage models across different key ages

in RF (top) and LP (bottom). Darker dots indicate the best fits. **(h)** Group differences in key ages between children with ADHD and TD children in RF (top) and LP (bottom). Bottom * indicates significance for the one-sample *T* test; Line * indicates significance for the paired-sample or two-sample *T* test; *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$; # $P < 0.08$; NS, not significant.

		ADHD	TD	χ^2/T	*P*
N		114	109		
Mean Age ± SD		8.39 ± 1.32	8.62 ± 1.37	1.279	0.202
Gender(male:female)		83:31	69:40	2.319	0.128
IQ		93.51 ± 12.70	100.68 ± 12.40	4.263***	<0.001
Symptom	**Inattention**	17.77 ± 4.07	5.73 ± 3.68	23.124***	<0.001
	Hyperactivity	17.33 ± 5.05	3.93 ± 3.53	22.868***	<0.001
Encoding	**Accuracy (%)**	91.52 ± 4.61	93.90 ± 4.46	3.914***	<0.001
	RT (ms)	858.95 ± 93.18	830.25 ± 107.81	2.130*	0.034
	RTSD (ms)	147.64 ± 28.54	138.11 ± 31.71	2.362*	0.019
Retrieval	***Pr***	0.63 ± 0.20	0.70 ± 0.15	3.030**	0.003
	Hit (%)	76.64 ± 13.81	79.24 ± 10.38	1.583	0.115
	False Alarm (%)	14.14 ± 11.57	9.36 ± 9.88	3.317**	0.001
	RT (ms)	1208.91 ± 218.48	1106.71 ± 177.91	3.820***	<0.001
	RTSD (ms)	324.97 ± 117.64	253.15 ± 83.38	5.238***	<0.001

Table 1. Summary statistics for demographic variables in the sample of children. Gender differences between children with ADHD and TD children were assessed using a single-tailed χ^2 test. For all the other between-group comparisons, two-tailed two-sample *T* tests were employed. ADHD, attention deficit/hyperactivity disorder; TD, typically developing; IQ, intelligence quotient; RT, response time; RTSD, standard deviation of response time; *Pr*, corrected recognition score (hits – false alarms). **P* < 0.05; ***P* < 0.01; ****P* < 0.001.

Supplementary Files

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- ss.pdf