REMOTENESS SENSITIVE THETA NETWORK DYNAMICS DURING EARLY AUTOBIOGRAPHICAL MEMORY ACCESS

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ABSTRACT

Autobiographical memory (AM) is a core component of human cognition; it defines who we are, it helps us relate to others, and supports decision-making and future planning. The variability embedded in AMs offers a unique opportunity to examine the neural dynamics engaged during the retrieval of memories of different ages. Here, we focus on the early access (or search) phase and test whether theta-band (4-9 Hz) cortical activity carries age-sensitive signatures distinguishing recent (<1 year) from remote (>3 years) AMs. Forty-one participants performed an AM retrieval task while EEG was recorded. Theta power and time-resolved Granger causality (GC) were quantified during the first 1200 ms of the access period. Remote AM access elicited a significant increase in midline fronto-central theta power around 900 ms, consistent with enhanced internally driven, reconstructive processing. GC analyses further revealed that remote AMs exhibited denser, more widespread theta-band connectivity, including a prominent anterior-to-posterior information flow between 600-800 ms, whereas recent AMs showed more localized fronto-central interactions. These findings demonstrate that the earliest phase of AM access is shaped by memory age, with remote memories recruiting broader, long range theta mediated coordination. Our results identify theta oscillations and their directed network interactions as temporally precise markers of AM remoteness, providing new insights into the systems-level mechanisms that support autobiographical retrieval.

Keywords EEG · Theta band · Granger causality · Autobiographical Memory

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1 Introduction

Autobiographical memory (AM) is a complex cognitive process that enables individuals to recall personal experiences along their lifespan. In contrast to typical laboratory memory tasks where participants are asked to encode and retrieve experimentally controlled stimuli, AM paradigms are less constrained due to the inherent variability of individual life experiences. Although this variability poses challenges for experimental control, it provides a unique opportunity to track the neural mechanisms underlying the retrieval of memories of different ages.

Recalling an AM typically begins with a signal that triggers a controlled search process (or access period), followed by an elaboration period during which memory is reconstructed through mental imagery, the evaluation of emotional valence and personal relevance of the event [1, 2]. These two phases are based on the coordinated activity of multiple brain regions[3, 4]. Previous studies have suggested a temporal progression of activation: beginning in frontal regions during the initial controlled search (access period), and gradually shifting towards posterior temporal and occipital areas as memory elaboration unfolds (elaboration period) [5, 6, 7]. During the access period, controlled search and effort have been linked to regions such as the right and medial prefrontal cortex (PFC) and regions involved in accessing the memory trace (hippocampus, retrosplenial cortex). As the process progresses into the elaboration phase, the reconstruction of the memory recruits posterior regions involved in the retrieval of contextual details[6, 3]. Also, the cortical midline subsystem (CMS), formed by the anteromedial prefrontal cortex and posterior cingulate cortex is associated with self-referential processes during AM recollection [8, 9]. In addition, the access of richly detailed episodic AMs relies on emotional processing in the amygdala [10] and visual imagery in occipital and precuneus/cuneus regions [11].

A fundamental constrain in the field of AM comes from the technical approaches implemented to study it. Most of the evidence supporting the functional progression of activation during AM recall comes from fMRI studies, which provide precise spatial localization but suffer from limited temporal resolution, typically on the order of seconds. This makes the fMRI technique better suited to describe the elaboration phase, as it is a longer process that allows for more extended periods of brain activity to be captured. In contrast, this technique constrains our ability to characterize the earlier stages of the access period, when memory search is initiated and fast dynamical interactions between regions may play a crucial role. Consequently, the fine grained temporal structure and information flow underlying the early onset of AM access remain poorly understood. Some electrophysiological approaches have begun to shed light on the early temporal dynamics of AM, with some studies implicating theta-band (θ) activity in AM access [12, 13, 14]. Using EcoG, Foster et al. have shown transient θ phase-locking between the left medial temporal lobe and the left retrosplenial cortex peaking around 200 - 600 ms post stimulus presentation associated with successful AM access [15]. In line with this, Nicolás et al. found a significant theta power decrease around 1000 ms after stimulus presentation over fronto-central regions when comparing pictures of AM events against unknown pictures [16]. Despite this evidence, how these neural rhythms organize the very first moments of AM access remains largely unexplored.

Another key aspect of AMs is how their representations evolve and reorganize over time, shaping our sense of self and influencing how we perceive and interpret the world. Changes in AM over time have been reported in different domains: The analysis of speech of free-recall interviews has shown that remote AMs tend to contain fewer episodic details and instead rely more heavily on semantic or abstract information [17]. Also, different patterns of AM representations using high-resolution fMRI and multivoxel pattern analysis (MVPA) were found for recent (two-week-old) and remote (ten-year-old) AMs in the ventromedial prefrontal cortex (vmPFC) and the hippocampus. Interestingly, the vmPFC presented higher activity related to remote AMs than recent AMs, suggesting a pattern change related to long-term consolidation. In contrast, the hippocampus represented both types of memories, with a spatial dissociation indicating that the posterior hippocampus was more strongly involved in the representation of remote AMs [18]. Using prospectively collected audio recordings as access cues in healthy participants, Sheldon and Levine were able to match remote ($\approx$ 1.5 years old) and recent ($\approx$ 1 month - 3 months old) AMs in terms of vividness for fMRI analysis. The authors proposed that vividness is a primary factor modulating both the activity and functional connectivity of a brain network involving the hippocampus, exerting a stronger influence than the age of the memory itself, although subtle effects related to memory age were also observed. Overall, vivid AMs were associated with early and focused activation, whereas non-vivid AMs showed broader and later activation. They also found that Remote AMs showed activation in the right frontal cortex and left temporal cortex, occurring later ($\approx$ 12-20 seconds), while recent AMs were associated with the right precuneus and the posterior part of the left hippocampus, regardless of the vividness ratings [19]. Boccia et al, conducted an fMRI meta-analysis to compare changes in cortical representations of recent (< 1 year old) and remote (> 5 years old) AMs, they found that recent and remote AMs recruit partially different nodes within a broad network. Recent memories tend to engage the angular gyrus, dorsomedial prefrontal cortex, and hippocampal-parahippocampal regions, whereas remote memories are more strongly associated with posterior cingulate cortex activity [8]. This network-level perspective highlights the importance of examining how information flows across distributed cortical regions during early memory access.

Remembering relies not only on localized activity within specific brain networks [20, 7] but also on fast moment-to-moment interactions across those networks. iEEG evidence supports that both encoding and retrieval involve sub-second fluctuations in functional connectivity with unique patterns that are reinstated during successful episodic recall [21]. These findings suggest that the early stages of memory access depend on transient shifts of information exchange among a broad set of regions rather than on a sequential progression of activation. This perspective highlights the need for analytical tools that capture directionality and temporal structure in network communication. In this sense, Granger Causality, a mathematical measure that assesses whether one time series predicts another [22], provides an appropriate framework for quantifying directed information flow and is well suited to characterizing how neural systems coordinate during the initial moments of AM access.

Recent AMs are typically rich in sensory and contextual details and have some kind of freshness in our mental representations. In contrast, remote AMs are often reconstructed in a more schematic way, drawing on generalized knowledge or gist-like representations [17, 23]. This reduced level of detail may require greater reconstructive effort, potentially giving rise to more stereotyped or shared patterns of neural interactions. To capture these differences in information flow that emerge during the earliest moments of memory access, we employ Granger Causality analyses of theta-band oscillatory activity, thereby characterizing the directionality and temporal structure of functional interactions associated with memory age.

Together, this evidence highlights the dynamic and distributed nature of AM access and emphasizes the need for integrated spatial and temporal approaches to uncover its underlying mechanisms. This study aims to clarify this matter by characterizing both the broad areas involved and the manner in which they communicate during the initial moments of AM access. The aim of this work is to characterize the differences in the access of autobiographical memories (AMs) based on their age. To test this, we developed an experimental protocol specifically designed to capture both the unique characteristics of each AM and the fine-grained temporal dynamics of the early access period for recent and remote AMs. Specifically, we'll focus on the first 1200 ms of the access period and we'll be using theta band as a neural marker to examine the flow of information among regions through Granger Causality.

2 Methods

2.1 Participants

41 undergraduate and graduate students, aged from 19 to 33 years old ($mean = 24.6$, $SD = 3.9$; 21 female), participated in the study. All participants self-reported no history of neuropsychiatric conditions. Data from 8 participants were discarded due to noisy neurophysiological recordings. The exclusion criterion was the presence of excessive noise in 10% or more of the channels for prolonged time periods, as determined by visual inspection. All participants provided written consent of the Hospital Lanari, in accordance with the Declaration of Helsinki.

2.2 Stimuli

The stimuli were designed to elicit neutral autobiographical memory (AM) events, specifically targeting the recall of either recent or remote memories. To enhance the distinction between memory age within our experimental population, we adapted the stimulus set initially developed by [24].

2.3 Autobiographical protocol

Each participant completed 24 trials, 12 of which corresponded to remote autobiographical memory (AM) events and 12 to recent AM events. These trials were randomly selected from a dataset of neutral events and presented in a randomized order ($N = 37$; stimuli Translated to English are in supplementary material). Note that the original stimuli are in Rioplatense Spanish. In each trial, participants were cued to retrieve a specific memory via an on-screen sentence such as *"Remember the FIRST TIME you cooked by yourself"* targeting a remote memory or *"Remember the LAST TIME you took a bus"* targeting a recent memory. The time spent attempting to access that memory is referred to as the access Period. Once the memory came to mind, participants pressed the space bar and mentally elaborated on the event for 8 seconds, this phase is referred to as the Elaboration Period ([6, 2, 25, 24, 26]). Afterward, participants provided subjective ratings of the memory, including its emotional valence from very negative to very positive (-2 to 2), level of detail from no detail to a lot of detail (1 to 5), access difficulty from no difficulty to a lot of difficulty (1 to 5), perceived importance from no importance to a lot of importance (1 to 5), and estimated time of occurrence from today to more than 3 years ago (1 to 7). If participants were unable to recall a memory, they pressed the 's' key to skip the trial. Figure 1 provides a schematic representation of the experimental protocol. While vividness is a commonly used measure of memory richness in AM studies, and there is no single Spanish term for vividness, we decomposed this construct into

multiple subjective ratings to provide a more nuanced and comprehensive understanding of the characteristics of each AM.

After data collection, the recent and remote labels were reassigned based on participants' self-reported event timing. Events occurring up to 1 year before the session were labeled as recent, whereas those occurring more than 3 years before the session were labeled as Remote ($Nrem = 367$ y $Nrec = 297$).

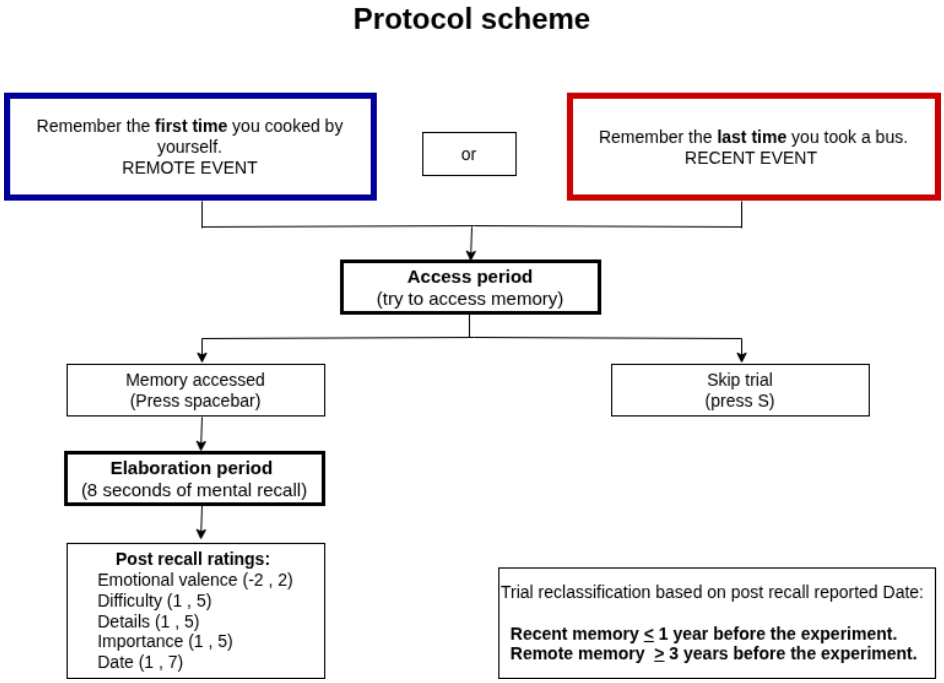

Figure 1: **Overview of the Autobiographical Memory task** Participants were cued to recall either a remote AM (blue) or a recent AM (red). The appearance of the cue on screen marked the beginning of the access period which lasted until the participants wether pressed the space bar once the target memory was accessed (left) or skipped the trial (right). Right after pressing the spacebar, the elaboration period started: Participants were asked to mentally elaborate the memory with as many details as possible during 8 seconds. After the elaboration, they had to rate that memory in the following categories: level of details recalled, level of difficulty to access the memory, emotional valence of the memory recalled, importance of the event and how long ago the event had happened. Posteriorly, the reported date was used to re-classificate the memories into recent or remote.

2.4 Equipment

Participants sat comfortably in a chair while stimuli were presented on a screen positioned 60 cm in front of them. The experimental paradigm was developed and presented using custom software written in PsychoPy v2023.2.3 [27]. Brain activity was continuously recorded throughout the task using an Akonic EEG device (`https://www.akonic-argentina.com/`), with a sampling rate of 256 Hz and 30 EEG channels arranged according to the international 10-20 system. Two additional reference electrodes were placed bilaterally on the mastoids. Behavioral responses were collected via keyboard input. Each response triggered a synchronization marker sent to an external EEG channel via an Arduino Nano (`http://www.arduino.cc/`), an open source electronics prototyping platform, enabling a temporal resolution of 1 ms.

2.5 Data Analysis

2.5.1 Behavioral data

The behavioral data were analyzed using custom software implemented in Python and R. Access times ranged from 1900 ms to 65000 ms, yielding a total of 664 trials. Access times were statistically compared for remote and recent AMs using the nonparametric Mann-Whitney U test.

To identify the most relevant behavioral predictors of AM age (recent vs remote), we applied a regularized Logistic Regression model. Logistic regression is a classification algorithm that models the probability of a binary outcome as a function of a set of predictors:

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p)}} \tag{1}$$

To prevent overfitting and perform automatic predictor selection, we incorporated the Elastic Net regularization, which combines L1 (Lasso) and L2 (Ridge) penalties to perform shrinkage and variable selection simultaneously [28]. It does so by minimizing a cost function where parameter λ controls the strength of the regularization and α the balance between L1 and L2 penalties.

We conducted a grid search over 100 log-scaled values of the regularization parameter lambda (ranging from -4 to 0) and 11 values of the mixing parameter alpha (ranging from 0 to 1) using the glmnet method from the Glmnet package in R. We evaluated the model performance through 5 fold stratified cross validation, and the optimal alpha-lambda combination was selected based on the area under the ROC curve (AUC). The best-performing Elastic Net model was then validated on a held out test set, with classification performance assessed via overall accuracy and confusion matrix. To further evaluate the stability of the selected model coefficients, we performed nonparametric bootstrapping (1,000 iterations) on the training set, refitting the Elastic Net model on each resample using the optimal hyperparameters. Percentile and bias corrected accelerated (BCa) 99% confidence intervals for each coefficient were estimated using the boot package in R. This approach allowed us to identify features with robust and consistent contributions across resamples.

2.5.2 EEG data preprocessing

EEG data were band pass filtered between 1 and 35 Hz using a zero phase 8th order Butterworth IIR filter to eliminate slow oscillatory trends, high frequency noise, and periodic artifacts such as heartbeat. Then, the data were re-referenced to the average activity using MNE's projection method. Noisy channels were identified through visual inspection and subsequently interpolated. In total, 22 subjects had interpolated channels, with a maximum of 3 channels interpolated per subject (10%). We applied Independent Component Analysis (ICA) to look for eyeblink artifacts. After visual inspection, we removed the components reflecting these physiological responses. ICA was computed using the FastICA algorithm [29], as implemented in the MNE-Python toolbox (`https://mne.tools/stable/index.html`) [30].

Raw data were then epoched into 2500 ms trials centered around the presentation of the "Remember..." screen. Each epoch began 700 ms before the screen onset and extended until 1800 ms after its appearance. This window ensured that all epochs across subjects captured the access period. Then, we performed a trial rejection using the Autoreject algorithm [31], which automatically estimates an optimal global amplitude threshold for rejecting noisy epochs. This threshold is determined via a data driven cross validation approach. For a range of candidate thresholds, the algorithm splits the data into k folds. It compares the median signal of the training set (after rejecting bad trials using each candidate threshold) with the median signal of the test set. The error between these signals is quantified using the Frobenius norm, and the threshold that minimizes this error is selected.

2.5.3 Time-frequency analysis

For spectral analysis, a Morlet wavelet transform was applied to each epoch using the FieldTrip toolbox in Matlab `https://www.fieldtriptoolbox.org/` [32]. Spectral power was estimated between 2 and 30 Hz, with a frequency resolution of 1 Hz, using a 3-cycle wavelet per frequency. Time-frequency decomposition was performed for a time window of 0 to 1200 ms from the stimulus onset, representing the first 1200 ms of the access period. Spectral power was normalized using a baseline defined as the average power across time for each frequency and channel. Finally, the resulting power values were converted to decibels (dB).

2.5.4 Cluster-based time-frequency comparison

To compare remote and recent access periods, we performed a non-parametric cluster-based permutation test using the FieldTrip toolbox from Matlab. We employed a within-subjects design, utilizing a dependent samples t-test to investigate differences between the two conditions. We conducted this statistical analysis on all EEG channels and across the full epoch time window of 0 to 1200 ms within θ range defined from 4 to 9 Hz. Cluster correction for multiple comparisons was performed using the Monte Carlo method with 1500 permutations. The forming cluster's threshold was set at $p < 0.05$, with a minimum of two neighboring channels to form a cluster. A two-tailed test was conducted, and the statistic for cluster level inference was the sum of t-values.

2.5.5 Granger Causality

To estimate directed functional connectivity in the frequency domain, we first preprocessed the EEG signals before applying Granger Causality (GC) analysis. First, we subtracted the ERP (event-related potential) of recent and remote trials for each subject to improve stationarity. Then, we segmented the EEG signals into sliding time windows of 200 ms with 10 ms steps from 0 to 1200 ms from the presentation of the screen, and we verified stationarity using the augmented Dickey Fuller test [33]. Next, we concatenated those segments for all recent or remote trials of each subject. Lastly, for each pair of electrodes of interest, we fit auto-regressive bivariate models of order 80 ms (20 samples).

Frequency-domain Granger Causality

To estimate directional functional connectivity between electrodes in the frequency domain, we used frequency resolved Granger Causality [34, 35], as implemented in the BSMART toolbox freely available for download online under the GNU general public license `https://brain-smart.org/)` [36]. The method is based on fitting bivariate autoregressive models (AMAR) to pairs of EEG channels. Let $X(t) = [X_1(t), X_2(t)]^\top$ represent a bivariate stationary process within a time window, where $\top$ denotes the transpose.

The signals are modeled using a p-th order autoregressive process:

$$X(t) = \sum_{k=1}^{p} A_k X(t-k) + E(t) \tag{2}$$

where $A_k \in \mathbb{R}^{2\times 2}$ are the coefficient matrices and $E(t)$ is a zero mean white noise process with covariance matrix Σ.

The model parameters are estimated using the Levinson Wiggins Robinson (LWR) algorithm [37] via the Yule Walker equations.

Once the model is estimated, it is projected into the frequency domain via the transfer function:

$$H(f) = \left(I - \sum_{k=1}^{p} A_k e^{-i2\pi f k/f_s} \right)^{-1} \tag{3}$$

wheref_s is the sampling frequency.

The spectral density matrix $S(f)$ is then computed as:

$$S(f) = H(f)\,\Sigma\,H^*(f), \tag{4}$$

where $H^*(f)$ denotes the conjugate transpose of $H(f)$.

The frequency resolved Granger Causality from channel j to channel i is defined as:

$$GC_{j\to i}(f) = \ln\left(\frac{S_{ii}(f)}{S_{ii}(f) - \frac{|H_{ij}(f)|^2 \Sigma_{jj|i}}{f_s}} \right) \tag{5}$$

where:

$S_{ii}(f)$ is the power spectral density of channel i

$H_{ij}(f)$ is the transfer function component from j to i

$\Sigma_{jj|i}$ is the residual noise variance when excluding the influence of channel j.

A value of $GC_{j\to i}(f) > 0$ indicates that past activity in channel j helps predict the activity in channel i at frequency f, a *directed Granger-causal influence* from j to i, while $GC_{j\to i}(f) \approx 0$ suggests no predictive information from j to i at that frequency.

2.5.6 Functional conectivity: Directed Weighted Networks

We constructed time-resolved, weighted, and directed networks for recent and remote conditions. Formally, each network can be represented as a directed weighted graph:

$$G = (V, E, W)$$

where:

$V = \{v_1, v_2, \ldots, v_9\}$ is the set of nodes (EEG channels),

$E \subseteq V \times V$ is the set of directed edges representing significant connections

$W = [w_{ij}]$ is the weighted adjacency matrix, where w_{ij} denotes the mean GC value from node j to node i.

Each network consisted of nine nodes, corresponding to the significant EEG channels identified in the cluster-based comparison: Fp1, Fpz, Fz, Pz, Cz, FC2, CP1, CP2, AFz (Figure 3 upper right). The network edges represent directed connections $i \rightarrow j$, based on significant GC values in θ, with i driving j. Edge weights reflected the mean GC value across subjects for the corresponding direction $i \rightarrow j$ in the corresponding time window of 200 ms.

To build the networks, we performed Wilcoxon signed-rank tests for each channel pair, time window and condition to identify moments of statistically significant GC directionality in θ across all subjects. Significance was defined at $p < .05$ (uncorrected), and the direction of the effect was determined by the sign of the test statistic (Z value).

In the functional connectivity section of the results, we analyzed the GC networks in two ways: (1) we computed a static network by adding all GC connectivity networks along the entire 1200 ms of access Period and performed a paired samples non parametric Wilcoxon signed rank test. (2) We examined the dynamic evolution of network topology across time, characterizing how connectivity patterns unfolded during the first 1200 ms of access Period using 10ms steps. To delimit a more fine-grained time window within this period, we calculated the distribution of the GC network values in both conditions and, for each node, we marked the windows that held GC values above the 95% of the distribution (Figure 5 , Supplementary Figure 6).

3 Results

3.1 Behavioural: Characterization of recall

The aim of this work is to characterize the differences in the access of autobiographical memories (AMs) based on their age. To this end, we compared the behavioral auto-reported measures for recent (less than 1 year) and remote (more than 3 years) AMs. We first explored the duration of the access period between recent and remote AMs. The search access time was defined as the latency from the onset of the cue ("Remember the last time you…") until participants pressed the space bar to indicate that a specific AM was located. No statistically significant difference was found between recent and remote periods (Mann-Whitney U = 57791.5, p = 0.18); the median latency of access Period was 7.1 seconds for recent AMs and 6.6 seconds for remote AMs Figure 2 a. Then, we explored the ratings for each self-reported measure: emotional valence, importance of the event, details recalled, and difficulty remembering. We show the distributions of responses for each condition Figure 2 c. To better understand the relationships among these variables, we conducted a Spearman correlation among the self reported measures. We found a relevant negative correlation between details and difficulty, and a positive one between importance and emotional valence Figure 2 b. Following this, to discard redundant information due to variable co-linearity, we performed an Elastic Net logistic regression: Age group ~1 + emotional valence + importance + difficulty + details. We found that the most important features to differentiate our recent and remote AM stimuli were importance (β = -0.56, IC 99 % (-0.77, -0.35)) and details (β = 0.75, IC 99 % (0.49, 1.00)). This shows that despite remote stimuli being rated as more important, they tended to be recalled with fewer details than recent ones.

3.2 Neural correlates

3.2.1 θ band (4-9 Hz) power

We investigated whether θ power serves as an age-sensitive neural marker of autobiographical memory (AM) access. Specifically, we compared θ power during the access Period of Recent and Remote AMs. A permutation cluster-based paired samples t-test was conducted in this band. As shown in Figure 3, we identified a statistically significant cluster between 870 and 1000 ms, involving electrodes Fp1, Fpz, Fz, Pz, Cz, FC2, CP1, CP2, and AFz. This cluster reflected greater θ power over midline frontal and central sites during the early stages of access for Remote compared to Recent AMs (p = 0.04). To further validate this effect, we compared the mean θ power across these electrodes and time window

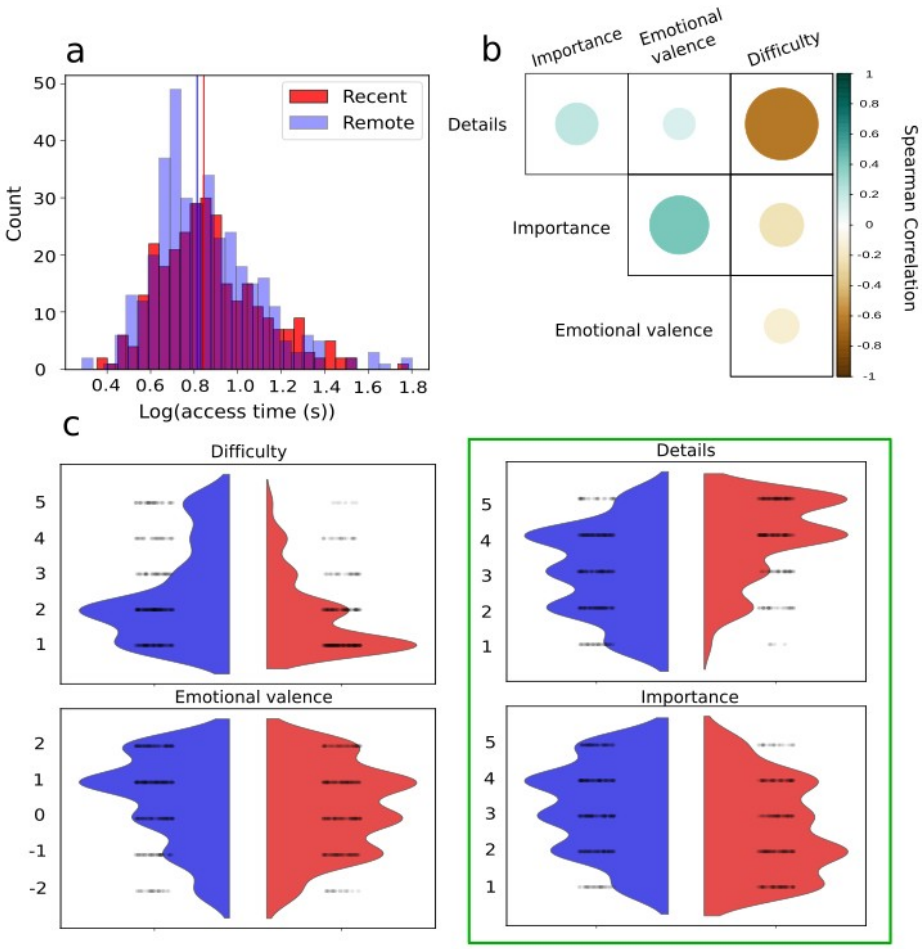

Figure 2: **Behavioral results - a:** access time histogram for recent (red) an remote (blue) trials. Mann-Whitney U = 57791.5, p = 0.18; Vertical lines represent the median latency of access Period for recent (7.1 seconds) and remote (6.6 seconds) AMs. **b:** Correlation matrix of the self reported measures. **c:** Distribution of responses for the self-reported measures. The green frame highlights the two measures that are significantly important in distinguishing between recent and remote events, based on a logistic regression with regularization parameter $\alpha = 1$, and $\lambda = 0.009$. The following coefficients and 99% confidence intervals (CI) were obtained: $\beta_{\text{Intercept}} = -0.97, IC99\% = (-2.41, 0.45)$,$\beta_{\text{Access time}} = 0.04, IC99\% = (-0.0016, 0.08)$,$\beta_{\text{Difficulty}} = -0.22, IC99\% = (-0.48, 0.032)$,$\beta_{\text{Importance}} = -0.56, IC99\% = (-0.77, -0.35)$,$\beta_{\text{Emotivity}} = -0.02, IC99\% = (-0.18, 0.12)$,$\beta_{\text{Details}} 0.75, IC99\% = (0.49, 1.00)$

using a Wilcoxon signed rank test, which confirmed significantly greater θ activation for Remote than for Recent AMs (p = 0.007, Z = –2.69). Finally, to gain deeper insight into the role of θ power as a potential biomarker of AM access, we examined its relationship with level of detail and importance ratings through a linear mixed model (GLMM). The model included fixed effects for age group (recent, remote), level of detail and importance, as well as their two way interactions (group × detail and group × importance). Random intercepts for participant and question number were included to account for variability between participants and questions. No linear associations were found between mean θ power and the ratings of event importance or level of detail for the age groups.

3.2.2 Functional connectivity

In order to delve into the neural flow of information underlying early AM access, we built directional connectivity networks using GC in θ band for the previously found subset of fronto-central electrodes. In this section, we first analyzed the overall topologies of the remote and recent AMs networks in the whole 1200 ms window of access, and then, we broke them down into 200 ms windows every 10 ms to explore the temporal dynamics of the networks connections in more detail. We applied GC in θ band across all electrode pairs within the cluster region spanning the first 1200 ms window of AM access period. The most salient finding in these results is that the remote AM network

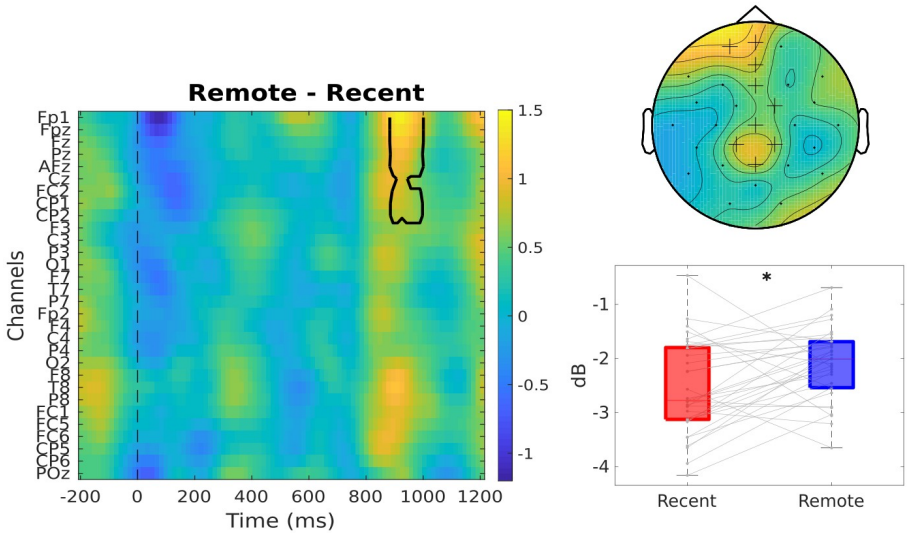

Figure 3: **Theta power – Left:** Difference between Remote and Recent activity. The black trace shows a significant cluster in time p=0.04 ($\approx 880 - 980\,\mathrm{ms}$), identified using a non-parametric cluster-based permutation test (1500 permutations, $\alpha = 0.05$, correction: Monte Carlo). **Top right:** mean θ activity for the significant time window. **Bottom right:** mean activity for significant channels in a significant time window. Wilcoxon signed rank test p=0.0072, Z-val=-2.6891, SignedRank=130.

exhibited a significantly greater number of connections, indicating a higher network density compared to the recent AM network (Non parametric paired Wilcoxon signed rank test, Z= -2.847, p = 0.003). Figure 4 left panel shows the network topologies of significant directed GC connections across the initial 1200 ms. The remote condition (bottom, blue) presents a denser and more distributed connectivity pattern. To depict the weight of the edges, we show a representation of the networks as the directed and weighted adjacency matrix for both conditions in the middle panel. The rows represent the outgoing connections and the columns represent the ingoing connections for every channel during the first 1200 ms window of the access period. The right panel of Figure 4 presents the net Granger causal flow per electrode, calculated as the difference between the outgoing (rows) and ingoing (columns) weights. The right fronto-central (FC2) shows dominant inflow in both AM conditions, suggesting that it may act more as a target rather than a source of information during the early AM access period. Additionally, Fp1 and Cz exhibit distinct patterns of activity across conditions. In the remote condition, Fp1 acts as a source, while Cz primarily acts as a target. In contrast, during the recent condition, Cz acts as the most prominent source, followed by AFz and Fpz. Meanwhile, Fp1 shows an attenuated inflow pattern. In summary, these findings suggest a more strongly connected θ network for remote AMs and a general Granger Causal flow of information towards the right hemisphere over the fronto-central region in AM access, regardless of memory age. Particularly, for recent events, the flow comes from the fronto-central midline, and for remote events, it comes from a wider distribution of posterior and anterior regions.

Lastly, to further investigate the temporal dynamics of information flow during the early AM access Period, we analyzed the wiring diagram of the θ band GC networks across the 1200 ms of the access period every 10 ms. (See Suplementary figure 6 for temporal dynamics of in and out connections for every channel in the network). Figure 5 top panel shows the evolution of networks densities every 10 ms for both AM conditions. We highlighted the period from $\approx$ 600 to 800 ms where the densities of the remote networks were higher than the recent ones as per the 95th percentile of the empirical distribution for each condition. The topomaps below show the GC networks connections within that window. We observe that in this window the remote network shows a stronger anterior to posterior directionality of θ band GC, suggesting an early, long-range coordination across frontal and parietal regions. The recent network shows weaker anterior localized connections. In both cases, there's a flow going to the right central region. In summary, these results suggest that early remote and recent AM memory access engage distinct spatiotemporal patterns of θ band GC connectivity along the mid-fronto-central region. Remote memories rely more on anterior to posterior long range interactions, while recent memories show weaker right lateralized flow.

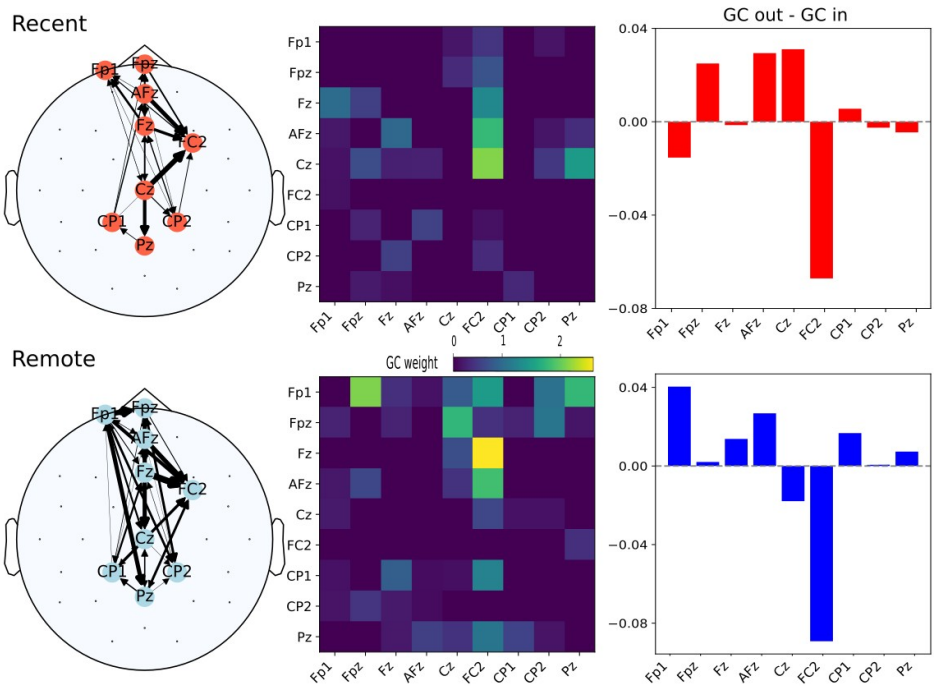

Figure 4: **Recent (top) and remote (bottom) θ GC networks for the 1200 ms of access period: Right panel:** network topologies. Density of the remote network is statistically denser than the recent one. (Non-parametric paired Wilcoxon signed-rank test, Z= -2.847, p = 0.003). **Middle panel:** Networks presentes as adjacency matrix: rows represent the outgoing degree of each channel and the columns represent the ingoing degree for each channel, the color is the weight of the edge. **Left panel:** Difference between out degree - in degree for each channel.

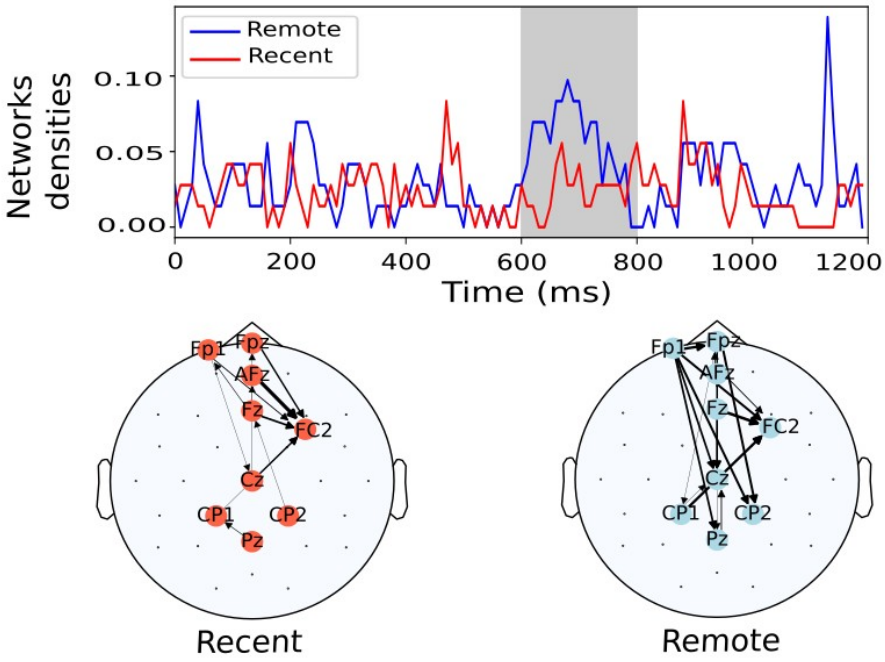

Figure 5: **GC θ networks over time — Upper panel:** Time series of network densities. The highlighted window (600–800 ms) indicates the period where the difference between conditions reaches its maximum, based on the 95th percentile distribution. **Bottom panel:** Topology of the networks in the highlighted time window.

4 Discusion

In the present study, we developed an EEG protocol to characterize the early neural dynamics of autobiographical memory (AM) access, focusing on the first 1200 ms of the access period. Building on previous electrophysiological evidence implicating theta-band oscillations in AM processes, we hypothesized that cortical theta activity serves as an age-sensitive neural marker distinguishing recent (less than 1 year old) from remote (more than 3 years old) memories. To test this, we analyzed theta power and, innovatively, applied time-resolved Granger causality (GC) to examine directional information flow in theta networks. Our key findings support this hypothesis: remote AMs elicited significantly greater theta power over midline fronto-central regions around 900 ms, alongside denser and more persistent theta-band connectivity patterns, particularly involving anterior-to-posterior flows. This original application of dynamic GC analysis reveals qualitative differences in network topology, with remote access demanding enhanced long-range coordination, highlighting theta oscillations as a robust marker of memory age during initial search phases.

Early prefrontal activation typically accompanies initial search strategies for AMs [38, 39]. Also, θ activity has been linked to both hippocampal cortical interactions and internal attentional states required for memory search and reconstruction [12]. The increased θ power observed around 900 ms over midline frontal and central electrodes during the access of remote AMs aligns with prior studies suggesting a key role for theta oscillations in autobiographical memory processes [12, 13] and specifically a change in theta power around 1000 ms over fronto-central regions during an AM old-new task [16]. In this sense, our results may reflect an enhanced recruitment of internal cognitive resources for the access of remote memory traces, requiring more effortful, reconstructive processes. Notably, the increased θ activity was not statistically associated with the subjective measures of detail or importance, suggesting that it may reflect a more complex memory age-dependent neural mechanism not directly captured in our protocol through these self reported measures. Overall, this supports the idea that θ power serves as a neural marker of AMs age in the early stages of access.

Our fine-grained analysis of θ - band Granger Causality (GC) connectivity in 200 ms windows revealed distinct temporal profiles for recent and remote AMs, particularly within the 600-800 ms time window. Bridging the time scale differencies, Sheldon and Levine found that Remote non-vivid AMs were associated with more expanded neural activity, particularly in frontal regions (e.g., bilateral superior and middle frontal gyri) than remote vivid and recent AMs. And discussed that this likely reflects a more effortful or generative mode of access that must occur before specific detailed information is accessed [19]. Here, during remote AM access, we observed a more pronounced, denser anterior-to-posterior flow of information, suggesting the engagement of long-range interactions that may support this view of an integrated network required for effortful AM access. In contrast, recent AM access was characterized by more localized frontal-central connectivity, potentially reflecting the recovery of vivid episodic details, which require less distributed coordination [19]. Both conditions showed a consistent going right pattern of connectivity, aligning with previous findings implicating the right hemisphere in AM access [19, 1], possibly due to its role in self-referential processing and imagery-based recall. This is in line with the involvement of midline regions. Particularly frontal midline θ activity has been associated with cognitive control, monitoring, and self-referential processing key components in the reconstruction of autobiographical memories [1, 2]. Remote AMs are typically associated with more effortful access, greater reliance on schematic structures, and integration of contextual and self-related information [5, 40]. In line with this, recent work from Rao et al showed that both θ-band power and synchronization was higher prior to the successful associative retrieval of words compared to intrusions and failed retrievals. This increase in θ power and synchronization is thought to enhance long-range communication between regions involved in complex cognitive operations, including visual imagery, emotional processing, and multimodal integration. θ oscillations may thus serve as a neural index of retrieval precision. Comparisons between successful and unsuccessful retrievals have highlighted the role of synchronized activity across multiple regions, such as the prefrontal cortex, lateral temporal lobe, lateral parietal cortex, and medial temporal lobe, in supporting attentional control and integration processes. In this sense, access can be understood as a distributed and cooperative process involving a network of θ synchronized regions[41]. While our current study does not distinguish between successful and unsuccessful access (i.e., hits vs. misses), our results provide insight into the large-scale network dynamics underlying autobiographical memory access.

The denser pattern of connections observed in the remote network can be framed within two models of system consolidation over time: the classical Standard Consolidation Theory (SCT) [42] and the Multiple Trace Theory (MTT) [43]. SCT proposes that there's a slow consolidation process of memories. It states that, over time, the neocortical connections of a memory trace gradually strengthen and, eventually, become independent of the hippocampus and surrounding structures in the Medial Temporal Lobe (MTL) for retrieval. On the other hand, the MTT holds that each time a memory is retrieved, a new hippocampally mediated trace is created so that old memories are represented by more, or stronger, MTL and neocortical traces than are new ones and, therefore, are less susceptible to disruption from MTL damage than are more recent memories [44, 45]. Here, we cannot determine whether the denser pattern of θ connections in the remote AMs' access period supports one model or the other, because the EEG measures cortical

activity that may be mixed with activity from deeper structures. Additionally, it cannot be ruled out that there is an intermediate process between the two models, involving the specification of sub-areas of the hippocampus for recent and remote AMs and strengthened neocortical connections for remote ones [18]

Our behavioural results revealed that the 2 most descriptive self-reported ratings of our protocol to differentiate remote and recent AMs were the level of detail and the importance of the event. Particularly, remote events were, overall, rated as less detailed but, yet, more important than recent ones. In this context, our behavioural results suggest that remote autobiographical memories (AMs), while less detailed, retain their perceived importance, supporting the notion that the shift from episodic to more semantic representations is linked to the loss of contextual specificity. In particular, as we age, our recollection of remote AMs tends to become more semantic in nature compared to recent ones[17, 46, 5, 25, 47, 48], this means that for remote AMs we may remember more common structures or schemas related to the specific period of our lifetime at the time of occurrence, such as general knowledge about the world, about us or people around us, rather than fine-grained specific episodic details. In literature, this is usually related to the process of semanticization, by which, as we gain experiences through life, the creation of multiple, related traces for similar events facilitates the extraction of the neocortically mediated information common among them [49, 50]. Regarding the importance ratings, this could be due to a bias of the presented stimuli for the remote condition, given that we needed participants to recall events remote than 3 years and this could be difficult to achieve for non-salient or insignificant events in someone's life.

A limitation of the present work is the absence of deep-structure activity measurements inherent to EEG techniques. Future studies could combine high-density EEG and source reconstruction techniques to better capture subcortical dynamics. Additionally, although our behavioral protocol was designed to be as ecological as possible, the reliance on self-reported measures introduces subjectivity and potential biases. Also, the self-paced nature of the task, while advantageous for capturing naturalistic memory processes, introduces variability that complicates traditional time-locked EEG analyses. Future studies will extend this ecological approach by incorporating speech analysis and memory reactivation to assess AM access in a multimodal manner. Finally, to better understand the temporal evolution of AM access processes, it is also relevant to evaluate neural correlates during the elaboration phase of AMs.

Together, our results highlight qualitative differences in the neural mechanisms supporting the access of recent versus remote autobiographical memories. While behavioral ratings indicate that remote memories are rated as more important but recalled with fewer details, neural data show that these remote memories involve stronger and more widespread θ-band interactions, possibly reflecting compensatory mechanisms or semantization processes. The combination of power and connectivity measures in the theta band offers an approach to dissect the dynamics of early AM access with high temporal resolution. In conclusion, this study elucidates the age-dependent neural signatures of autobiographical memory access, demonstrating that theta oscillations and their directional connectivity serve as key markers distinguishing remote from recent events. By integrating high-temporal-resolution EEG with innovative Granger causality analysis, our findings bridge behavioral phenomenology with underlying brain dynamics, paving the way for refined models of AM access and elaboration

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6 Suplementary Material

Table 1: Remote and Recent Memory Prompts (English Translations)

Remote	**Recent**
Remember one of the FIRST TIMES you rode a bike.	Remember one of the LAST TIMES you hung out with friends.
Remember one of the FIRST TIMES you rode a train.	Remember one of the LAST TIMES you took an exam.
Remember one of the FIRST TIMES you rode the subway.	Remember one of the LAST TIMES you went to a bar.
Remember one of the FIRST TIMES you rode a boat.	Remember one of the LAST TIMES you went to a birthday party.
Remember one of the FIRST TIMES you went on vacation without your parents.	Remember one of the LAST TIMES you hugged a loved one.

Remote	Recent
Remember one of the FIRST TIMES you ran an errand.	Remember one of the LAST TIMES you kissed someone.
Remember one of the FIRST TIMES you went to the movies.	Remember one of the LAST TIMES you got angry or argued with someone.
Remember one of the FIRST TIMES you experienced heartbreak.	Remember one of the LAST TIMES you ate your favorite food.
Remember one of the FIRST TIMES you kissed someone.	Remember one of the LAST TIMES your favorite sports team won a match.
Remember one of the FIRST TIMES you were scared by a storm.	Remember one of the LAST TIMES you played a sport you like.
Remember one of the FIRST TIMES you went to a concert.	Remember one of the LAST TIMES you did an activity you enjoy.
Remember one of the FIRST TIMES you played a sport.	Remember one of the LAST TIMES you slept in without an alarm.
Remember one of the FIRST TIMES you went to college/university.	Remember one of the LAST TIMES someone made fun of you.
Remember one of the FIRST TIMES you lost a tooth.	Remember one of the LAST TIMES a bus didn't stop at your stop.
Remember one of the FIRST TIMES you went to a childhood friend's house.	Remember one of the LAST TIMES you got on a very crowded form of transportation.
Remember one of the FIRST TIMES you did poorly on an exam.	Remember one of the LAST TIMES you found something on the street.
Remember one of the FIRST TIMES you completed paperwork on your own.	Remember one of the LAST TIMES you lost something.
Remember one of the FIRST TIMES you went to school on your own.	Remember one of the LAST TIMES you fell in a public place.
Remember one of the FIRST TIMES you went to high school.	Remember one of the LAST TIMES you arrived late somewhere.
Remember one of the FIRST TIMES you wore a school coat or uniform.	Remember one of the LAST TIMES someone stood you up or kept you waiting.
Remember one of the FIRST TIMES you used a cellphone.	Remember one of the LAST TIMES you stepped in dog poop.
Remember one of the FIRST TIMES you cooked something.	Remember one of the LAST TIMES bird poop fell on you.
Remember one of the FIRST TIMES you read a book on your own.	Remember one of the LAST TIMES you cooked something that turned out really well.
Remember one of the FIRST TIMES you participated in a school performance.	Remember one of the LAST TIMES you cooked something that turned out badly.
Remember one of the FIRST TIMES you went camping.	Remember one of the LAST TIMES you started a new activity.
Remember one of the FIRST TIMES you swam on your own.	Remember one of the LAST TIMES you tried a new food or drink.
Remember one of the FIRST TIMES you tried alcohol.	Remember one of the LAST TIMES you discovered an artist or band you liked.
Remember one of the FIRST TIMES you flew on a plane.	Remember one of the LAST TIMES someone gave you a gift you really liked.
Remember one of the FIRST TIMES you went on vacation.	Remember one of the LAST TIMES someone gave you a gift you didn't like.
Remember one of the FIRST TIMES you lost a loved one.	Remember one of the LAST TIMES you got injured while doing physical activity.
Remember one of the FIRST TIMES you were able to whistle.	Remember one of the LAST TIMES you got ready for an outing or event.
Remember one of the FIRST TIMES you got a vaccine.	Remember one of the LAST TIMES you canceled plans because you were tired or had to study.
Remember one of the FIRST TIMES you dressed up in a costume.	Remember one of the LAST TIMES you went out even though you didn't feel like it.
Remember one of the FIRST TIMES you were given a toy you really wanted.	Remember one of the LAST TIMES you got a vaccine.

Remote	**Recent**
Remember one of the FIRST TIMES you took a long trip.	Remember one of the LAST TIMES something you ate made you feel sick.
Remember one of the FIRST TIMES you built a sandcastle.	Remember one of the LAST TIMES you got a haircut.
Remember one of the FIRST TIMES you went out alone with your friends.	Remember one of the LAST TIMES you skipped a class.

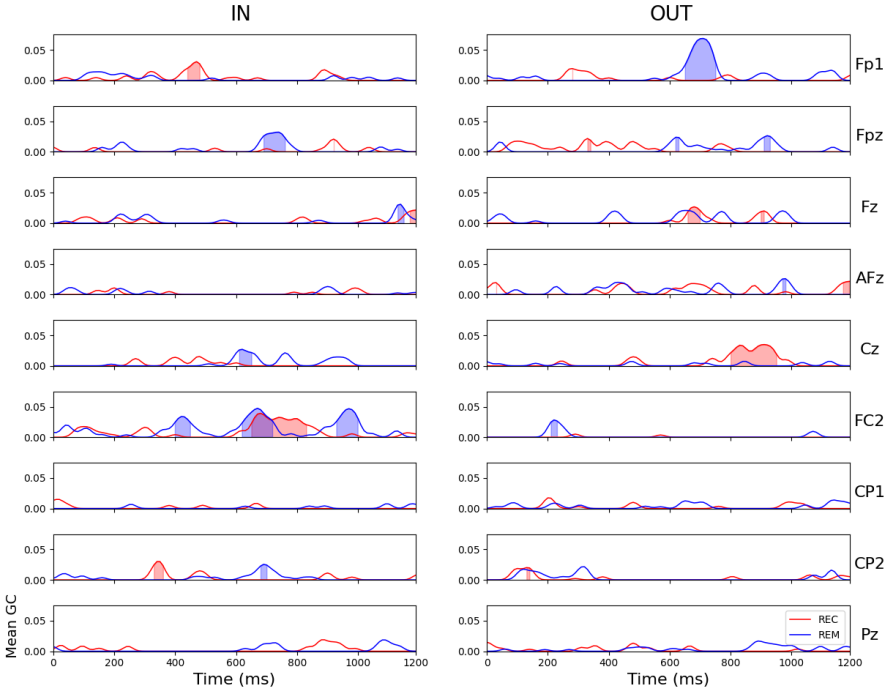

Figure 6: **GC networks Degree in time:** Mean GC values for every channel of the cluster. The left column represents the mean IN degree and the right column the mean OUT degree. The shading highlights the moments where the IN or OUT degree was in the 95th $\%$ percentile of the in or out distribution.

To delimit a more fine-grained time window of interest, we highlighted periods in which GC values exceeded the 95th percentile of the empirical distribution for each channel In Suplementary figure 6 we present the temporal dynamics of every channel in the network shown as in and out time series. It is important to note that all non-zero values in these time series represent statistically significant connections, as determined by group-level testing conducted prior to network's construction.

References

[1] Eva Svoboda, Margaret C McKinnon, and Brian Levine. The functional neuroanatomy of autobiographical memory: a meta-analysis. *Neuropsychologia*, 44(12):2189–2208, 2006.

[2] Roberto Cabeza and Peggy St Jacques. Functional neuroimaging of autobiographical memory. *TRENDS in Cognitive Sciences*, 11(5).

[3] Peggy L St Jacques, Anne Botzung, Amanda Miles, and David C Rubin. Functional neuroimaging of emotionally intense autobiographical memories in post-traumatic stress disorder. *Journal of psychiatric research*, 45(5):630–637, 2011.

[4] Asaf Gilboa, R Shayna Rosenbaum, and Avi Mendelsohn. Autobiographical memory: From experiences to brain representations. 2018.

[5] Martin A Conway and Christopher W Pleydell-Pearce. The construction of autobiographical memories in the self-memory system. *Psychological review*, 107(2):261, 2000.

[6] Sander M Daselaar, Heather J Rice, Daniel L Greenberg, Roberto Cabeza, Kevin S LaBar, and David C Rubin. The spatiotemporal dynamics of autobiographical memory: neural correlates of recall, emotional intensity, and reliving. *Cerebral cortex*, 18(1):217–229, 2008.

[7] Cory S Inman, G Andrew James, Katherine Vytal, and Stephan Hamann. Dynamic changes in large-scale functional network organization during autobiographical memory retrieval. *Neuropsychologia*, 110:208–224, 2018.

[8] Maddalena Boccia, Alice Teghil, and Cecilia Guariglia. Looking into recent and remote past: Meta-analytic evidence for cortical re-organization of episodic autobiographical memories. *Neuroscience & biobehavioral reviews*, 107:84–95, 2019.

[9] Hongkeun Kim. A dual-subsystem model of the brain's default network: self-referential processing, memory retrieval processes, and autobiographical memory retrieval. *Neuroimage*, 61(4):966–977, 2012.

[10] Kevin S LaBar and Roberto Cabeza. Cognitive neuroscience of emotional memory. *Nature Reviews Neuroscience*, 7(1):54–64, 2006.

[11] Daniel L Greenberg and David C Rubin. The neuropsychology of autobiographical memory. *Cortex*, 39(4-5):687–728, 2003.

[12] Lluis Fuentemilla, Gareth R Barnes, Emrah Düzel, and Brian Levine. Theta oscillations orchestrate medial temporal lobe and neocortex in remembering autobiographical memories. *Neuroimage*, 85:730–737, 2014.

[13] Sarah Steinvorth, Chunmao Wang, Istvan Ulbert, Donald Schomer, and Eric Halgren. Human entorhinal gamma and theta oscillations selective for remote autobiographical memory. *Hippocampus*, 20(1):166–173, 2010.

[14] Nicolas Roehri, Lucie Bréchet, Martin Seeber, Alvaro Pascual-Leone, and Christoph M Michel. Phase-amplitude coupling and phase synchronization between medial temporal, frontal and posterior brain regions support episodic autobiographical memory recall. *Brain Topography*, 35(2):191–206, 2022.

[15] Brett L Foster, Anthony Kaveh, Mohammad Dastjerdi, Kai J Miller, and Josef Parvizi. Human retrosplenial cortex displays transient theta phase locking with medial temporal cortex prior to activation during autobiographical memory retrieval. *Journal of Neuroscience*, 33(25):10439–10446, 2013.

[16] Berta Nicolás, Xiongbo Wu, Josué García-Arch, Mariella Dimiccoli, Joanna Sierpowska, Cristina Saiz-Masvidal, Carles Soriano-Mas, Petia Radeva, and Lluís Fuentemilla. Behavioural and neurophysiological signatures in the retrieval of individual memories of recent and remote real-life routine episodic events. *cortex*, 141:128–143, 2021.

[17] Brian Levine, Eva Svoboda, Janine F Hay, Gordon Winocur, and Morris Moscovitch. Aging and autobiographical memory: dissociating episodic from semantic retrieval. *Psychology and aging*, 17(4):677, 2002.

[18] Heidi M Bonnici, Martin J Chadwick, Antoine Lutti, Demis Hassabis, Nikolaus Weiskopf, and Eleanor A Maguire. Detecting representations of recent and remote autobiographical memories in vmpfc and hippocampus. *Journal of Neuroscience*, 32(47):16982–16991, 2012.

[19] Signy Sheldon and Brian Levine. Same as it ever was: Vividness modulates the similarities and differences between the neural networks that support retrieving remote and recent autobiographical memories. *NeuroImage*, 83:880–891, 2013.

[20] Andrew J Watrous, Nitin Tandon, Chris R Conner, Thomas Pieters, and Arne D Ekstrom. Frequency-specific network connectivity increases underlie accurate spatiotemporal memory retrieval. *Nature neuroscience*, 16(3):349–356, 2013.

[21] Audrey T Phan, Weizhen Xie, Julio I Chapeton, Sara K Inati, and Kareem A Zaghloul. Dynamic patterns of functional connectivity in the human brain underlie individual memory formation. *Nature Communications*, 15(1):8969, 2024.

[22] Ali Shojaie and Emily B Fox. Granger causality: A review and recent advances. *Annual Review of Statistics and Its Application*, 9(1):289–319, 2022.

[23] Morris Moscovitch, Roberto Cabeza, Gordon Winocur, and Lynn Nadel. Episodic memory and beyond: the hippocampus and neocortex in transformation. *Annual review of psychology*, 67(1):105–134, 2016.

[24] Valerio Santangelo, Clarissa Cavallina, Paola Colucci, Alessia Santori, Simone Macrì, James L McGaugh, and Patrizia Campolongo. Enhanced brain activity associated with memory access in highly superior autobiographical memory. *Proceedings of the National Academy of Sciences*, 115(30):7795–7800, 2018.

[25] Donna Rose Addis, Alana T Wong, and Daniel L Schacter. Age-related changes in the episodic simulation of future events. *Psychological science*, 19(1):33–41, 2008.

[26] Sarah Daviddi, Tiziana Pedale, Peggy L St Jacques, Daniel L Schacter, and Valerio Santangelo. Common and distinct correlates of construction and elaboration of episodic-autobiographical memory: An ale meta-analysis. *Cortex*, 163:123–138, 2023.

[27] Jonathan Peirce, Jeremy R Gray, Sol Simpson, Michael MacAskill, Richard Höchenberger, Hiroyuki Sogo, Erik Kastman, and Jonas Kristoffer Lindeløv. Psychopy2: Experiments in behavior made easy. *Behavior research methods*, 51:195–203, 2019.

[28] Hui Zou and Trevor Hastie. Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 67(2):301–320, 2005.

[29] Aapo Hyvärinen and Erkki Oja. Independent component analysis: algorithms and applications. *Neural networks*, 13(4-5):411–430, 2000.

[30] Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A Engemann, Daniel Strohmeier, Christian Brodbeck, Lauri Parkkonen, and Matti S Hämäläinen. Mne software for processing meg and eeg data. *neuroimage*, 86:446–460, 2014.

[31] Mainak Jas, Denis A Engemann, Yousra Bekhti, Federico Raimondo, and Alexandre Gramfort. Autoreject: Automated artifact rejection for meg and eeg data. *NeuroImage*, 159:417–429, 2017.

[32] Robert Oostenveld, Pascal Fries, Eric Maris, and Jan-Mathijs Schoffelen. Fieldtrip: open source software for advanced analysis of meg, eeg, and invasive electrophysiological data. *Computational intelligence and neuroscience*, 2011(1):156869, 2011.

[33] David A Dickey and Wayne A Fuller. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a):427–431, 1979.

[34] John Geweke. Measurement of linear dependence and feedback between multiple time series. *Journal of the American Statistical Association*, 77(378):304–313, 1982.

[35] Maciej Kaminski and Katarzyna J Blinowska. A new method of the description of the information flow in the brain structures. *Biological Cybernetics*, 65(3):203–210, 1991.

[36] Jianfeng Cui, Lei Xu, Steven L Bressler, Mingzhou Ding, and Hualou Liang. Bsmart a matlab c toolbox for analysis of multichannel neural time series. *Neural Networks*, 21(8):1094–1104, 2008.

[37] Simon Haykin. *Adaptive Filter Theory*. Prentice Hall, 4th edition, 2002.

[38] Alisha C Holland, Donna Rose Addis, and Elizabeth A Kensinger. The neural correlates of specific versus general autobiographical memory construction and elaboration. *Neuropsychologia*, 49(12):3164–3177, 2011.

[39] Hedvig Söderlund, Morris Moscovitch, Namita Kumar, Marina Mandic, and Brian Levine. As time goes by: hippocampal connectivity changes with remoteness of autobiographical memory retrieval. *Hippocampus*, 22(4):670–679, 2012.

[40] Martin A Conway. Memory and the self. *Journal of memory and language*, 53(4):594–628, 2005.

[41] Aditya M Rao, Riley D DeHaan, and Michael J Kahana. Synchronous theta networks characterize successful memory retrieval. *Journal of Neuroscience*, 45(16), 2025.

[42] Larry R Squire and Pablo Alvarez. Retrograde amnesia and memory consolidation: a neurobiological perspective. *Current opinion in neurobiology*, 5(2):169–177, 1995.

[43] Lynn Nadel and Morris Moscovitch. Memory consolidation, retrograde amnesia and the hippocampal complex. *Current opinion in neurobiology*, 7(2):217–227, 1997.

[44] Morris Moscovitch, R Shayna Rosenbaum, Asaf Gilboa, Donna Rose Addis, Robyn Westmacott, Cheryl Grady, Mary Pat McAndrews, Brian Levine, Sandra Black, Gordon Winocur, et al. Functional neuroanatomy of remote episodic, semantic and spatial memory: a unified account based on multiple trace theory. *Journal of anatomy*, 207(1):35–66, 2005.

[45] Gordon Winocur, Morris Moscovitch, Stuart Fogel, R Shayna Rosenbaum, and Melanie Sekeres. Preserved spatial memory after hippocampal lesions: effects of extensive experience in a complex environment. *Nature neuroscience*, 8(3):273–275, 2005.

[46] Pascale Piolino, Béatrice Desgranges, Karim Benali, and Francis Eustache. Episodic and semantic remote autobiographical memory in ageing. *Memory*, 10(4):239–257, 2002.

[47] Kellie McWilliams, Alexander Kaplan, Ellen Eline, Isabelle Kaminer, Shauna Zodrow, Julie Petersen, J Michael Williams, and Karol Osipowicz. Cortical semantization of autobiographical memory over subjective chronological time: An fmri study. *European Journal of Neuroscience*, 55(7):1798–1809, 2022.

[48] Gordon Winocur and Morris Moscovitch. Memory transformation and systems consolidation. *Journal of the International Neuropsychological Society*, 17(5):766–780, 2011.

[49] Jessica Robin and Morris Moscovitch. Details, gist and schema: hippocampal–neocortical interactions underlying recent and remote episodic and spatial memory. *Current opinion in behavioral sciences*, 17:114–123, 2017.

[50] Vanessa E Ghosh, Morris Moscovitch, Brenda Melo Colella, and Asaf Gilboa. Schema representation in patients with ventromedial pfc lesions. *Journal of Neuroscience*, 34(36):12057–12070, 2014.