

Contents lists available at ScienceDirect

Developmental Cognitive Neuroscience



journal homepage: www.elsevier.com/locate/dcn

Intersubject neural similarity reveals the development trajectory of recognition memory in children

Yiwen Li^{a,1}, Chaoqun Wang^{b,1}, Weiyu Hu^a, Qinfen Zhang^b, Haitian Mei^b, Shiyan Ji^b, Dongwei Li^{c,d}, Yiyang Wang^a, Yuanjun Kong^a, Yan Song^{a,*}, Xuan Dong^{b,*}

^a State Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University, Beijing 100875, China

^b Children's Health Research Center, Changzhou Children's Hospital of Nantong University, Changzhou, Jiangsu 213000, China

^c Department of Psychology, Faculty of Arts and Sciences, Beijing Normal University, Zhuhai 519087, China

^d Beijing Key Laboratory of Applied Experimental Psychology, National Demonstration Center for Experimental Psychology Education, Faculty of Psychology, Beijing

Normal University, Beijing 100875, China

ARTICLE INFO

Keywords: EEG RSA Neural representation Memory Development

ABSTRACT

Recognition memory improves with child development, but the neural mechanisms underlying such improvement and the developmental variation remain poorly understood. Herein, we investigated how the neural representations during the encoding and retrieval phases of recognition memory change with age, using representational similarity analysis in a sample of children aged 6–13 years (n = 137). Our results indicated that the encoding and retrieval phases have distinct neural patterns of development. Similarly, using a model-free approach, we confirmed that there is a key developmental stage (about 9–10 years old) for the neural representation during the encoding phase, whereas the neural representation during the retrieval phase tends to be stable with child development. Additionally, we identified that the neural similarity between the encoding and retrieval phases in children is primarily located in the left parietal-occipital region. Overall, these findings refine the developmental process underlying memory representation and enhance our understanding of the neural mechanisms of recognition memory.

1. Introduction

Recognition memory is an essential component of episodic memory (Bird, 2017), and is widely employed in studies of children's memory capacities. Recognition memory for vividly recalled scenes improves with age (Ofen et al., 2007), generally during childhood (Cycowicz et al., 2001) and further during adolescence and young adulthood (Sprondel et al., 2011; Ofen et al., 2012). This improvement may be associated with continued neurological evolution throughout childhood and adolescence (Golarai et al., 2007; Ghetti et al., 2010). However, how the neural system develops and the developmental variation across memory phases remain poorly understood (Haese and Czernochowski, 2016; Koenig et al., 2020). Investigating the neural mechanisms underlying the development of recognition memory can help us better understand the mechanisms of memory formation.

The development of recognition memory is associated with neural similarity during two crucial memory phases: encoding and retrieval.

Numerous studies have demonstrated that the neural activity triggered in response to an event is partially reactivated during recognition (Wheeler et al., 2000; Polyn et al., 2005; Danker and Anderson, 2010). Further research has demonstrated that the reactivation of representations of previously remembered content facilitates successful memory encoding (Kuhl et al., 2010; Koen and Rugg, 2016). Researchers have also identified a connection between neural representations and subsequent memory, demonstrating that items showing greater neural pattern similarity between encoding and retrieval were associated with better subsequent memory performance (Xue et al., 2010). This variation in neural similarity between the encoding and retrieval processes supports the development of recognition memory in children.

The development of recognition memory is also related to the neural representation stability during the encoding or retrieval phase (i.e., the individual-group representation pattern). The robustness of memory encoding is associated with the response reliability evoked by repeated stimuli (Yao et al., 2007), which translates into cross-individual

* Corresponding authors.

https://doi.org/10.1016/j.dcn.2025.101553

Received 21 October 2024; Received in revised form 11 March 2025; Accepted 14 March 2025 Available online 18 March 2025 1878-9293/© 2025 The Author(s). Published by Elsevier Ltd. This is an open access article under the C

E-mail addresses: songyan@bnu.edu.cn (Y. Song), dx6868@126.com (X. Dong).

¹ These authors contributed equally to this work.

^{1878-9293/© 2025} The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

response reliability (Hasson et al., 2009; Byrge et al., 2015). It has previously been confirmed that neural responses are more strongly associated, and neural patterns are more similar between individuals during successful memory encoding (Hasson et al., 2008; Koch et al., 2020). Memory representations can further be shared across individuals to create group memory representations (Xiao et al., 2020). Meanwhile, the similarity of neural representation and activity between individuals and groups contributes to memory capacity (Sheng et al., 2023). Specifically, group-averaged neural activity and representations are believed to reflect typical stimulus processing, whereas individual-group similarity may indicate overall attentional engagement and fidelity of the stimulus representations, thus underlying the memory capacity of individuals (Cohen and Parra, 2016). As such, the development of recognition memory in children may also depend on the neural representation similarity between individuals and groups.

Furthermore, intersubject variability may potentially affect the recognition memory. It has been found that individuals' neural transformation of learning materials during the encoding or retrieval phase affects subsequent memory (Favila et al., 2020; Liu et al., 2021; Xue, 2022). As memory involves effective interaction between the existing long-term knowledge of each individual and the learning materials (Xue, 2018), each individual performs his or her own unique neural transformations to stimuli, resulting in unique memory content. For example, individuals' unique semantic representations predicted their false memories better than the group memory representations (Chadwick et al., 2016). Since intersubject variations in representation patterns may not be well captured by individual-group similarities. For instance, representation patterns may diverge throughout development, resulting in children with closer maturity having more similar patterns. Therefore, we also used intersubject similarity analysis to verify the feasibility of different developmental models.

The aim of this study was to reveal the neural mechanisms underlying the development of recognition memory through representational similarity analysis on high-temporal resolution data recorded by electroencephalography (EEG). We investigated variations of individualgroup neural representations during two memory phases, encoding and retrieval. We further systematically compared the neural representations of encoding and retrieval specific items to examine the representational features and temporal dynamics of distinct memory phases. In addition, intersubject variations in neurological development were confirmed by intersubject similarity analysis. Overall, our findings revealed the time course and functional relevance of representational changes during memory processing, contributing to a further understanding of the generative and constructive nature of recognition memory.

2. Materials and methods

2.1. Participants

This study recruited 137 healthy children (57 females; age range: 6–13; Mean \pm SD = 9.24 \pm 1.80) from local schools (detailed in Table S1). The normality test (Shapiro-Wilk) indicated no significant deviation in the normality of children's ages (p = 0.392). All participants had an IQ score \geq 80 according to the Wechsler Intelligence Scale for Chinese Children-Revised (WISCC-R). All participants were right-handed, had normal or corrected-to-normal vision, and had no history of neurological or psychiatric problems. Informed consent was obtained from children and their parents prior to the experiment, in accordance with the protocols approved by the local ethics committee.

2.2. Stimuli

The stimuli material comprised 80 images extracted from the Snodgrass and Vanderwart image set (Snodgrass and Vanderwart, 1980), which included two categories: animal and non-animal. These original images were preprocessed for transformation into white-line drawings on a black background. Additionally, the physical properties, including size, background, contrast, and brightness were normalized to each other.

2.3. Procedure

During the EEG recording, the participants viewed the stimulus images continuously displayed on the screen. The stimuli were presented using the E-Prime 2.0 software (Psychological Software Tools, Pittsburgh, PA, USA), with all images presented on a black background. The participants viewed all images from a seat placed 90 cm from the screen at a viewing angle of $3.18^{\circ} \times 3.18^{\circ}$. The experimental task comprised an encoding phase and a retrieval phase with a 1-minute interval. The formal experiment lasted approximately 10 min in total. To ensure comprehension, participants underwent a practice before the formal experiment.

The encoding phase (Fig. 1A) comprised 60 trials, half consisting of animal images and the other half consisting of non-animal images. Each trial began with the presentation of stimulus images for 1000 ms, followed by a black screen with an interstimulus interval (ISI) of 1500 ms. Participants were instructed to discriminate whether the image presented was of an animal (right-hand-pressed key) or a non-animal (lefthand-pressed key), responding as quickly and accurately as possible using their index fingers. The retrieval phase (Fig. 1B) comprised 80 trials, including 40 with images appeared in the encoding phase (termed old items) and 40 with images did not appear (termed new items). Considering the recording time for children (Brooker et al., 2020) and performing representational similarity analysis between the encoding and retrieval phases, the 40 old items were selected from the 60 images in the encoding phase and remained constant across all participants, but the presentation sequence was randomized. Each trial was initiated with the presentation of a white fixation cross in the center of the screen for 250 ms, followed by a black screen for 500 ms. Subsequently, the stimulus image was presented for 500 ms, followed by a black-screen ISI of 3000 ms. Participants were instructed to determine whether the image presentation was old (right-handed key) or new (left-handed key), responding quickly and accurately using their index fingers. To mitigate artifacts from blinking and eye movements, the participants were instructed to fixate on the white cross on the screen throughout the experiment and to blink in response to key presses.

2.4. EEG recording and preprocessing

EEG data were recorded continuously using a 21-channel amplifier, following the standard 10-20 system (Stellate System Inc., CA, USA). Sampling was conducted at 500 Hz, with online referencing at the CPz electrode, and all inter-electrode impedance maintained below 5 kΩ. The EEG data were preprocessed using EEGLAB (Delorme and Makeig, 2004) in MATLAB 2018b (MathWorks, MA, USA). Initially, bandpass filtering (Hamming-windowed sinc FIR filter) was applied between 0.1 and 30 Hz, with subsequent attenuation of the remaining electrical line noise at 50 Hz performed using the CleanLine plugin (https://www. nitrc.org/projects/cleanline). Off-line re-referencing was subsequently performed using the global average (Bentin et al., 1996). The criteria for identifying and removing bad channels were as follows: 1. Continuously flat for more than 5 s; 2. More than four standard deviations of line noise (relative to their signal); 3. Correlation of less than 0.8 with the estimates of nearby channels. Artifact subspace reconstruction (ASR) was implemented to eliminate data segments containing artifacts (Mullen et al., 2015). Additional data segments were excised if more than 25 % of the channels displayed a power exceeding seven standard deviations. Independent component analysis (ICA; Jung et al., 2000) was further applied to correct eye or muscle artifacts within the continuous data. The ICA matrix was applied to the full-length data prior to the removal of artifactual segments by ASR. The ICLabel plugin (Pion-Tonachini



Fig. 1. Experimental paradigms and the development of behavioral performance. (A) Encoding phase. Participants performed a task to discriminate animal or nonanimal while viewing 60 images. (B) Retrieval phase. Participants recognized whether an image was new or old while viewing 80 images. (C) Correlation between participant age and sensitivity index d' in the retrieval phase. (D) Correlation between participant age and response time in the retrieval phase.

et al., 2019) was used to remove components with a probability for eye or muscular artifacts greater than 0.6. Subsequently, epochs of -200-1000 ms were created from each image, and the same time length was used for all trials. Epochs were eliminated using the TBT plugin (Ben-Shachar, 2018) if at least 10 channels met the following criteria: 1. Amplitudes exceeding $\pm 100 \ \mu$ V; 2. The joint probability of the local/global thresholds exceeded three standard deviations. If fewer than 10 channels matched the rejection criteria, the epoch was retained; however, only the channels at that epoch were interpolated. Finally, the previously-removed channels were interpolated using a spherical spline and a baseline correction was performed. Ultimately, 99.17 % \pm 0.99 % of the trials were retained for subsequent data analysis.

2.5. Data analysis

2.5.1. Behavioral data analysis

According to signal detection theory, the sensitivity index d' (hit rate of old items minus false alarm rate of new items) and the mean response time (RT) in correctly responded trials (comprising hits of old items and correct rejections of new items) in the retrieval phase were calculated. Extreme values exceeding \pm 2.5 standard deviations of the mean RT, accounting for 2.67 % of all correct trials, were excluded. To explore the relationship between behavioral performance (d', RT) and age (Fig. 1C and Fig. 1D), we conducted a correlation analysis between these two factors using SPSS 25.0 (SPSS Inc., Chicago, IL, USA). Correlations were considered significant when the *p*-value was less than 0.05. To further explore the major contributors of sensitivity index d', we calculated the correlation between hits of old items and false alarms of new items in the retrieval phase with age, respectively. Additionally, behavioral performance during the encoding phase was also calculated.

2.5.2. Individual-group representational similarity analysis

To explore the neural similarity between the encoding and retrieval phases, we performed a representational similarity analysis (RSA: Kriegeskorte et al., 2008) of the images presented in both phases (i.e. 40 old items). Potential differences in the scalp among participants may have affected the direct calculation of representational similarity for each item between participants (i.e. first-level pattern similarity). Therefore, we calculated the similarity of representational patterns when participants processed the same set of stimuli (i.e. second-level pattern similarity; Chen et al., 2017; Sheng et al., 2023). We initially averaged all trials across all participants to obtain group-averaged trials (Fig. 2A). Subsequently, for each participant, the removed trials were interpolated using the corresponding group-averaged trials, and no difference between ages in the number of interpolated trials (encoding phase: p = 0.552; retrieval phase: p = 0.873). The cross-trial pattern similarity was subsequently calculated for each participant, resulting in a representational similarity matrix (RSM) of size 40×40 (i.e. representational space). Similarly, RSA was conducted on group-averaged trials to produce a 40×40 canonical representation matrix (group-averaged RSM). Finally, individual-group representational similarity was calculated using the Spearman correlation between each individual's RSM and the group-averaged RSM. Similarly, the representational similarity between the different phases was obtained by correlating each individual's RSM from the encoding phase with that extracted from the retrieval phase (Fig. 2B).



Fig. 2. Schematic diagram of the representational similarity analysis. (A) Schematic for the RSM of individuals and group average. RSA was conducted for each participant to generate an individual's RSM. Similarly, the RSA was conducted on the group-averaged data to generate a group-averaged RSM. (B) The similarities between the encoding and retrieval were calculated from the correlation between the individuals' RSM in the encoding phase and the RSM in the retrieval phase (blue). The similarities between individuals and groups in different phases were obtained by calculating the correlation between the individuals' RSM and the group-averaged RSM (encoding phase: green; retrieval phase: red). (C) Schematic for the intersubject pattern similarity. The intersubject pattern similarity was generated by calculating the correlation between each pair of individuals. (D) Four developmental models of memory representational similarity (nearest neighbor, convergence, divergence, and key stage) were constructed using individual maturity.

To mitigate the interference of the low-level features of the stimulus images with the RSA results, we further constructed a low-level feature RSM using the Hierarchical Model and X (HMAX) model (Serre et al., 2005). Specifically, the features extracted from each of the 40 images were computed in the C2 layer, and their Euclidean distances were calculated. The similarity between the HMAX units in each image was quantified by subtracting the Euclidean distance from 1. After excluding the low-level feature RSM, we computed the Spearman partial correlation for different RSMs. This partial correlation analysis can eliminate all sources of variance shared between specific and low-level feature RSMs (Giordano et al., 2013).

2.5.3. Intersubject representational similarity analysis

Model fitting for individual-group similarity may not completely capture intersubject variations of memory representations, such as the possibility that children with more similar maturity have more similar memory representations. Therefore, we also employed a model-free approach to identify intersubject differences associated with memory representations (Finn et al., 2020; Camacho et al., 2023). To accomplish this, we calculated the intersubject correlation (ISC) separately for each individual's RSM pair to obtain intersubject pattern similarity (Fig. 2C). Then, we tested whether the intersubject pattern similarity corresponded to one of the four developmental models (Fig. 2D). All four models used the chronological age of the participants as the metric of maturity (Camacho et al., 2023). There were four methods of calculating maturity similarity, each of which examined different hypotheses about how memory representations change with age:

1. Nearest Neighbor: children with similar maturity have similar memory representation (metric: sample maximum minus pair absolute difference). 2. Convergence: memory representation was more similar in older children, representing convergence on shared memory representations (metric: pair average). 3. Divergence: memory representation was more similar in younger children, with developmental variations representing the effects of individual differences in experience (metric: sample maximum minus pair average). 4. Key stage: children have more similar memory representation as their maturity nearer to the key stage, representing the effect of the key stage in child development (metric: sample maximum minus the absolute difference between the pair and the key age, with key age ranging from median chronological age ± 1 year and steps in 0.1 years).

We calculated the Spearman correlation between the intersubject pattern similarity and the four models separately. For the key stage model, we defined the key age by the model with the highest correlation coefficient. Finally, the model with the highest-ranked correlation coefficient among the four models was determined to be the best fitting. Furthermore, we also conducted a channel-by-channel searchlight analysis to explore the spatial sources (i.e., the contribution of different **3.** channels) underlying the best-fitting model.

2.5.4. Spatiotemporal pattern similarity analysis

To more precisely investigate the neural similarity between the encoding and retrieval phases, we constructed spatiotemporal features from the EEG data of these two phases and performed a spatiotemporal pattern similarity analysis (STPS; Lu et al., 2015). We further divided all scalp electrodes into six regions and used the scalp voltage from one of the six regions as a spatial feature. The temporal features were selected using a 100 ms sliding window (50 sampling points) with a step size of 2 ms (one sampling point). We divided the 40 previously-presented items into the 'remembered' and 'forgotten' categories, based on memory performance during the retrieval phase. At each sliding window, we separately calculated the correlation coefficients of each remembered item between the encoding and retrieval phases, representing the cross-phase similarity. The same procedure was also performed for forgotten items (Fig. 5A).

The within-item STPS was obtained by calculating the similarity of the same item between two phases. In addition, to determine whether the similarity of within-items reflected the common cognitive processes or item-specific representations, we further calculated the similarity of between-item pairs matched with the within-item pairs. Specifically, for the between-item pairs, two of the items were different and showed the same memory performance as the within-item pairs. As differences in the number of items between the remembered and forgotten conditions may have influenced the reliability of similarity estimates, we excluded participants with fewer than six remembered or forgotten items (Sheng et al., 2023). For the remaining participants, the number of remembered and forgotten items was matched using 1000 bootstrapped sampling. The entire procedure was finally repeated for each participant and time point, thus yielding spatiotemporal estimates of cross-phase similarity.

2.6. Statistical inference

Regression models were constructed between all RSM correlation coefficients and age using SPSS 25.0. Fisher *r*-to-*z* transformations were performed on all of the RSM correlation coefficients prior to performing further statistical analysis, and the resulting *z*-scores represented the normalized differences in the representation patterns. We further separately evaluated the goodness of fit of the linear, quadratic, and cubic regression models (Ferguson et al., 2021). We then compared the values of Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). Finally, the model with the smallest values was selected as the best-fitting model (Table S2). In addition, a multiple linear regression analysis (Uyanık and Güler, 2013) was conducted to identify the RSM correlations that could act as predictors of memory performance.

The intersubject similarity analysis procedure was repeated 5000 times and maturity was systematically shuffled to create the null distribution. The *p*-values were estimated from this ranked distribution for the four independent models. In the spatiotemporal pattern similarity analysis, we performed t-tests and calculated p-values separately for each time window. These p-values were corrected for multiple comparisons with a false discovery rate (FDR) of 0.05. Time windows with statistical values greater than the threshold (p < 0.05) were selected and grouped into connected clusters based on their temporal adjacency. For significant clusters, a two-way repeated-measures analysis of variance (ANOVA) with memory performance (remembered, forgotten) \times item specificity (within-item, between-item) was conducted. Statistical effects that violated the test of sphericity were corrected for p-values using the Greenhouse-Geisser correction. The Bonferroni correction method was applied for post-hoc comparisons, and a simple effects analysis was performed when the interaction effect was significant.

3. Results

3.1. Behavioral performance and development

To evaluate memory performance, we calculated the sensitivity index d' and the mean RT of correctly responded trials in the retrieval phase according to signal detection theory. The results showed that participants were highly sensitive to image recognition (mean sensitivity index $d' \pm SEM$: 2.40 \pm 0.06), and responded rapidly (mean RT \pm SEM: 1073 \pm 19 ms after stimulus onset). Meanwhile, correlation analysis between memory performance and participant age revealed that the sensitivity index d' in the retrieval phase was significantly correlated with age (r = 0.244, p = 0.004; Fig. 1C), as was the RT in the retrieval phase (r = -0.445, p < 0.001; Fig. 1D). The development of d'may be driven by both increased hit rates of old items (r = 0.186, p = 0.030; Fig. S1) and decreased false alarm rates of new items (r = -0.236, p = 0.006). Moreover, age was also significantly correlated with response time in the encoding phase (r = -0.500, p < 0.001), but not with accuracy (r = 0.054, p = 0.532). These behavioral results indicated a gradual improvement in recognition memory as children develop.

3.2. Individual-group similarity revealed by RSA

EEG was recorded during both the encoding and retrieval phases, and then we performed RSA to explore the neural similarity between these two phases. We first constructed a RSM for each individual and group respectively (Fig. 2A). Then we conducted RSA of the individuals' RSM and the group-averaged RSM (Fig. 2B) in the encoding (E&Em) or retrieval (R&Rm) phases, as well as the individuals' RSM in the encoding phase and the individuals' RSM in the retrieval phase (E&R).

This analysis revealed that the neural representational similarity of E&R did not reach statistical significance (p = 0.134, one-sample *t*-test; Fig. 3A), nor did correlation between E&R and age (r = 0.108, p = 0.214; Fig. 3B). In contrast, the similarity of E&Em was significant (p < 0.001), one-sample *t*-test). The similarity of E&Em revealed a significant quadratic relationship with age (r = 0.229, p = 0.029; Fig. 3C). Specifically, the development trajectory of the correlation increased relatively flatly during ages 9-10, while a downward trend occurred after 10 years old. We further found that the similarity of R&Rm reached significance (p < 0.001, one-sample *t*-test) and was significantly and linearly increased with age (r = 0.201, p = 0.020; Fig. 3D). These results revealed that the individual's pattern is similar to the group-averaged pattern in both phases, but that the encoding and retrieval phases have different neural patterns of development. To exclude the potential interference of the stimulus image features on the RSA results, we additionally constructed low-level feature RSM for these images. Similar results were obtained after eliminating the interference from low-level features of the stimulus images (Fig. S2).

However, when individuals' RSMs and group-averaged RSMs were restricted to only remembered items in both phases, there was no age-related difference in similarity ($ps \ge 0.743$; Fig. S3). These results suggested that the age-related increase in individual-group neural representation similarity may not only be driven by age-related increase in the proportion of remembered items. The individual-group neural representation similarity may depend on the combined role of remembered and forgotten items.

Furthermore, in order to identify which correlation coefficients were determinants of memory performance, we applied multiple linear regression analysis. The results revealed that the correlation of R&Rm was borderline significant ($\beta = -0.157$, p = 0.071) in predicting the behavioral response time, whereas none of the other correlations were significant ($ps \ge 0.521$). Similarly, none of these correlations were significant ($ps \ge 0.413$) in predicting behavioral accuracy (Table S3). Together, these results indicated that the neural representational patterns of individuals in the retrieval phase tend to stabilize with age (i.e.



Fig. 3. Results of representational similarity analysis. (A) Correlation between the RSMs of different participants. Boxes indicate data from the 25th to the 75th percentiles, dots indicate individual participants, lines indicate medians, error bars indicate maximum and minimum non-outliers, dots outside the error bars indicate outliers, and asterisks above the boxes indicate significance (***p < 0.001, one-sample *t*-test). E&R refers to the correlation between the encoding phase and the retrieval phase of individuals, E&Em refers to the correlation between individuals and groups in the encoding phase. (B–D) The relationship between different neural representational similarities and age. Dots indicate correlation co-efficients for individuals, colored lines/curves indicate the best fit using the regression model, and shaded areas indicate 95 % confidence intervals.



Fig. 4. Results of intersubject similarity analysis. (A) Model fitting of intersubject similarity in the encoding phase. (B) Model fitting of intersubject similarity in the retrieval phase. Gray bars indicate 5000 random distributions. Colored lines indicate real model fitting, in which the solid lines indicate the best-fitting model. N: Nearest neighbor; C: Convergence; D: Divergence; K: Key stage. Topographic maps show the topographic distribution of the best-fitting model, color scales indicate the correlations, and white dots in topographic maps indicate significant channels (p < 0.05, one-sided permutation test).

closer to the group-averaged representational pattern) and this stability may be partially associated with better behavioral performance of individuals. In contrast, the neural representation in the encoding phase presented a key developmental stage during the 9–10 years of children.

3.3. Intersubject similarity across development

To further confirm the variation of developmental patterns between memory encoding and retrieval phases, and also to capture the memory representation across individuals, we used a model-free approach in addition to individual-group similarity. Specifically, we calculated intersubject pattern similarity in the encoding and retrieval phases separately (Fig. 2C) and tested whether they corresponded to four different developmental models (nearest neighbor, convergence, divergence, and key stage; Fig. 2D). In addition, we performed a searchlight analysis to identify the spatial sources underlying the model fitting.

The results revealed that the intersubject similarity in the encoding phase best fitted the key stage model with a key stage range of 9–10 years (key age = 9.8 years; r = 0.019, p = 0.107, one-sided permutation test; Fig. 4A) and that children with maturity closer to the key stage had more similar neural representation patterns. The searchlight analysis revealed high correlations for occipital electrodes, but none of them were significant ($rs \le 0.043$, $ps \ge 0.137$, one-sided permutation test, FDR-corrected).

In contrast, in the retrieval phase, the intersubject similarity was only significantly correlated with the convergent model (r = 0.026, p = 0.044, one-sided permutation test; Fig. 4B) and not with any of the other developmental models ($ps \ge 0.277$). The searchlight analysis showed that the frontal and right occipital-temporal regions were significant in the retrieval phase ($rs \ge 0.038$, $ps \le 0.049$, one-sided permutation test, FDR-corrected). These results further indicated that older children have more similar neural representation patterns in the retrieval phase, and that frontal and occipital-temporal regions account for a higher contribution to this similarity.

3.4. Spatiotemporal representations revealed by STPS

To more precisely investigate the neural similarity between the encoding and retrieval phases, we performed STPS (Fig. 5A). Specifically, all the scalp electrodes were divided into six regions (left frontal, right frontal, left central, right central, left parietal-occipital, and right parietal-occipital), and sliding windows were employed to explore the time course of neural similarity in each region. As shown in Fig. S4, the time course of the neural representational similarity shows that the correlation between the encoding and retrieval phases increased rapidly following stimulus presentation. For example, in the left parietal-occipital region, the remembered item reached significance at 62 ms ($t_{(136)} = 2.086$, p = 0.040, Cohen's d = 0.356, one-sample *t*-test, FDR-



Fig. 5. Schematic diagram and results of spatiotemporal pattern similarity analysis. (A) Schematic diagram of the STPS. (B) Repeated-measures ANOVA of mean STPS in the temporal cluster (150–450 ms, **p < 0.01). (C) STPS differences (remembered items minus forgotten items) of within-item and between-item on the left parietal-occipital region. The gray-shaded areas indicate temporal clusters with significant differences. (D) The relationship between age and STPS differences (within-item minus between-item) in the temporal cluster.

corrected) and the correlation peaked for the first time at 130 ms, with a mean correlation of 15.85 %. In contrast, the forgotten item reached significance at 76 ms ($t_{(136)} = 2.232$, p = 0.028, Cohen's d = 0.381, one-sample *t*-test, FDR-corrected) and the correlations first peaked at 124 ms, with a mean correlation of 13.30 %. These results indicated that the brain can distinguish between remembered and forgotten items very shortly after the stimulus appears, and this distinction persists for a long time.

Furthermore, to determine whether neural similarity can reflect item-specific representations or common cognitive processes, we separately calculated the similarities between the within- and between-item pairs (remembered items minus forgotten items). The results of this analysis indicated that the interaction between memory performance and item specificity was significant only for the temporal cluster (150-450 ms) on the left parietal-occipital region following stimulus appearance $(F_{(1, 92)} = 4.661, p = 0.033, \eta_p^2 = 0.048, Fig. 5C)$. Simple effects analysis further revealed that the within-item STPS was significantly higher for the remembered items than for forgotten items ($F_{(1, 92)}$) = 9.089, p = 0.003, $\eta_p^2 = 0.090$; Fig. 5B), whereas the difference in the between-item STPS was not significant ($F_{(1, 92)} = 3.245$, p = 0.075, η_p^2 = 0.034). For the remembered items, within-items were significantly more similar than between-items $(F_{(1, 92)} = 9.791, p = 0.002, \eta_p^2)$ = 0.096), whereas no significant difference between within- and between-item similarity for forgotten items ($F_{(1, 92)} = 0.511$, p = 0.476, $\eta_p^2 = 0.006$). None of the clusters revealed within- or between-item differences across the other five brain regions (Fig. S5). In addition, we identified a significant quadratic correlation between the STPS differences (within-item minus between-item) and age (r = 0.297, p = 0.019; Fig. 5D). This indicated that the similarity between memory encoding and retrieval in children develops with age. Interestingly, the STPS differences also showed a key developmental stage during the 9-10 years old, which may also reflect the interaction of memory encoding and retrieval process at the individual level.

4. Discussion

The present study revealed the development of memory representation by performing RSA of recognition memory in children. First, we found there are different neural representation patterns in the encoding and retrieval phases of memory in children. Specifically, the neural representation in the retrieval phase gradually stabilized with the children's age, and this stability was partially associated with improved memory performance. Whereas, the neural representation in the encoding phase presented a key developmental stage during 9-10 years old of children. Similarly, intersubject similarity analysis confirmed the distinct neural representation patterns of the encoding and retrieval phases. Finally, we determined that the neural similarity between the encoding and retrieval phases in children predominantly manifested in the left parietal-occipital region and changed with age. Overall, these findings provide significant insights into the representational features and temporal dynamics of different memory phases, thus contributing to a better understanding of the neural mechanisms underlying recognition memory development.

Each brain generates distinctive representational patterns when perceiving, remembering, and recognizing events (Xiao et al., 2020). Additionally, shared memory representations, known as group memory representation patterns, are formed (Vilarroya, 2017). These group memory representation patterns reflect shared memory patterns and play a role in transforming memory representations, resulting in the individuation of memory content (Sheng et al., 2023). Xue et al. (2010) found that the similarity between individual and group representation patterns contributes to memory capacity. Based on this research, our results first provided neurophysiological evidence that the neural representations of memory during the retrieval phase gradually stabilize with increasing age, approaching the group representation pattern. In contrast, neural representations during the encoding phase tend to

stabilize initially, with maximum at about 10 years old, but subsequently gradually diverge over time.

The neural representation of memory during the encoding phase involves the constructive neural transformation of learning material through interactions with existing long-term knowledge (Nguyen et al., 2019; Zhu et al., 2019; Bein et al., 2020), as well as incorporating the reliance of children's memory processes on semantics (Gupta et al., 2024). In the early stages of child development, they gradually established shared cognitive schemas, leading to the stabilization of neural representations. Subsequently, a knee point in language learning mechanisms occurred in late (9–10 years old) childhood (Ramos-Escobar et al., 2021), who performed adult-like semantic processing (Coch, 2015). Children at this age exhibit richer memory conversion and semantic encoding, achieving better success in forming unique memorable mental images of the joint image-word pairs (Sommer et al., 2019). Consequently, they exhibited divergent individual-group neural representations.

Conversely, neural representation in the retrieval phase relies on shared patterns evoked during the retrieval process, as well as the influence of early encoding patterns (Chen et al., 2017). Previous studies have demonstrated that hippocampal representations are not solely driven by stimulus-specific features during encoding, but rather reflect an underlying shared pattern of encoded neural activity (Richter et al., 2016). The dedifferentiation theory of cognitive aging proposes that the specificity of neural representations decreases with age (Abdulrahman et al., 2017). Comparatively, this shared pattern became incrementally similar during development, resulting in an apparent gradual stabilization of the neural representations in the retrieval phase appearing with age.

Identical to the individual-group similarity, intersubject similarity also confirmed these findings. Intersubject similarity reflects a shared reconstruction of the learning material by each participant pair (Chadwick et al., 2016), encompassing both typical representations shared by the group and unique representations specific to particular pairs (Sheng et al., 2023). This study confirmed the existence of a key stage of intersubject memory representation during the encoding phase, which initially converges and then gradually diverges. In contrast, older children exhibited a more similar neural representation pattern during the retrieval phase, predominantly involving the frontal and occipital-temporal regions. The involvement of occipital-temporal regions aligns with the known contribution of the visual cortex to memory representation. The decline in memory among older adults is attributed to the reduction in representational fidelity within the visual cortex (Zheng et al., 2018). Regarding the frontal regions, these may play a crucial role in the memory development of children. Activity in the frontal regions enhances pattern similarity in memory, leading to better subsequent memory performance (Xue et al., 2013).

Concerning the similarities between the encoding and retrieval phases of memory, no such patterns were observed at the whole-brain level. This discrepancy may arise from the possibility that neural representations during encoding undergo a switch during retrieval (Xiao et al., 2017). Specifically, the retrieval patterns of individuals are more similar to those of other individuals than their own encoding patterns (Koch et al., 2020). Through a fine-grained decomposition of spatiotemporal dynamics, we identified memory features distinguishing encoding successes and failures among individuals, and we subsequently explored whether these shared patterns contain episode-specific information, or were relevant to global encoding (Zhang et al., 2015; Koch et al., 2020). Overall, our findings show that the similarity in neural responses between the encoding and retrieval phases in children primarily occurs in the left parietal-occipital region and varies with age. However, previous adult studies have found that similarities in neural responses between the encoding and retrieval phases occur in the right frontal regions (Feng et al., 2019). This variation in brain regions may involve the strategy used by children to facilitate image memory through semantics (Gupta et al., 2024). Furthermore, it has also been demonstrated that encoding-retrieval neural pattern similarity varies with age (Chamberlain et al., 2022). Memory processes supported by the medial temporal lobe (MTL) do not mature in early childhood and only begin to approach adult-like levels in middle or late childhood (Benear et al., 2022). Kazemi et al. (2022) have also demonstrated that hippocampal patterns in older children are similar to those in adults. Together, these findings indicate a gradual switch in neural similarity between the encoding and retrieval phases during development, however, further validation is warranted.

In the present study, simple images were used as experimental materials instead of complex natural scenes. While complex natural scenes offer high ecological validity, their strong stimulating effects tend to diminish individual differences in memory performance and neural representation (Sheng et al., 2023). To mitigate these effects, we opted to use simple stimuli to reveal the significant individual differences in memory capacity and neural activation patterns. However, this study has some limitations. While we confirmed that neural similarity changes with age, this change has limited ability to predict individual behavior, particularly memory accuracy. This limitation may be attributed to the use of a binary classification for measuring remembering and forgetting, which may fail to provide a comprehensive description of memory (Weilbächer et al., 2021). Additionally, the limited trial number and the ceiling effect due to the overly simple encoding task may have also prevented a complete exploration of memory. The limited forgotten items in the task also restricted further exploration of the neural mechanisms of forgetting. Future studies could benefit from employing more complex task paradigms and larger sample sizes.

5. Conclusions

In summary, our study delved into the relationship between memory representation patterns and development, offering new perspectives to improve our understanding of memory formation. We investigated the neural mechanisms underlying memory development and confirmed that the encoding and retrieval phases of memory have distinct neural patterns of development. These findings contribute to expanding the developmental model of memory and provide strong support for the generative and constructive nature of memory.

Ethics statement

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

CRediT authorship contribution statement

Mei Haitian: Data curation. Ji Shiyan: Data curation. Li Dongwei: Writing – review & editing. Wang Yiyang: Writing – review & editing. Kong Yuanjun: Writing – review & editing. Song Yan: Writing – review & editing, Supervision, Project administration, Funding acquisition. Dong Xuan: Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. Li Yiwen: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis. Wang Chaoqun: Writing – review & editing, Data curation, Conceptualization. Hu Weiyu: Writing – review & editing, Visualization. Zhang Qinfen: Funding acquisition, Data curation.

Declaration of Competing Interest

The authors have no potential conflicts of interest to report.

Acknowledgements

This work was supported by the STI 2030–Major Projects (No.2021ZD0200500), the National Natural Science Foundation of China (No.32271094), and Top Talents of Changzhou Health Commission (No.2022CJBJ94).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dcn.2025.101553.

Data availability

The available data and code can be found at the Open Science Framework (https://osf.io/ghbpj).

References

- Abdulrahman, H., Fletcher, P.C., Bullmore, E., Morcom, A.M., 2017. Dopamine and memory dedifferentiation in aging. Neuroimage 153, 211–220. https://doi.org/ 10.1016/j.neuroimage.2015.03.031.
- Bein, O., Reggev, N., Maril, A., 2020. Prior knowledge promotes hippocampal separation but cortical assimilation in the left inferior frontal gyrus. Nat. Commun. 11 (1), 4590. https://doi.org/10.1038/s41467-020-18364-1.
- Benear, S.L., Horwath, E.A., Cowan, E., Camacho, M.C., Ngo, C.T., Newcombe, N.S., Olson, I.R., Perlman, S.B., Murty, V.P., 2022. Children show adult-like hippocampal pattern similarity for familiar but not novel events. Brain Res 1791, 147991. https:// doi.org/10.1016/j.brainres.2022.147991.
- Ben-Shachar, M.S., 2018. TBT: Reject and interpolate channels on a trial-by-trial basis. Zenodo. https://doi.org/10.5281/zenodo.1241518.
- Bentin, S., Allison, T., Puce, A., Perez, E., McCarthy, G., 1996. Electrophysiological studies of face perception in humans. J. Cogn. Neurosci. 8 (6), 551–565. https://doi. org/10.1162/jocn.1996.8.6.551.
- Bird, C.M., 2017. The role of the hippocampus in recognition memory. Cortex 93, 155–165. https://doi.org/10.1016/j.cortex.2017.05.016.
- Brooker, R.J., Bates, J.E., Buss, K.A., Canen, M.J., Dennis-Tiwary, T.A., Gatzke-Kopp, L. M., Hoyniak, C., Klein, D.N., Kujawa, A., Lahat, A., 2020. Conducting event-related potential (ERP) research with young children: a review of components, special considerations, and recommendations for research on cognition and emotion. J. Psychophysiol. 34 (3), 137–158. https://doi.org/10.1027/0269-8803/a000243.
- Byrge, L., Dubois, J., Tyszka, J.M., Adolphs, R., Kennedy, D.P., 2015. Idiosyncratic brain activation patterns are associated with poor social comprehension in autism. J. Neurosci. 35 (14), 5837–5850. https://doi.org/10.1523/JNEUROSCI.5182-14.2015.
- Camacho, M.C., Nielsen, A.N., Balser, D., Furtado, E., Steinberger, D.C., Fruchtman, L., Culver, J.P., Sylvester, C.M., Barch, D.M., 2023. Large-scale encoding of emotion concepts becomes increasingly similar between individuals from childhood to adolescence. Nat. Neurosci. 26 (7), 1256–1266. https://doi.org/10.1038/s41593-023-01358-9.
- Chadwick, M.J., Anjum, R.S., Kumaran, D., Schacter, D.L., Spiers, H.J., Hassabis, D., 2016. Semantic representations in the temporal pole predict false memories. Proc. Natl. Acad. Sci. U. S. A. 113 (36), 10180–10185. https://doi.org/10.1073/ pnas.1610686113.
- Chamberlain, J.D., Bowman, C.R., Dennis, N.A., 2022. Age-related differences in encoding-retrieval similarity and their relationship to false memory. Neurobiol. Aging 113, 15–27. https://doi.org/10.1016/j.neurobiolaging.2022.01.011.
- Chen, J., Leong, Y.C., Honey, C.J., Yong, C.H., Norman, K.A., Hasson, U., 2017. Shared memories reveal shared structure in neural activity across individuals. Nat. Neurosci. 20 (1), 115–125. https://doi.org/10.1038/nn.4450.
- Coch, D., 2015. The N400 and the fourth grade shift. Dev. Sci. 18 (2), 254–269. https:// doi.org/10.1111/desc.12212.
- Cohen, S.S., Parra, L.C., 2016. Memorable audiovisual narratives synchronize sensory and supramodal neural responses. eNeuro 3 (6), 1–11. https://doi.org/10.1523/ ENEURO.0203-16.2016.
- Cycowicz, Y.M., Friedman, D., Snodgrass, J.G., Duff, M., 2001. Recognition and source memory for pictures in children and adults. Neuropsychologia 39 (3), 255–267. https://doi.org/10.1016/S0028-3932(00)00108-1.
- Danker, J.F., Anderson, J.R., 2010. The ghosts of brain states past: remembering reactivates the brain regions engaged during encoding. Psychol. Bull. 136 (1), 87. https://doi.org/10.1037/a0017937.
- Delorme, A., Makeig, S., 2004. EEGLAB: an open source toolbox for analysis of singletrial EEG dynamics including independent component analysis. J. Neurosci. Methods 134 (1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009.
- Favila, S.E., Lee, H., Kuhl, B.A., 2020. Transforming the concept of memory reactivation. Trends Neurosci. 43 (12), 939–950. https://doi.org/10.1016/j.tins.2020.09.006.
- Feng, K., Zhao, X., Liu, J., Cai, Y., Ye, Z., Chen, C., Xue, G., 2019. Spaced learning enhances episodic memory by increasing neural pattern similarity across repetitions. J. Neurosci. 39 (27), 5351–5360. https://doi.org/10.1523/JNEUROSCI.2741-18.2019.

- Ferguson, H.J., Brunsdon, V.E., Bradford, E.E., 2021. The developmental trajectories of executive function from adolescence to old age. Sci. Rep. 11 (1), 1382. https://doi. org/10.1038/s41598-020-80866-1.
- Finn, E.S., Glerean, E., Khojandi, A.Y., Nielson, D., Molfese, P.J., Handwerker, D.A., Bandettini, P.A., 2020. Idiosynchrony: from shared responses to individual differences during naturalistic neuroimaging. Neuroimage 215, 116828. https://doi. org/10.1016/j.neuroimage.2020.116828.
- Ghetti, S., DeMaster, D.M., Yonelinas, A.P., Bunge, S.A., 2010. Developmental differences in medial temporal lobe function during memory encoding. J. Neurosci. 30 (28), 9548–9556. https://doi.org/10.1523/JNEUROSCI.3500-09.2010.
- Giordano, B.L., McAdams, S., Zatorre, R.J., Kriegeskorte, N., Belin, P., 2013. Abstract encoding of auditory objects in cortical activity patterns. Cereb. Cortex 23 (9), 2025–2037. https://doi.org/10.1093/cercor/bhs162.
- Golarai, G., Ghahremani, D.G., Whitfield-Gabrieli, S., Reiss, A., Eberhardt, J.L., Gabrieli, J.D.E., Grill-Spector, K., 2007. Differential development of high-level visual cortex correlates with category-specific recognition memory. Nat. Neurosci. 10 (4), 512–522. https://doi.org/10.1038/nn1865.
- Gupta, P., Vogelsang, M., Vogelsang, L., Shah, P., Gilad-Gutnick, S., Sinha, P., 2024. The influence of semantics on long-term visual memory capacity in children and adults. Br. J. Dev. Psychol. 42 (3), 392–408. https://doi.org/10.1111/bjdp.12498.
- Haese, A., Czernochowski, D., 2016. Task characteristics are critical for the use of familiarity: an ERP study on episodic memory development in middle childhood. Cogn. Dev. 40, 82–100. https://doi.org/10.1016/j.cogdev.2016.08.008.
- Hasson, U., Furman, O., Clark, D., Dudai, Y., Davachi, L., 2008. Enhanced intersubject correlations during movie viewing correlate with successful episodic encoding. Neuron 57 (3), 452–462. https://doi.org/10.1016/j.neuron.2007.12.009.
- Hasson, U., Malach, R., Heeger, D.J., 2009. Reliability of cortical activity during natural stimulation. Trends Cogn. Sci. 14 (1), 40–48. https://doi.org/10.1016/j. tics.2009.10.011.
- Jung, T.-P., Makeig, S., Westerfield, M., Townsend, J., Courchesne, E., Sejnowski, T.J., 2000. Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. Clin. Neurophysiol. 111 (10), 1745–1758. https://doi.org/ 10.1016/\$1388-2457(00)00386-2.
- Kazemi, A., Coughlin, C.A., DeMaster, D.M., Ghetti, S., 2022. Contextual features in the developing hippocampus: a representational similarity analysis. Hippocampus 32 (4), 286–297. https://doi.org/10.1002/hipo.23405.
- Koch, G.E., Paulus, J.P., Coutanche, M.N., 2020. Neural patterns are more similar across individuals during successful memory encoding than during failed memory encoding. Cereb. Cortex 30 (7), 3872–3883. https://doi.org/10.1093/cercor/ bhaa003.
- Koen, J.D., Rugg, M.D., 2016. Memory reactivation predicts resistance to retroactive interference: evidence from multivariate classification and pattern similarity analyses. J. Neurosci. 36 (15), 4389–4399. https://doi.org/10.1523/ JNEUROSCI.4099-15.2016.
- Koenig, L., Wimmer, M.C., Trippas, D., 2020. Item repetition and response deadline affect familiarity and recollection differently across childhood. Memory 28 (7), 900–907. https://doi.org/10.1080/09658211.2020.1790612.
- Kriegeskorte, N., Mur, M., Bandettini, P., 2008. Representational similarity analysisconnecting the branches of systems neuroscience. Front. Syst. Neurosci. 2, 4. https:// doi.org/10.3389/neuro.06.004.2008.
- Kuhl, B.A., Shah, A.T., DuBrow, S., Wagner, A.D., 2010. Resistance to forgetting associated with hippocampus-mediated reactivation during new learning. Nat. Neurosci. 13 (4), 501–506. https://doi.org/10.1038/nn.2498.
- Liu, J., Zhang, H., Yu, T., Ren, L., Ni, D., Yang, Q., Lu, B., Zhang, L., Axmacher, N., Xue, G., 2021. Transformative neural representations support long-term episodic memory. Sci. Adv. 7 (41), eabg9715. https://doi.org/10.1126/sciadv.abg9715.
- Lu, Y., Wang, C., Chen, C., Xue, G., 2015. Spatiotemporal neural pattern similarity supports episodic memory. Curr. Biol. 25 (6), 780–785. https://doi.org/10.1016/j. cub.2015.01.055.
- Mullen, T.R., Kothe, C.A., Chi, Y.M., Ojeda, A., Kerth, T., Makeig, S., Jung, T.-P., Cauwenberghs, G., 2015. Real-time neuroimaging and cognitive monitoring using wearable dry EEG. IEEE Trans. Biomed. Eng. 62 (11), 2553–2567. https://doi.org/ 10.1109/TBME.2015.2481482.
- Nguyen, M., Vanderwal, T., Hasson, U., 2019. Shared understanding of narratives is correlated with shared neural responses. NeuroImage 184, 161–170. https://doi. org/10.1016/j.neuroImage.2018.09.010.
- Ofen, N., Chai, X.J., Schuil, K.D.I., Whitfield-Gabrieli, S., Gabrieli, J.D.E., 2012. The development of brain systems associated with successful memory retrieval of scenes. J. Neurosci. 32 (29), 10012–10020. https://doi.org/10.1523/JNEUROSCI.1082-11.2012.
- Ofen, N., Kao, Y.-C., Sokol-Hessner, P., Kim, H., Whitfield-Gabrieli, S., Gabrieli, J.D.E., 2007. Development of the declarative memory system in the human brain. Nat. Neurosci. 10 (9), 1198–1205. https://doi.org/10.1038/nn1950.

- Pion-Tonachini, L., Kreutz-Delgado, K., Makeig, S., 2019. ICLabel: an automated electroencephalographic independent component classifier, dataset, and website. NeuroImage 198, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026.
- Polyn, S.M., Natu, V.S., Cohen, J.D., Norman, K.A., 2005. Category-specific cortical activity precedes retrieval during memory search. Science 310 (5756), 1963–1966. https://doi.org/10.1126/science.11176.
- Ramos-Escobar, N., Segura, E., Olivé, G., Rodriguez-Fornells, A., François, C., 2021. Oscillatory activity and EEG phase synchrony of concurrent word segmentation and meaning-mapping in 9-year-old children. Dev. Cogn. Neurosci. 51, 101010. https:// doi.org/10.1016/j.dcn.2021.101010.
- Richter, F.R., Cooper, R.A., Bays, P.M., Simons, J.S., 2016. Distinct neural mechanisms underlie the success, precision, and vividness of episodic memory. eLife 5, e18260. https://doi.org/10.7554/eLife.18260.
- Serre, T., Wolf, L., Poggio, T., 2005. Object recognition with features inspired by visual cortex. 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). IEEE, pp. 994–1000.
- Sheng, J., Wang, S., Zhang, L., Liu, C., Shi, L., Zhou, Y., Hu, H., Chen, C., Xue, G., 2023. Intersubject similarity in neural representations underlies shared episodic memory content. Proc. Natl. Acad. Sci. U. S. A. 120 (35), e2308951120. https://doi.org/ 10.1073/pnas.2308951120.
- Snodgrass, J.G., Vanderwart, M., 1980. A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity. J. Exp. Psychol. Hum. Learn 6 (2), 174–215. https://doi.org/10.1037/0278-7393.6.2.174.
- Sommer, V.R., Fandakova, Y., Grandy, T.H., Shing, Y.L., Werkle-Bergner, M., Sander, M. C., 2019. Neural pattern similarity differentially relates to memory performance in younger and older adults. J. Neurosci. 39 (41), 8089–8099. https://doi.org/ 10.1523/JNEIROSCI.0197-19.2019.
- Sprondel, V., Kipp, K.H., Mecklinger, A., 2011. Developmental changes in item and source memory: evidence from an ERP recognition memory study with children, adolescents, and adults. Child Dev. 82 (6), 1638–1953. https://doi.org/10.1111/ j.1467-8624.2011.01642.x.
- Uyanık, G.K., Güler, N., 2013. A study on multiple linear regression analysis. Procedia-Soc. Behav. Sci. 106, 234–240. https://doi.org/10.1016/j.sbspro.2013.12.027.
- Vilarroya, O., 2017. Neural representation. A survey-based analysis of the notion. Front. Psychol. 8, 278840. https://doi.org/10.3389/fpsyg.2017.01458.
- Weilbächer, R.A., Krajbich, I., Rieskamp, J., Gluth, S., 2021. The influence of visual attention on memory-based preferential choice. Cognition 215, 104804. https://doi. org/10.1016/j.cognition.2021.104804.
- Wheeler, M.E., Petersen, S.E., Buckner, R.L., 2000. Memory's echo: vivid remembering reactivates sensory-specific cortex. Proc. Natl. Acad. Sci. U. S. A. 97 (20), 11125–11129. https://doi.org/10.1073/pnas.97.20.11125.
- Xiao, X., Dong, Q., Gao, J., Men, W., Poldrack, R.A., Xue, G., 2017. Transformed neural pattern reinstatement during episodic memory retrieval. J. Neurosci. 37 (11), 2986–2998. https://doi.org/10.1523/JNEUROSCI.2324-16.2017.
- Xiao, X., Zhou, Y., Liu, J., Ye, Z., Yao, L., Zhang, J., Chen, C., Xue, G., 2020. Individualspecific and shared representations during episodic memory encoding and retrieval. NeuroImage 217, 116909. https://doi.org/10.1016/j.neuroimage.2020.116909.
- Xue, G., 2018. The neural representations underlying human episodic memory. Trends Cogn. Sci. 22 (6), 544–561. https://doi.org/10.1016/j.tics.2018.03.004.
- Xue, G., 2022. From remembering to reconstruction: the transformative neural representation of episodic memory. Prog. Neurobiol. 219, 102351. https://doi.org/ 10.1016/j.pneurobio.2022.102351.
- Xue, G., Dong, Q., Chen, C., Lu, Z., Mumford, J.A., Poldrack, R.A., 2010. Greater neural pattern similarity across repetitions is associated with better memory. Science 330 (6000), 97–101. https://doi.org/10.1126/science.1193125.
- Xue, G., Dong, Q., Chen, C., Lu, Z.-L., Mumford, J.A., Poldrack, R.A., 2013. Complementary role of frontoparietal activity and cortical pattern similarity in successful episodic memory encoding. Cereb. Cortex 23 (7), 1562–1571. https://doi. org/10.1093/cercor/bhs143.
- Yao, H., Shi, L., Han, F., Gao, H., Dan, Y., 2007. Rapid learning in cortical coding of visual scenes. Nat. Neurosci. 10 (6), 772–778. https://doi.org/10.1038/nn1895.
- Zhang, H., Fell, J., Staresina, B.P., Weber, B., Elger, C.E., Axmacher, N., 2015. Gamma power reductions accompany stimulus-specific representations of dynamic events. Curr. Biol. 25 (5), 635–640. https://doi.org/10.1016/j.cub.2015.01.011.
- Zheng, L., Gao, Z., Xiao, X., Ye, Z., Chen, C., Xue, G., 2018. Reduced fidelity of neural representation underlies episodic memory decline in normal aging. Cereb. Cortex 28 (7), 2283–2296. https://doi.org/10.1093/cercor/bhx130.
- Zhu, B., Chen, C., Shao, X., Liu, W., Ye, Z., Zhuang, L., Zheng, L., Loftus, E.F., Xue, G., 2019. Multiple interactive memory representations underlie the induction of false memory. Proc. Natl. Acad. Sci. U. S. A. 116 (9), 3466–3475. https://doi.org/ 10.1073/pnas.1817925116.