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Hippocampal event updating and narrative relation-map updating during naturalistic memory encoding and retrieval

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Abstract

Naturalistic memory depends on whether an event can be recalled and how accurately its original memory state is reinstated during successful recall. However, how brain-state changes around event transitions and changes in story relationships relate to these aspects of memory remains unclear. Here, we analysed functional magnetic resonance imaging data from 24 participants who viewed and freely recalled 43 naturalistic narrative events, measuring post-boundary hippocampal state changes and changes in narrative relationships. We found that larger late hippocampal state changes predicted successful event recall, with the effect confined to a specific post-boundary window. Among successfully recalled events, larger changes in narrative relationships were associated with more accurate reinstatement of hippocampal states. The relative associations of the two types of change also differed between memory outcomes. These findings suggest that brain-state updating and narrative-relation updating provide complementary perspectives on memory formation and reinstatement under naturalistic conditions.

Introduction

In everyday life, people must form and retrieve memories of events from continuous and complex experience in the real world. Understanding how events are organized, encoded and retrieved under naturalistic conditions is therefore an important problem in memory research. In this process, the brain must segment a continuous stream of information into recallable events[1]. Event segmentation theory proposes that, while viewing a movie, observers maintain an event model that describes the current situation. When the situation, location, characters or goals change, perceptual prediction error rises transiently, the event model is updated, and the moment of updating is perceived as an event boundary[2–4]. Updating is not instantaneous. Cortical activity patterns[5] and hippocampal responses[6] change systematically for several seconds after a boundary. A boundary may therefore provide a brief transitional window in which the event that has just ended is integrated into a coherent representation. This perspective has motivated naturalistic paradigms that preserve temporal, semantic and social dependencies[7,8]. Recent work on naturalistic narratives also indicates that information updating at higher levels can be concentrated at semantic boundaries[9]. A key question, therefore, is how neural representations are updated during this brief post-boundary window and how such updating relates to subsequent event memory.

The hippocampus is well positioned to link event model updating during this window to subsequent memory. Post-boundary hippocampal response magnitude predicts whether events will later be remembered[10,11], while hippocampal representations can link narrative information across temporal gaps[12–14]. At boundaries, hippocampal–cortical interactions support memory retention[15] and context-specific information is reactivated in the hippocampus and default mode network[16]. Yet much of this work has focused on response magnitude or boundary-related activation. Single-neuron recordings showed that boundary-induced shifts in medial temporal lobe population states were associated with better subsequent memory[17], although this result came from several independent short clips. More recent naturalistic imaging work further linked hippocampal–default mode network interactions at neural event boundaries to across-boundary pattern changes and later event recollection[18]. Whether shifts in hippocampal representational state between adjacent events are likewise related to memory during free recall of a continuous narrative, and whether such information is preserved across participants, remains untested.

These studies have often treated whether an event was recalled as the primary outcome, with less attention to distinguishing raw memory scores from the degree of neural reinstatement of the encoding state during recall. Encoding and retrieval rely on partly dissociable neural operations. Encoding–retrieval similarity reflects the reinstatement of patterns from the original experience during recall[19–23] and has been linked to hippocampal function[24–27]. Natural communication and verbal retelling reuse, condense and adapt the original memory[28–30]. An event can therefore be recalled without reinstating its encoding state with equivalent fidelity. This suggests that encoding success and retrieval fidelity are two related but distinguishable memory outcomes and may be associated with different forms of event updating information. Recent work has further dissociated hippocampal contributions to event content and narrative order[31], while showing that event novelty and memorability occupy coordinated hippocampal subspaces during encoding and retrieval[32]. These findings motivate further examination of how events are related within the broader narrative structure and how those relations change as a story unfolds.

Previous work represented movie narratives as networks composed of events and their semantic and causal links[33]. In that analysis, central events with broader network connectivity were more likely to be recalled and were accompanied by stronger post-boundary hippocampal responses and more consistent cortical representations during retrieval. However, these results reflect only static positions within the network and do not capture the dynamic relationship between memory and narrative structure as a story unfolds. Research on spatial and sequential representations shows that location, distance and transition structure can organize adjacent states in ways that support prediction[34–36]. Similar geometric organization extends beyond physical space: abstract variables and conceptual relations can occupy structured spaces[37–40]. Recent naturalistic work extends this idea to movie narratives, showing that statistical regularities in character interactions, including co-occurrence, can support the organization of social relationship knowledge[41], while complex social relationships can be organized along a small number of principal dimensions that engage distinct neural systems during movie viewing[42]. Yet how dynamic relational changes unfolding across a story can be quantified, and whether they relate to naturalistic memory outcomes, remains to be directly tested.

Here, we reanalysed an open functional magnetic resonance imaging dataset acquired while 24 participants watched and freely recalled continuous naturalistic narratives, including 43 events in the present analyses. The first measure was a late hippocampal local update derived with leave-one-participant-out cross-validation. We used it to test whether shared post-boundary shifts in hippocampal state predicted binary encoding success, with the raw continuous memory score as a secondary behavioural outcome. To characterize narrative relation changes as the story unfolded, we further tracked changes in characters and their relationship states as they met, separated, cooperated or conflicted. The second predictor, MSU_map, represented each movie event in a two-dimensional space of narrative relation changes defined by character co-occurrence novelty and relationship-valence novelty, from which we constructed strength of narrative relation structure updating. This measure quantified deviations of the current event from the preceding state, accumulated history and recent trajectory, thereby describing the extent to which story relations were modified, and was used to test whether narrative relation structure change predicted hippocampal retrieval fidelity for recalled events. We further compared the relative contributions of the two measures to encoding success and retrieval fidelity. This design is consistent with accounts of concurrent hippocampal differentiation and integration during naturalistic stimulation and with frameworks across participants for predicting relationships between brain activity and behaviour from movie viewing[43,44]. We found that late hippocampal local updating predicted successful event encoding, whereas

narrative relation-map updating was associated with hippocampal retrieval fidelity during recall, with their relative predictive weights differing across the two memory outcomes.

Results

Memory performance and characterization of event updating measures

We first quantified participants' free recall performance and constructed a representable measure for each movie event from two perspectives: narrative relation structure and hippocampal representational state. Using events as the common unit of analysis, we then aligned recall performance with these two measures at the event level.

Analyses were based on data from 24 participants, who watched and freely recalled naturalistic narratives comprising three television episodes. A total of 43 events were included. Across all 1,032 combinations of participants and events, the mean raw continuous memory score was 0.228 (standard deviation [SD] = 0.163, range = 0–0.714). At the event level, the mean encoding success rate across the 43 events was 0.761 (SD = 0.252, range = 0.083–1.000), and every event left a trace in the recall of at least one participant. We ultimately matched 504 usable recall segments, corresponding to 499 unique participant–event pairs across 42 events, for the retrieval-fidelity analyses.

We defined the narrative position of each event in a two-dimensional space whose axes were standardized character co-occurrence novelty and standardized relationship-valence novelty. MSU_map further combined three deviations of the current event from the preceding event, the centroid of the previous trajectory and the linearly predicted position to capture the overall extent to which the story's relation structure was rewritten. At the level of neural representation, the state was defined by 664 voxels in the bilateral hippocampus. Leave-one-participant-out cross-validation was used to construct a hippocampal representational map for each participant, and the local displacement between adjacent events within a specified post-boundary time window was extracted as the measure of hippocampal updating.

The 43 events were widely and unevenly distributed in the two-dimensional narrative relation space (Fig. 1a). MSU_map was moderately correlated with relationship-valence novelty (Pearson $r(41) = 0.519$, two-sided $P = 0.00036$, 95% confidence interval [CI] = 0.26–0.71) but was not significantly correlated with character co-occurrence novelty ($r(41) = 0.241$, $P = 0.119$, 95% CI = − 0.06–0.50), indicating that the composite measure was not equivalent to either individual input. To express hippocampal representational states as spatial coordinates, multidimensional scaling (MDS) was used to project the distance structure among the 43 events into two dimensions, and displacement between adjacent events was used to quantify hippocampal local updating (Fig. 1b). The bilateral hippocampal region of interest (ROI) is shown in Fig. 1c.

These measures at the event level formed the basis for subsequent tests of how hippocampal local updating and MSU_map were related to memory outcomes.

Late hippocampal local updating predicts encoding success

To test whether post-boundary changes in hippocampal state predicted successful event encoding, we first illustrate the analysis using participant 10. Figure 2a shows the late multivoxel blood-oxygen-level-dependent

(BOLD) patterns for adjacent events E28 and E29 within the bilateral hippocampus. The primary analysis used leave-one-participant-out cross-validation, such that the hippocampal local update for each participant was constructed from the remaining 23 participants (Fig. 2b). With participant 10 held out, signals from + 4 to + 14 s after each event boundary were first averaged over time within each event and then across the remaining 23 participants, yielding a 43 × 664 event-by-voxel matrix (Fig. 2c). Each voxel was then standardized across the 43 events, and pairwise correlation distances (1 − Pearson *r*) between events were calculated to obtain an event-distance matrix (Fig. 2d). MDS was subsequently used to map this distance matrix into two dimensions, and displacement between adjacent event coordinates was defined as hippocampal local updating (Fig. 2e).

In the base model with binary encoding success as the outcome, late hippocampal local updating had a positive effect in all 24 participants (mean $\beta = 0.1080$, $t(23) = 11.9534$, two-sided $P = 2.39 \times 10^{-11}$, Cohen's $d = 2.44$, sign-flip $P = 0.0010$; Fig. 2f). This consistent effect across participants indicates that shared changes in hippocampal state evoked by particular events predicted whether individual participants subsequently recalled those events, rather than merely reflecting neural fluctuations specific to individual participants. When the 43 events were ordered by encoding success rate, events with higher success rates generally showed stronger late hippocampal updating (Fig. 2g). As a secondary behavioural outcome, late hippocampal local updating also positively predicted the raw continuous memory score (mean $\beta = 0.0415$, $t(23) = 10.1099$, $P = 6.22 \times 10^{-10}$).

This predictive relationship changed around the event boundary. On the haemodynamic-delay-adjusted time axis, a significant negative cluster occurred from − 10 to − 8 s (cluster mass = 12.9726, *P* corrected for family-wise error rate = 0.0098). The association then became positive, peaking at + 1 s ($\beta = 0.0324$, $t(23) = 9.8180$, uncorrected pointwise $P = 1.08 \times 10^{-9}$) and forming a significant positive cluster from − 1 to + 10 s (cluster mass = 64.1549, *P* corrected for family-wise error rate = 0.0002; Fig. 2h).

These results show that late hippocampal state updating shared across participants predicted whether events were successfully encoded, with convergent support from the raw continuous memory score.

MSU_map is associated with hippocampal retrieval fidelity

An event can be recalled without reinstating its encoding state to the same degree. We therefore tested whether, among recalled events, the strength of updating of narrative relation structure was associated with hippocampal retrieval fidelity. For each matched recall segment, we extracted the bilateral hippocampal activity pattern across 664 voxels for the corresponding movie event during viewing and for the matched recall segment. For participant 3 and event E09, hippocampal activity during movie encoding (+ 4 to + 14 s after the event boundary) and matched free recall (− 6 to + 14 s around recall onset) is shown in Fig. 3a. Hippocampal retrieval fidelity was defined as the Pearson correlation between the two time-averaged 664-voxel patterns. The narrative relation state was defined by character co-occurrence novelty and relationship-valence novelty, and narrative relation-map updating was calculated as MSU_map, the sum of three standardized components: local update, global deviation and prediction error (Fig. 3b).

MSU_map positively predicted mean hippocampal retrieval fidelity ($\beta = 0.0251$, $t(33) = 2.7927$, two-sided $P = 0.0086$, $R^2 = 0.2282$; one-sided *P* from event label permutation = 0.0050, 1,000 permutations; Fig. 3c). This result indicates that events involving larger changes in narrative relations showed stronger reinstatement of the hippocampal encoding state during subsequent recall. The association remained significant when all matched

recall segments were retained and participant fixed effects were controlled (β = 0.0188, $t(472)$ = 2.3719, P = 0.0181).

Together, among events that entered free recall, stronger updating of narrative relation structure was associated with higher hippocampal retrieval fidelity, indicating that MSU_map was related to the degree of neural state reinstatement conditional on successful recall.

Relative predictive weights differ across memory outcomes

The preceding analyses showed that late hippocampal local updating was associated with whether an event was successfully encoded, whereas narrative relation-map updating was associated with hippocampal retrieval fidelity for recalled events. We next tested whether the relative predictive weights of the two updating signals differed between these memory outcomes.

After controlling for character co-occurrence novelty, relationship-valence novelty, event duration and event order, and residualizing each predictor against the other, we obtained standardized coefficients for each participant from the binary encoding-success model and the continuous retrieval-fidelity model. In the model for encoding success, the mean coefficient for late hippocampal local updating exceeded that for MSU_map. In the model for retrieval fidelity, the mean coefficient for MSU_map was numerically higher than that for hippocampal updating (Fig. 4a, b). To directly test this difference in relative weighting, we calculated the coefficient difference “hippocampal updating minus MSU_map” for each participant in each model. This difference changed from positive in the model for encoding success to negative in the model for retrieval fidelity. The difference-in-differences between the two models was 0.3533 ($t(23)$ = 5.7810, $P = 6.87 \times 10^{-6}$, Cohen’s d = 1.18, 95% CI = 0.2269–0.4797; sign-flip P = 0.0001, 10,000 permutations; Fig. 4c). The result remained stable when the raw continuous memory score was used as the secondary encoding outcome (difference-in-differences = 0.3352, $t(23)$ = 5.0211, $P = 4.43 \times 10^{-5}$). Analyses at the event level further tested whether this pattern was reflected in differences across events (Table 1). Late hippocampal local updating positively predicted the encoding success rate at the event level (β = 0.1013, P = 0.0025), whereas MSU_map was not significantly associated with the encoding success rate. For retrieval fidelity, MSU_map was a significant positive predictor (β = 0.0234, P = 0.0111), whereas hippocampal local updating showed no significant direct association.

Table 1
Regression results at the event level for the two updating measures.

Outcome	Prespecified path	β (X standardized)	Bootstrap 95% CI	SE	t(df)	P (two-sided)	Model R^2	Number of events
Encoding success rate	Late hippocampal local updating → encoding success rate	**0.1013**	**[0.0334, 0.1612]**	0.0311	3.2581 (35)	**0.0025**	0.4214	42
Encoding success rate	MSU_map → encoding success rate	−0.0193	[− 0.1221, 0.0892]	0.0370	−0.5215 (35)	0.6053	0.4214	42
Retrieval fidelity	MSU_map → hippocampal retrieval fidelity	**0.0234**	**[0.0040, 0.0413]**	0.0087	2.7024 (31)	**0.0111**	0.3365	42
Retrieval fidelity	Late hippocampal local updating → hippocampal retrieval fidelity	−0.0094	[− 0.0251, 0.0050]	0.0077	−1.2261 (31)	0.2294	0.3365	42
Retrieval fidelity	Encoding success rate → hippocampal retrieval fidelity	**0.0224**	**[0.0053, 0.0467]**	0.0100	2.2461 (31)	**0.0320**	0.3365	42

Note: β, standardized regression coefficient; X, predictor variable; CI, confidence interval; SE, standard error; df, degrees of freedom; P, two-sided P value; R^2, coefficient of determination. Covariates for the models for encoding success rate and retrieval fidelity are described in the Methods. Bootstrap 95% CIs were based on 5,000 resamples at the event level. Bold type indicates $P < 0.05$.

Discussion

Learning, communication and information exchange in everyday life depend on selectively retaining important events from continuous experience and later reinstating those experiences as accurately as possible. Understanding which events are more likely to enter long-term memory, and how faithfully their original information can be reinstated after successful recall, is therefore important for explaining how memory is formed under naturalistic conditions and reconstructed during subsequent communication. This study decomposed naturalistic narrative memory into two related but distinguishable outcomes: whether an event was successfully encoded and how accurately the encoding state was reinstated during successful recall. Analyses of the same open dataset showed that late post-boundary hippocampal local updating robustly predicted binary encoding success, with convergent support from the raw continuous memory score, whereas narrative relation-map updating based on changes in character co-occurrence and relationship valence was associated with hippocampal retrieval fidelity. When the two measures were compared within the same models, their relative predictive weights differed significantly between the models for encoding success and retrieval fidelity. The

advantage of hippocampal local updating over MSU_map was greater in the model for encoding success, whereas the mean coefficient for MSU_map was numerically higher in the model for retrieval fidelity. This pattern received directionally consistent support from analyses at the participant and event levels. Overall, these results indicate that neural state updating and updating of narrative relation structure in naturalistic narratives characterize complementary aspects of successful encoding and neural state reinstatement during recall.

Late hippocampal local updating provided the most robust evidence for event encoding. Previous work has shown that the hippocampus is sensitive to event boundaries in naturalistic experiences[6,45] and that post-boundary hippocampal activity predicts subsequent memory[10,11]. Contextual reactivation near boundaries, interactions between the hippocampus and cortex and integration across events are also associated with the retention and reorganization of event representations[12,13,15,16]. However, these studies have largely focused on response magnitude or local activation changes after boundaries, even though identical mean response magnitudes do not imply identical multivoxel representational states. By focusing on changes in hippocampal multivoxel representational state between adjacent events, the present study showed that late hippocampal changes in event state constructed from data from other participants still predicted whether a held-out participant subsequently recalled the event. The effect was consistent across all 24 participants and was supported by the raw continuous memory score, indicating that the relationship was not restricted to a binary memory measure. The time-resolved analysis further localized predictive information to a specific post-boundary period, consistent with previous evidence that post-boundary hippocampal activity supports event memory[6,10,11]. Beyond existing boundary effects, these results therefore show that, in addition to hippocampal activity magnitude, multivoxel state displacement between consecutive narrative events carries information related to subsequent memory and that this information can be extracted across participants.

Narrative relation-map updating revealed a different form of event information associated with neural state reinstatement during recall. Previous work has shown that an event's position in a relational network and its connections to other events can influence subsequent memory[33]. Such studies, however, primarily describe event position within a relatively stable structure, whereas character co-occurrence and relationship valence change continuously as a story unfolds. We therefore integrated the local displacement of the current event from the preceding event, its global deviation from the history of prior relations and its prediction error relative to the recent trajectory into MSU_map, thereby quantifying how much each event rewrote the existing narrative relation structure. Among recalled events, higher MSU_map values were associated with greater similarity between hippocampal multivoxel patterns during encoding and retrieval. This finding extends the focus from "where an event lies within a relational structure" to "how much an event changes the relation structure as the story unfolds".

After controlling for character co-occurrence novelty, relationship-valence novelty, event duration and event order, and residualizing hippocampal local updating and MSU_map against one another, the relative weights of the two measures differed significantly between the models for encoding success and retrieval fidelity. The advantage of hippocampal local updating over MSU_map was greater in the model for encoding success, whereas the mean coefficient for MSU_map was numerically higher in the model for retrieval fidelity. Analyses across events yielded results in the same direction. Importantly, this pattern reflects a change in the relative weights of the two predictors across memory outcomes, rather than a complete double dissociation. Future naturalistic memory studies could use the same approach to compare how other quantifiable changes in narrative structure and measures of neural dynamics relate to encoding and retrieval outcomes.

Several points warrant consideration. First, the analyses were based on 24 participants who viewed the same set of continuous narratives. Future work should test the stability of the findings across different narrative materials and independent participant samples. Second, MSU_map was based on character co-occurrence and relationship valence and therefore did not capture all narrative attributes, including causality, goals, locations, semantics and affect. These dimensions could be incorporated into the same updating framework at the event level in future work. Third, the current neural analyses were restricted to the bilateral hippocampal ROI and therefore cannot determine whether other brain regions involved in narrative processing and memory exhibit similar or complementary updating patterns.

In summary, event updating in continuous narratives can be quantified at the levels of neural state and narrative relation structure, each providing information associated with encoding success and retrieval fidelity. Late hippocampal displacement of event state was robustly associated with which events were subsequently remembered, whereas narrative relation-map updating was associated with the extent to which the encoding state was reinstated for recalled events. Direct comparison of the two measures further showed that their relative predictive weights differed between the two memory outcomes.

Methods

Dataset, participants and ethics

We performed a secondary analysis of the naturalistic memory dataset reported by Kwon et al. and released through OpenNeuro (ds005468, version 1.0.0)[32,46]. No new participants were recruited and no new imaging data were acquired. The original study was approved by the Institutional Review Board of Sungkyunkwan University (2018-05-005), and all participants provided written informed consent[32].

The original sample comprised 32 participants who were fluent in Korean and had normal or corrected to normal vision and hearing. The original study excluded eight participants because more than 5% of volumes had framewise displacement greater than 0.5 mm in at least one functional run. The final publicly available sample comprised 24 participants aged 19–25 years (mean = 21.38 years, SD = 2.10; six women), based on the demographic information in the public participants.tsv file. We retained the full public sample and applied no additional exclusions at the participant level.

Naturalistic movie, free recall and event segmentation

During functional magnetic resonance imaging, participants watched three episodes from season 1 of the Korean web series *Love Playlist* and freely recalled each episode immediately after viewing. Each episode lasted approximately 14 min. Adjacent episodes were separated by 10-s and 16-s blank intervals, and the repeated 30-s segment at the beginning of the next episode was excluded from analysis. Participants had not previously watched the series and made no overt responses during viewing[32].

Before scanning, participants practised free recall with an unrelated 90-s video. After each target clip, they recounted the story in chronological order and in as much detail as possible, with emphasis on social relationships. Recall began after a 10-s blank interval, continued for at least 5 min and ended 10 s after the participant indicated completion. Mean recall duration was 422 s (SD = 144, range = 180–866 s). Speech was

recorded with a magnetic resonance-compatible microphone, transcribed using NAVER CLOVA and aligned to movie events by the original investigators[32].

Four independent annotators segmented the movie into events based on changes in topic, location, time, characters or relationship configuration[32]. Of the original 61 events, 44 were retained because they lasted longer than 20 s and their boundaries were endorsed by at least three annotators within a 5-s window. Because novelty could not be calculated for the first event, 43 events were included in the final analyses (mean duration = 49.95 s, SD = 26.17, range = 22–134 s). Boundaries were additionally validated by 15 observers, with recognition rates exceeding 60% for all retained boundaries. Subsequent analyses used the event identifiers and timing information provided in the public dataset.

Imaging data and preprocessing

We directly used the preprocessed functional magnetic resonance imaging data and bilateral hippocampal response matrices released by Kwon et al. and did not repeat image preprocessing. The original acquisition parameters and the fMRIPrep preprocessing, denoising and normalization procedures are reported in full in the original study[32,47,48]. The functional data had a repetition time (TR) of 1,000 ms. The bilateral hippocampal ROI comprised parcels 215–218 of the Brainnetome Atlas and contained 664 voxels[32,49]. The movie data array used here had dimensions of 24 participants × 43 events × 664 voxels × 21 TRs, with each event spanning 6 s before to 14 s after the boundary. Recall data had the same 664-voxel × 21-TR structure and were matched to movie events using the public source-event identifiers. All neural analyses were restricted to this bilateral hippocampal ROI.

Memory outcomes and event variables

The original study defined each participant's raw continuous memory score for each event as the number of words in the recall transcript that matched the detailed event description divided by the total number of words in the description, after harmonizing semantically equivalent expressions before scoring. The primary encoding outcome was binary encoding success, defined as a raw continuous memory score greater than 0. The event-level encoding success rate was the proportion of the 24 participants who successfully encoded each event. The raw continuous memory score was used as a secondary behavioural outcome reflecting the extent to which event content was recalled.

The original study also provided two event novelty measures. Character co-occurrence novelty captured the change in the current event's pattern of character co-occurrence relative to previous events, whereas relationship-valence novelty captured the change in character relationship valence relative to the preceding narrative history. Higher values indicated greater divergence from the prior narrative structure.

Construction of narrative relation-map updating

Each event was first represented in a two-dimensional narrative relation space. The first dimension reflected the novelty of the character co-occurrence pattern relative to the preceding narrative history, whereas the second reflected the novelty of the relationship-valence pattern. Specifically, we calculated the similarity of the current event's character co-occurrence pattern and relationship-valence pattern to the preceding narrative history, converted each similarity into the corresponding novelty value by subtracting it from 1, and standardized the resulting values across the 43 events. This construction was motivated by prior work on structured relations and event maps[50,51].

On this basis, we characterized the extent to which the current event updated the existing narrative relation structure from three perspectives. Local updating was defined as the distance between the current event and the preceding event in the two-dimensional relation space and indexed the change between adjacent events. Global deviation was defined as the distance between the current event and the mean position of all preceding events and indexed the extent to which the current event departed from the accumulated narrative history. Prediction error was defined as the distance between the current event and the position predicted from the change between the two most recent events and indexed departure from the recent narrative trajectory. The three measures were standardized across the 43 events and summed to obtain narrative relation-map updating strength (MSU_map).

Because the first event had no preceding narrative state, all three updating measures were set to 0. For the second event, there were not enough preceding events to infer the recent trajectory, so the position of the first event was used as the predicted position. Larger MSU_map values indicated greater deviation of the current event from the preceding event, accumulated narrative history and recent trajectory, corresponding to a stronger overall update of the narrative relation structure.

Leave-one-participant-out hippocampal event maps

Leave-one-participant-out cross-validation was used to construct hippocampal event maps. For each held-out participant, only data from the other 23 participants were used. Within each event and time window, signals were averaged across these 23 participants and across time points, yielding one group hippocampal activity pattern retaining the 664-voxel dimension for each of the 43 events and a 43 × 664 event-by-voxel matrix. Each voxel was then standardized across the 43 events, and pairwise correlation distances (1 − Pearson *r*) were calculated between event patterns, yielding a 43 × 43 event-distance matrix[52]. MDS was then used to map this matrix into two dimensions[53]. Each held-out participant thus had a hippocampal event map comprising two-dimensional coordinates for 43 events. The held-out participant's own behavioural and hippocampal data were excluded from this procedure, ensuring independence between the resulting predictor and the participant being predicted. Figure 2a–e illustrate the construction steps only. The representative participant was selected by the median similarity between that participant's event-by-voxel patterns and the group-mean patterns, and the adjacent event pair was selected by the median local MDS displacement across all adjacent-event transitions. In this event map, the Euclidean distance between adjacent events in the two-dimensional MDS space was defined as hippocampal local updating, indexing the magnitude of the change in hippocampal representational state from the preceding event to the current event. Because the first analysed event had no predecessor, its raw update was set to 0 by convention. Updates for the remaining 42 events were calculated relative to the preceding event. The 43 event-level update values were standardized within participant before entering the encoding models.

The primary late time window was defined as 4–14 s after the event boundary. The complete 21-TR data covered 6 s before to 14 s after the event boundary and were used in the time-resolved analysis.

Hippocampal local updating and encoding success

For each participant, an ordinary least-squares regression model was fitted using the 43 movie events as observations. Character co-occurrence novelty, relationship-valence novelty, event duration and event order were included as covariates. To facilitate comparison of regression coefficients, predictors and covariates were standardized across events within participant. The raw continuous memory score retained its original scale and was analysed with the same model as a secondary behavioural outcome.

Each participant thus contributed one regression coefficient for late hippocampal local updating. The group effect across the 24 participants was evaluated using a two-sided one-sample *t*-test and a two-sided sign-flip test with 1,000 permutations.

Time course around event boundaries

The preceding analysis combined multiple time points within the late window and therefore estimated the overall effect during this period, but it may have obscured finer temporal variation. To examine the temporal distribution of the relationship between hippocampal local updating and memory around event boundaries, we repeated the leave-one-participant-out analysis separately at each of the 21 time points. For each held-out participant, a two-dimensional event map was constructed at each time point using hippocampal event patterns from the other 23 participants, and hippocampal local updating at that time point was calculated as the coordinate distance between adjacent movie events. The raw continuous memory score was then predicted from hippocampal local updating at that time point while controlling for MSU_map and the four event covariates described above. Each participant thus contributed one regression coefficient at each of the 21 time points, forming a time-resolved coefficient series.

Effects at the group level across the 21 time points were corrected for multiple comparisons using a temporal cluster-permutation test based on sign flips at the participant level. Candidate clusters were formed at one-sided $P < 0.05$. Cluster mass was the sum of *t* values across contiguous time points with the same direction, and the null distribution of the maximum cluster mass was obtained from 5,000 sign flips of the entire time series. After correction for a 4-s haemodynamic delay, the original − 6 to + 14 s time axis was displayed as − 10 to + 10 s.

Hippocampal retrieval fidelity analysis

Recall segments were matched to movie events using the public source-event identifiers. For each matched recall segment, the encoding pattern was the mean activity pattern across the 664 bilateral hippocampal voxels from 4 to 14 s after the boundary of the corresponding movie event. The retrieval pattern was the mean activity pattern from 6 s before to 14 s after the onset of the recall segment. The Pearson correlation between the two patterns was used as hippocampal retrieval fidelity for that segment. Higher correlations indicated that hippocampal activity during recall more closely resembled activity during viewing of the event[21,22,25].

There were 504 usable matched recall segments, corresponding to 499 unique participant–event pairs and 42 movie events. In the primary analysis, retrieval fidelity was first averaged within each movie event. We then tested whether MSU_map predicted event-mean retrieval fidelity while controlling for character co-occurrence novelty, relationship-valence novelty, movie-event duration, event order, mean recall duration, recall-order deviation and repeated-recall proportion. Continuous predictors were standardized before model fitting. To test whether the observed correspondence between MSU_map and specific events was stronger than expected by chance, MSU_map values were randomly permuted across events and the full model was refitted 1,000 times.

As a supplementary analysis, we retained all matched recall segments and re-examined the association between MSU_map and hippocampal retrieval fidelity, testing whether the event-level result was also present at the segment level. The model controlled for overall between-participant differences and for the duration, order deviation and repeated-recall status of each recall.

Relative predictive contributions of the two measures

To compare the relative contributions of hippocampal local updating and MSU_map to the two memory outcomes, we constructed encoding-success and retrieval-fidelity models separately within each participant. The encoding-success model used the binary encoding outcome for movie events as the primary outcome and the raw continuous memory score as a secondary outcome. The retrieval-fidelity model used standardized hippocampal retrieval fidelity as the outcome. Both models included late hippocampal local updating, MSU_map and the four event covariates described above.

Because hippocampal local updating and MSU_map could contain partially overlapping information, we further isolated the independent predictive component of each measure. Specifically, residuals for hippocampal local updating were obtained after controlling for MSU_map and the covariates, and residuals for MSU_map were obtained after controlling for hippocampal local updating and the same covariates. The standardized residuals were then used in the subsequent models, yielding coefficients for each updating measure after removing information shared with the other measure.

For each participant, we then calculated the difference between the standardized regression coefficients for hippocampal local updating and MSU_map and compared the change in this difference between the encoding-success and retrieval-fidelity models. A larger difference in the encoding-success model would indicate a clearer predictive advantage of hippocampal local updating over MSU_map for encoding success. The opposite pattern would indicate greater relative weight for MSU_map in retrieval fidelity. Each participant thus contributed one difference value reflecting the change in the relative advantage of the two measures across the two memory outcomes. This value was tested across the 24 participants using a one-sample *t*-test and a sign-flip test with 10,000 permutations to determine whether it was reliably greater than 0.

Outcome analyses at the event level

To test whether the preceding results were also expressed at the event level, we analysed the associations of the two updating measures with event-level encoding success rate and mean retrieval fidelity. For direct comparison across outcomes, both event-level models used the same 42-event set. Hippocampal local updating for each event was the mean of the 24 leave-one-participant-out estimates. Both models included hippocampal local updating and MSU_map simultaneously. The encoding-success-rate model controlled for character co-occurrence novelty, relationship-valence novelty, event duration and event order. In addition to these four covariates, the mean-retrieval-fidelity model controlled for event-level encoding success rate, mean recall duration, recall-order deviation and repeated-recall proportion. Uncertainty in the regression coefficients was assessed using 5,000 event-level bootstrap resamples.

Statistics and Reproducibility

Statistical analyses were conducted in Python using NumPy, pandas, SciPy, scikit-learn[54] and statsmodels. Analyses used the full publicly available sample of 24 participants, with no additional participant exclusions. Encoding analyses included 43 movie events per participant; retrieval analyses included 504 usable matched recall segments. Participants were independent units for participant-level inference, whereas events were the observational units for event-level analyses. No additional experimental or technical replicates were generated. Statistical significance was set at $\alpha = 0.05$. Parametric tests were two-sided unless a directional hypothesis was prespecified. Participant-level regression coefficients were evaluated using one-sample *t*-tests and 1,000 two-sided sign-flip permutations. Time-resolved effects were assessed using 5,000 sign-flip permutations with a one-sided cluster-forming threshold of $P < 0.05$ and family-wise error correction based on maximum cluster mass. The

association between MSU_map and retrieval fidelity was tested using 1,000 one-sided event-label permutations. Differences in relative predictive weights across memory outcomes were assessed using one-sample *t*-tests and 10,000 prespecified right-tailed sign-flip permutations. Event-level regression uncertainty was assessed using 5,000 bootstrap resamples and percentile 95% confidence intervals. Monte Carlo permutation *P* values used a plus-one correction. Missing observations were excluded only when required, with no imputation. Exact sample sizes and *P* values are reported with the corresponding analyses.

Declarations

Competing interests

The authors declare no competing interests.

Author Contribution

W.C.: Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. X.J.: Investigation, Methodology, Resources. H.S.: Software, Visualization. T.W.: Validation, Visualization. X.Z.: Funding acquisition, Supervision, Writing – review & editing. Y.C.: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Data availability

The data used in this study are publicly available through OpenNeuro under accession ds005468 (version 1.0.0; https://doi.org/10.18112/openneuro.ds005468.v1.0.0).

Code availability

Custom Python code used to reproduce the analyses reported in this study is publicly available on GitHub at https://github.com/NXIOANA/mapshift-memory. The repository includes scripts for constructing the narrative relation space and MSU_map, deriving late and time-resolved leave-one-participant-out hippocampal updates, and reproducing the encoding, retrieval-fidelity and relative-contribution analyses. Analysis-ready data tables, a data dictionary, and environment and dependency files required for reproducibility are also provided in the repository.

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Figures

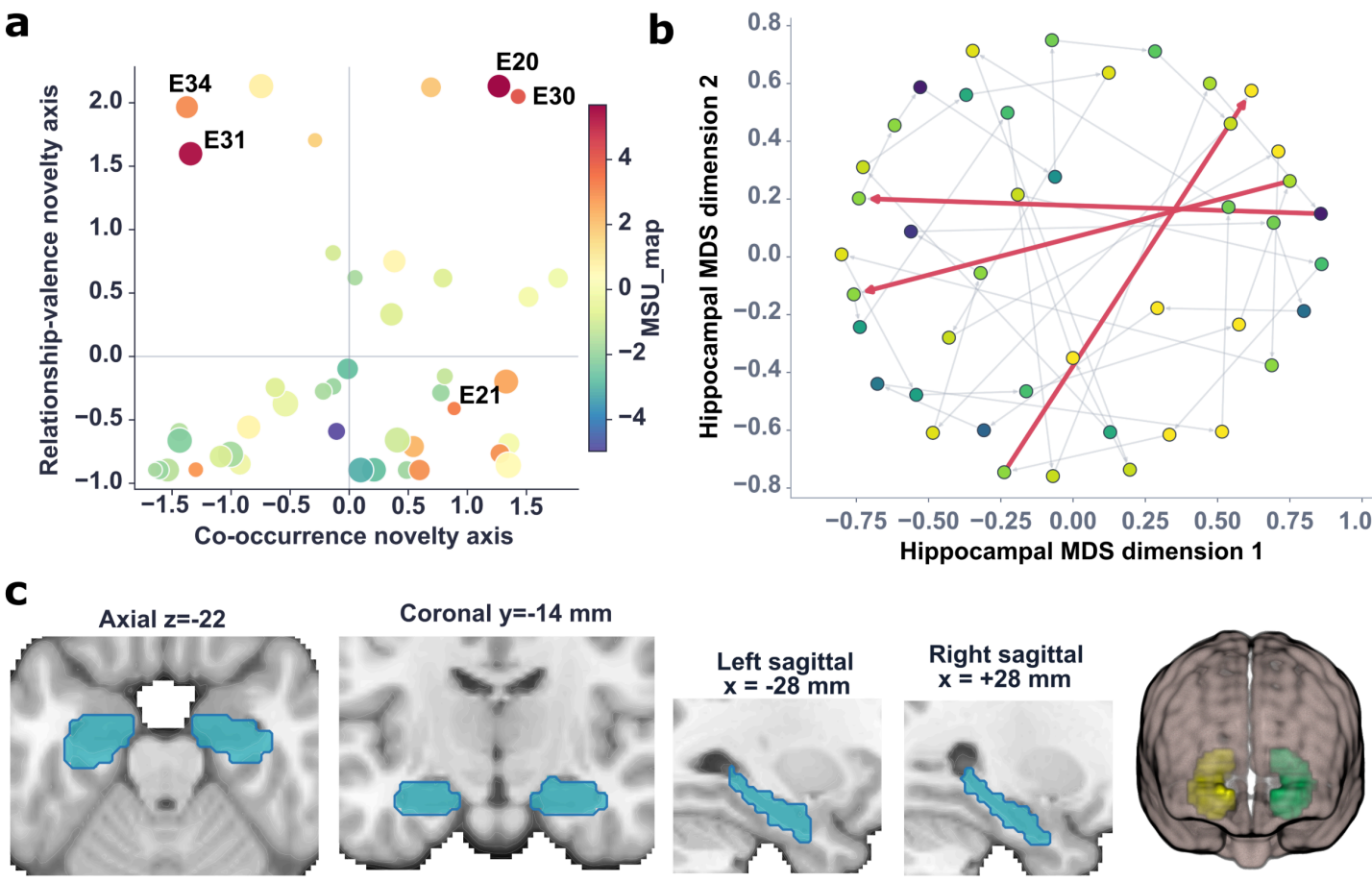


Figure 1

Narrative relation space, hippocampal event trajectories and hippocampal region of interest. a, Positions of the 43 movie events in the standardized two-dimensional narrative relation space defined by character co-occurrence novelty and relationship-valence novelty. Colour denotes narrative relation-map updating strength (MSU_map), and point size denotes the raw continuous memory score. **b,** Two-dimensional multidimensional scaling (MDS) representation of group-mean bilateral hippocampal multivoxel patterns 4–14 s after event boundaries (*n* = 24 participants). Grey lines connect adjacent events in movie order, red arrows mark the three largest adjacent-event hippocampal local updates, and point colour denotes event-level encoding success rate. **c,** Representative axial, coronal and sagittal slices and a three-dimensional rendering of the bilateral hippocampal region of interest (ROI) used for multivoxel analyses.

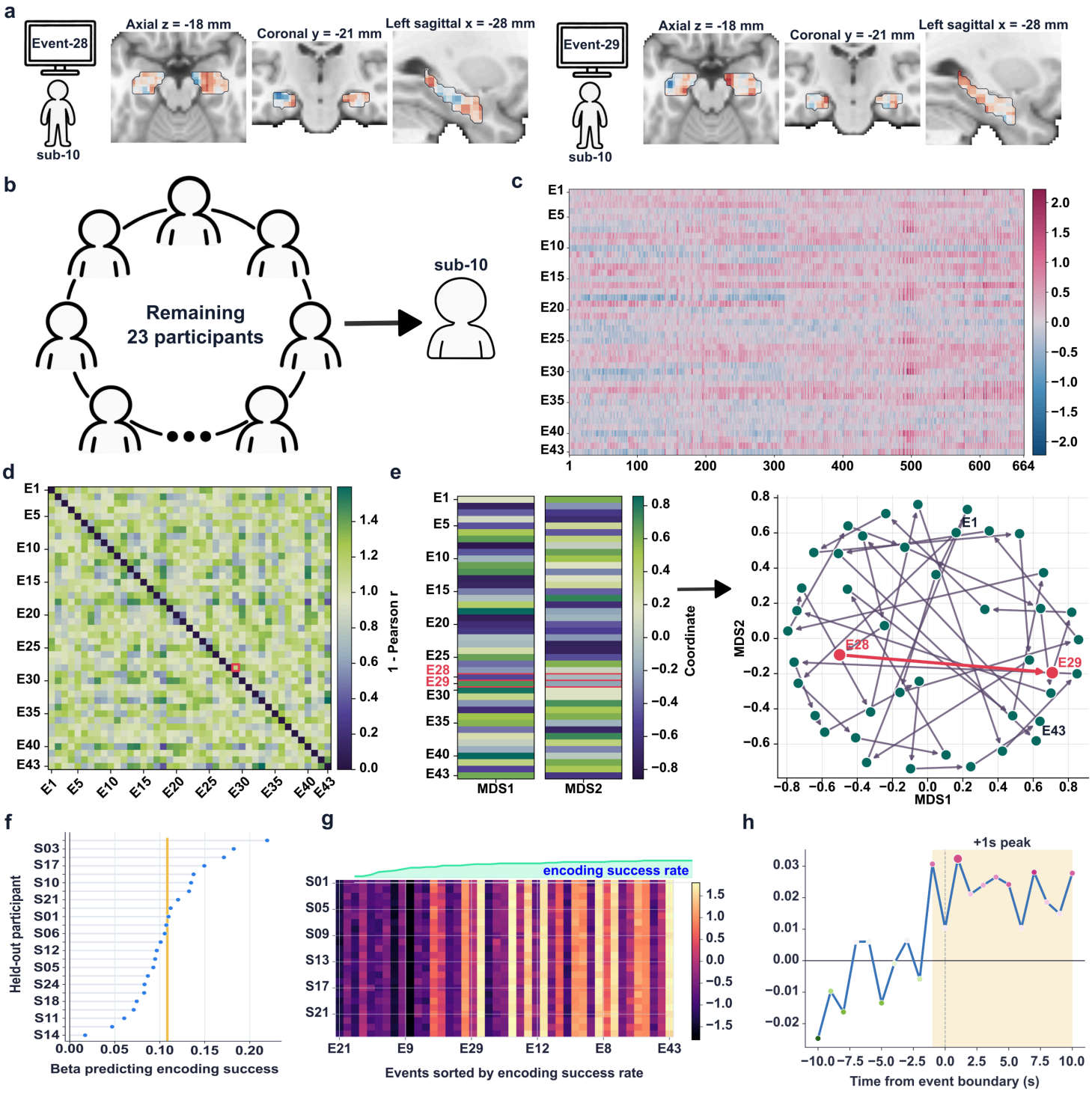


Figure 2

Hippocampal local updating and event encoding success. a, Bilateral hippocampal multivoxel blood-oxygen-level-dependent (BOLD) patterns for adjacent events E28 and E29 in participant 10. **b,** Schematic of the leave-one-participant-out procedure: participant 10 is held out, and the remaining 23 participants are used to construct the hippocampal event map for that participant. **c,** The 43 × 664 event-by-voxel matrix obtained by averaging signals from +4 to +14 s after each event boundary across the remaining 23 participants. **d,** The 43 × 43 pairwise correlation-distance matrix (1 − Pearson *r*) calculated from the standardized event patterns. **e,** MDS coordinates for the 43 events (43 × 2) and the resulting two-dimensional event map. Arrows connect adjacent events in movie

order; the E28–E29 transition is highlighted as an example of local displacement. **f,** Participant-level β coefficients for late hippocampal local updating predicting encoding success (n = 24); the yellow vertical line indicates the group mean. **g,** Standardized hippocampal local updates across participants and events, with events ordered by group encoding success rate. The green trace shows encoding success rate. **h,** Time-resolved β coefficients for hippocampal local updating predicting the raw continuous memory score. On the haemodynamic-delay-adjusted time axis, significant clusters occurred from −10 to −8 s in the negative direction (family-wise-error-corrected P = 0.0098) and from −1 to +10 s in the positive direction (family-wise-error-corrected P = 0.0002), peaking at +1 s. β denotes the regression coefficient for a standardized predictor.