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Seeing the Future:
Anticipatory Eye Gaze as a Marker of Memory

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The thesis was carried out under the supervision of
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Abstract

Human memory is typically studied by direct questioning, and the recollection of events is investigated through verbal reports. Thus, current research confounds memory per-se with its report. Critically, the ability to investigate memory retrieval in populations with limited verbal ability is lacking. Here, using the MEGA (Memory Episode Gaze Anticipation) paradigm, we show that monitoring anticipatory gaze using eye tracking can quantify memory retrieval without verbal report. Upon repeated viewing of movie clips, eye gaze patterns anticipating salient events can quantify their memory traces seconds before these events appear on the screen. A series of experiments with a total of 126 participants using either tailor-made animations or naturalistic movies consistently reveal that accumulated gaze proximity to the event can index memory. Machine learning-based classification can identify whether a given viewing is associated with memory for the event based on single-trial data of gaze features. Detailed comparison to verbal reports establishes that anticipatory gaze marks recollection of associative memory about the event, whereas pupil dilation captures familiarity. Finally, anticipatory gaze reveals beneficial effects of sleep on memory retrieval without verbal report, illustrating its broad applicability across cognitive research and clinical domains.

Keywords: eye tracking, consolidation, sleep, machine learning, real-life, gaze, eye-movements, anticipation

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Introduction

Traditionally, human memory assessment has predominantly relied on explicit retrieval tasks, where participants verbally categorize learned items as familiar or novel. For instance, Tulving (1985)[1] introduced the concept of episodic memory, emphasizing the recollection of personal experiences and specific events that occurred at a particular time and place, which typically requires verbal reporting. Gardiner (1988)[2] further differentiated between recollective experience and simple familiarity in memory tasks. Migo et al. (2012)[3] improved upon the remember/know procedure to measure these aspects of memory better. However, relying exclusively on verbal reports entails significant limitations. First, from a basic science standpoint, it confounds memory per se with the ability to access and report the memory. Accordingly, it remains unclear whether the underlying neural process, a deleterious effect of brain disease, or the benefit of sleep pertains to memory or the ability to access or report the memory engram. In addition, studying memory retrieval is limited (or completely impossible) in populations where explicit reports are unreliable or absent, such as in aphasia patients, newborns, or animals. A method to assess episodic-like memory of events independent of report would represent a major advance.

A similar challenge exists in the study of consciousness, where specialized paradigms have been developed to separate the neural correlates of consciousness from those related to its report. Tsuchiya et al. (2015)[4], discussed various 'no-report' paradigms in consciousness research, which aim to identify neural correlates without relying on subjective reports, thereby avoiding confounds related to verbalization and attentional processes. Many such paradigms employ eye tracking, suggesting that an eye-tracking-based “no-report” paradigm could also be effective in studying memory retrieval. Additional motivation arises from rodent studies, where differences in exploratory behavior are routinely used to index memory[5,6]. Rodent studies, such as the Morris water maze task[5], have demonstrated that exploratory behavior can be a reliable memory index. O’Keefe and Dostrovsky (1971)[6], showed that place cells in the hippocampus of freely moving rats reflect spatial memory, highlighting the importance of behavioral measures in memory research. Humans and other primates are visual-centric and primarily rely on eye movements to explore their environment[7–

[9]. We therefore hypothesized that profiles of visual gaze exploration could inform about distinct memory traces.

Indeed, over the past two decades, eye tracking has been increasingly used to study memory, either in conjunction with verbal reports or in their absence[10,11]. Hannula et al. (2009)[12], showed that eye movements can reflect the retrieval of associative memory, where participants' gaze patterns indicated memory for item-location associations. Ryan and Shen (2020)[11], reviewed evidence suggesting that eye tracking can reveal both conscious and unconscious memory processes. Urgolites et al. (2018)[13], found that eye movements support the link between conscious memory and medial temporal lobe function. Johansson et al. (2022)[14], demonstrated that eye-movement replay supports episodic remembering, further validating the use of eye tracking in memory research. A number of studies have shown that memory can affect the way people visually explore static images[10–16]. For example, recognition of photographs is associated with a decrease in distributed overt attention[16] and familiar faces elicit fewer fixations compared to unfamiliar ones[15,17]. We sought to go beyond the state-of-the-art by capturing gaze patterns when viewing dynamic video clips and relating them to memory without explicit retrieval.

We predicted that by using video clips, visual gaze could index context-dependent memory-guided prediction[18] in the absence of the remembered visual context about to appear, thereby going beyond familiarity and image recognition. This approach aligns with findings from research on visual anticipation, where gaze behavior during repeated viewing of stimuli can indicate learned expectations about future events. Studies on non-human primates, such as those by Kano and Hirata (2015)[19], have demonstrated similar anticipatory gaze patterns based on long-term memory. In humans, anticipatory gaze patterns have been linked to the ability to predict and react to dynamic events, as shown by Schroeder et al. (2010)[7], who discussed the dynamics of active sensing and perceptual selection. Hayhoe and Ballard (2005)[9], also emphasized the role of eye movements in natural behavior, highlighting how gaze anticipates future actions based on past experiences.

Moreover, gaze exploration is not limited to conscious retrieval[12] and could, therefore, potentially provide a more sensitive measure of memory compared to explicit report. This sensitivity is supported by findings showing that gaze metrics, such as fixation

duration and saccade patterns, can differentiate between remembered and forgotten items even without conscious recall[16,17]. Hannula and Ranganath (2009)[12], provided evidence that hippocampal activity predicts memory expression in eye movements, indicating the potential for eye tracking to reveal memory processes inaccessible through verbal reports. Thus, we developed a method that uses anticipatory gaze patterns to index and quantify memory-guided prediction of events occurring at a specific place and time.

Here we introduce and validate MEGA (Memory Episode Gaze Anticipation), a no-report method based on eye tracking during repeated movie viewing to assess memory for events. Participants watched movies with predefined surprising events. When participants watch the movies for the second time and have already formed a memory of the event, their gaze is drawn to its location, anticipating its occurrence before it appears. In a series of experiments, we evaluate MEGA as an approach to quantify memory without reporting. We introduce a distance-based metric and employ statistical analysis and machine learning on eye-tracking data to capture gaze characteristics indicative of memory at the single-trial level. We then explore its correspondence with multiple explicit memory reports about the movie event and contrast it with other eye-tracking metrics, such as pupillometry that index context and familiarity. Finally, we demonstrate one application by studying the influence of sleep on memory consolidation via MEGA without explicit reports.

Hypothesis and Objectives of the Study

Hypothesis

Our primary hypothesis is that anticipatory gaze, as monitored through eye tracking, can serve as a robust, non-verbal indicator of episodic-like memory retrieval. Specifically, we propose that during repeated viewings of movie clips containing surprising events, participants' gaze will anticipate the location and timing of these events during the second viewing.

Objectives

1. To develop and validate the MEGA (Memory Episode Gaze Anticipation) paradigm, we will create and test a novel eye-tracking-based method to quantify memory retrieval without relying on verbal reports.

2. Use naturalistic movies instead of still images: Naturalistic movies may have the potential to capture the characteristics of episodic-like memory than still images more accurately.

3. To compare anticipatory gaze patterns with explicit memory reports: This objective aims to analyze how gaze patterns reflect memory retrieval by correlating them with participants' verbal reports.

4. To employ machine learning techniques for single-trial memory prediction: We aim to develop a clinical tool to predict memory retrieval for new subjects based on a single trial rather than relying on averages.

5. To demonstrate an application of MEGA, investigate the impact of sleep on memory consolidation. This involves using MEGA to study how sleep affects memory retrieval.

By addressing these objectives, our study aims to advance the understanding of non-verbal memory assessment and provide a robust tool for cognitive neuroscience and clinical research.

Methods

Experimental Procedures

Four different experiments were carried out. Each included a first viewing session (encoding), a break (consolidation period with different durations), and a second viewing session (retrieval) of the same movies and, in some cases, additional new movies.

Experiment 1: tailor-made animation movies. Experiment 1 (Figures 1, 2, 3) was conducted during a daytime session with a two-hour break between the first and second movie viewing sessions. Following completion of consent forms and eye tracking setup (see below), the first viewing session started around noon (11:48 AM on average) and lasted an average of 45 minutes. Participants watched 65 animated movies while pupils and gaze were monitored (see below). The movies were separated by a 2-second fixation cross presented on a blank grey screen. Then, the participants had a ~2h break in which they were free to leave the lab unsupervised. During the second viewing session, each movie was followed by participants feedback indicating their explicit memory recall ("*Have you seen this movie before?*" with options Yes (1) or No (2)) and a second screen in which they rated their confidence ("*How confident are you in your answer?*" on a scale from "*Not at all (1)*" to "*Very confident (4)*").

Experiment 2: animation movies with extensive explicit memory reports. This experiment (Figure 4) examined the relation between anticipatory gaze and verbal reports, probing different aspects of memory in more detail. The experiment employed the exact same animation used in Experiment 1 for the first viewing. However, in the second viewing, the participants viewed an edited version of these movies where the surprising event E was omitted from each movie. In the first viewing, participants watched 48 movies. After a 2-hour break, participants were instructed about the tasks associated with the second viewing ahead, and a single training example verified that they could successfully follow the tasks. During the second session, participants watched the edited, event-lacking version of the 48 movies and 12 new movies in a random order. After each movie, the following five retrieval tasks were presented:

movie recognition: “Do you remember watching this movie before?” (“Yes” or “No”),
free recall: “Please describe what was missing in the video and where did it happen?” Participants were instructed to say their answer aloud (for example: “snake on the right” or “frog in the center”).
object recognition: two objects were presented, and the participant was asked to indicate, “What was missing in the movie?”. The lure object was created so that it was not unlikely to exist in the presented environment but only appeared once. For example, if the scene were underwater, possible lures would be “fish” or “crab” but not “elephant”. Hence the lure list was fixed so that each object appeared once as correct and once as incorrect answer.
Event location recall: A frame from the movie was presented, and participants were instructed to click on the screen where they thought the event should have happened. An answer was considered correct if they clicked in the correct quarter of the screen.
Temporal recall: Participants were asked about the timing of the event within the Movie: "When did the Surprising Event happen?" The answer options were a) “In the middle of the movie” or b) “At the end of the movie.” Event timing was considered in the middle or in the end according to the distribution of all events. If an event appeared before the median time of all SEs, it was considered in the middle, and vice versa.

The free recall was self-paced, whereas the other four questions were limited to 5 seconds. The movie order in the first and second viewing was randomized, but which movies were presented once or twice was fixed and identical for all participants.

Experiment 3: Naturalistic movies. Experiment 3 (Figure 5) investigated anticipatory gaze at our sleep lab using naturalistic videos from YouTube. After setting up the eye tracking and EEG (below), the first viewing session started around 2 PM and included watching 100 naturalistic movies. Then, the participants had a 2h break in which they were instructed to remain awake. The second viewing session also included 100 movies (80 seen movies and 20 new ones) as well as a simple recognition task ("*Have you seen this movie before?* (“Yes” or “No”),") and confidence feedback ("*How confident are you in your answer?"* on a scale from “*Not at all (1)*” to “*Very confident (4)*”)") as in Experiment 1.

Experiment 4: Naturalistic movies with nap or wake. In Experiment 4, the setup was identical to Experiment 3, but introduced new participants and a modification: participants were given a nap opportunity during the 2h break while we monitored EEG, electrooculogram (EOG), and electromyogram (EMG) to monitor sleep. Data collection and sleep scoring were previously described[20]. Data from 8/29 participants was excluded due to short sleep duration (<50% sleep efficiency or < 15 minutes in N2/N3 sleep, Figure 6).

Participants

We tested a total of 128 participants across the four different experiments. Written informed consent was obtained from each participant prior to their involvement in the study as approved by the Institutional Review Board at Tel-Aviv University (Experiments 1,2) or by the Medical Institutional Review Board at the Tel-Aviv Sourasky Medical Center (Experiments 3,4). All participants were required to have normal or corrected-to-normal vision, reported overall good health, and confirmed the absence of any history of neurological or psychiatric disorders. Experiment 1 (animation movies) included a total of 34 participants (age range: 19-61, M ± SD = 26.2 ± 9.01 years; 23 (67 %) female). Experiment 2 (animation movies - with elaborate memory assessments) included 32 participants (age range: 18-40, M ± SD = 26.48 ± 4.3 years; 23 (72 %) female). 2 participants in this experiment were excluded from the analysis due to technical issues. Experiment 3 (naturalistic movies) included 32 participants (age range: 19-44, M ± SD = 27.03 ± 5.09 years; 9 (27 %) female). One participant was excluded from this experiment due to the loss of more than 50% of the eye-tracking data. Experiment 4 (naturalistic movies - with sleep consolidation) initially recruited 25 participants. Three participants were excluded due to incomplete data, lacking either EEG or eye tracking data across two sessions, and three other participants were excluded due to insufficient sleep (<50% sleep efficiency: the ratio of time spent asleep to the total time from sleep onset to final awakening). Therefore, 19 participants were subsequently analyzed (age range: 20-34, M ± SD = 27.13 ± 3.44 years; 10 (34%) female).

Movie stimuli and visual presentation

Overall, we used 185 different movie clips. We presented movies in full-screen mode to maximize engagement. A gray background with a fixation cross was displayed

between the movie clips for 2 seconds to standardize the visual field and prepare the participants for the upcoming stimulus. In all experiments, the order of the movie clips was pseudo-randomized for each participant to avoid order effects that could influence memory encoding and retrieval processes. Previously unseen movies were incorporated in the second session to increase task difficulty and enhance performance variability but were not subsequently analyzed. The experiments were coded in Python, using the PsychoPy[21] package and the Pylink package, which facilitates interfacing with EyeLink eye-trackers (see below).

Animation Movies (Experiments 1 & 2). For Experiment 1, we used 65 silent animated colored movie clips (see examples in Supp. Movies A1 and A2), each rendered at a resolution of 2304x1296 pixels. These clips varied in duration from 8 to 15 seconds, with an average length of 12.68 seconds. Movies were prepared to be universally comprehensible, regardless of age, cultural background, or cognitive ability. A key feature of these animations was the inclusion of a surprising event designed to be unmistakably noticeable upon first viewing while adhering to the following criteria: i) The event occurred after a minimum of 5 seconds from the start of the clip, ensuring viewers are engaged and have enough time to recognize the context potentially. ii) Once introduced, the event remained visible for at least 2 seconds. iii) It appeared peripherally, not centrally, varying in location and timing across clips to prevent predictability. iv) There were little or no hints to spoil the surprise and indicate the event's appearance. Additionally, the movies were crafted to include background scenes that are visually similar, yet not identical, across different movie clips (e.g. more than one movie had the same underground water scenery) to increase difficulty and avoid ceiling performance. Animations were crafted by Studio Plonter® (https://www.plonteranimation.com/). For the second viewing in Experiment 2, the animation studio produced an alternative version of 60 animations, identical in every aspect but without the surprising event. Visual stimuli were presented using a 15.6-inch (35x20 cm) monitor with a resolution of 3840x2160 pixels.

Naturalistic movies (Experiments 3 & 4). Movies (examples in Supp. Movies R1 and R2) included 100 silent black and white movie clips with a duration of 3.5 to 26 seconds downloaded from YouTube. This collection encompassed carefully selected clips from classic films (e.g., Charlie Chaplin) or contemporary single-shot natural scenes

characterized by minimal camera movement, containing at least one SE. Scenes covered a broad spectrum of topics ranging from famous soccer goals through animal behaviors to human social interactions. Visual stimuli were presented using a 24-inch monitor (51x29 cm) with a resolution of 1920x1080 pixels.

Determining the surprising event. Determining the surprising event is central for quantification to the anticipatory gaze as event onset needs to be defined for data analysis. For animated movies (Experiments 1, 2), the location and timing of the surprising events were defined by the animation studio that compiled the animations according to the location and moment when the first pixel of the event becomes visible on the screen. For naturalistic movies (Experiments 3,4), an online human focus group defined the surprising event experimentally. We followed protocols used in prior research[22–24] and conducted an additional dedicated online experiment with 55 participants who were asked to mark the time and location of the surprising event E in a random subset of the 80 movies used for analysis (excluding the 20 unseen and those that were replaced by them, M = 51.05±1.16 rated movies per participant). During an additional viewing, participants watched the movies and then pressed their mouse at the moment (t) and location (x, y coordinate) where the surprising event occurred. Each movie's event onset, duration, and location were then defined as the median of marked events. We discarded from the study movies that did not reach a minimal consensus on the timing and location of the surprising event since such movies typically contained multiple events and could not yield consistent eye-tracking patterns. Accordingly, movies where less than 70% of participants agreed on the location were excluded (consent meant localizing the location within 1/9 of the screen size). 48 of the 80 YouTube movies (60%) were deemed suitable for eye-tracking experiments.

Eye tracking

Eye tracking employed EyeLink 1000 Plus (SR Research) as in Sharon et al.[25] with a sampling rate of 500Hz. We first determined the dominant eye of each participant, utilizing a modified version of the Porta test[26,27]. Participants were then instructed to position their heads on a chin rest positioned 50-70cm from the screen in order to maximize eye tracking quality. Next, a 9-point calibration and validation process were performed until the error was below 0.5° of the visual angle. EyeLink software recorded

gaze patterns, including fixations, saccades, and blinks, using its standard parser algorithms. The participants' gaze and pupil size data were recorded from the dominant eye, ensuring the capture of relevant eye movement metrics.

Data Analysis

Eye tracking Analysis

A pickle file containing time-stamped X-Y gaze coordinates and pupil radius measurements was created for each session, participant, and movie. A custom validation tool was employed to ensure data integrity, running several checks such as for the correct number of files and recording rates (see code below). Movie trials with more than 30% tracking loss were excluded. The EyeLink 1000 Plus's classifications (Fixation, Saccades, Blinks) were used to structure the analysis. Data points were organized into multi-index pandas DataFrame for in-depth processing with custom-made Python scripts. Next, we computed the Euclidean gaze distance between each sample and the event location point in degrees of visual angle (see below), generated features, etc. Data quality was further ensured by observing the raw data by superimposing the instantaneous gaze and the average distance metric on the actual movies, as in Supp. Movies A1, A1, R1, R2.

Degrees of Visual Angle (DVA). To compute the Degrees of Visual Angle (DVA), we utilized a series of steps designed to precisely measure the angular distance between the participant's gaze point and the event location on the screen. First, we calculated the difference between the gaze point and the event location separately for the X and Y coordinates by subtracting the ROI's middle point coordinates from the gaze coordinates for each data point. Next, we computed the Euclidean distance in pixels between the gaze point and the event location using the Pythagorean theorem, which involved squaring the differences in X and Y coordinates, summing these squares, and taking the square root of the result. To convert the pixel distances to degrees of visual angle, we used the following formula:

$$DVA = \frac{\text{distance\_in\_pixels} \times \left(\frac{\text{atan2}(0.5 \times \text{screen\_size\_in\_cm}, \text{distance\_between\_screen\_and\_eyes}) \times 180}{\pi}\right)}{0.5 \times \text{resolution\_in\_pixels}}$$

For this conversion, we considered the specific dimensions of the screen (both width and height) and the distance between the screen and the participant's eyes, using parameters such as screen width and height in centimeters and the screen resolution in pixels. Finally, the DVA measures for the X and Y coordinates were combined using the Euclidean distance formula, ensuring that the angular distance accounted for both horizontal and vertical deviations. The resulting DVA values were then indexed and organized in the DataFrame to align with other metrics, such as subjects, sessions, movies, and timestamps, allowing for seamless integration with other data processing steps and statistical analyses.

Gaze Average Distance (GAD). GAD quantifies the mean Euclidean distance between each gaze data point and the SE center point, calculated separately for each time point prior to the appearance of the SE and averaged across all computed distances (not just fixations). Thus, the GAD captures a cumulative estimate of how closely participants' gazes approximate the surprising event by reflecting the number of entries near the SE center point and the duration of each stay. GAD was averaged for each subject across all movies within each session.

MEGA Score. a metric for gaze anticipation. The MEGA Score is a normalized metric reflecting how anticipatory gaze behaviors change across repeated viewings of the same movie: MEGA Score = ($GAD^{1st\ viewing}$ - $GAD^{2nd\ viewing}$)\ max($GAD^{1st\ viewing}$, $GAD^{2nd\ viewing}$). A higher MEGA Score indicates that participants were looking closer to upcoming SEs during the second viewing, suggesting an enhanced anticipatory gaze indicative of effect once memory is present.

Pupillometry. Pupil size was extracted during all fixations prior to the surprising event using the EyeLink segmentation tool. As above, trials with >30% missing data were excluded. Pupil size dynamics comprised a time course prior to the events used to compute a normalized pupil size score (as for the MEGA score): pupil size score = (pupil size $^{1st\ viewing}$ - pupil size $^{2nd\ viewing}$) / max(pupil size $^{1st\ viewing}$, pupil size $^{2nd\ viewing}$). The pupil size score provides a nuanced measure of change in pupil size across repeated movie viewings, where a higher pupil size score reflects a larger pupil size in the 2^{nd} viewing.

Behavioral analysis

Explicit report

To disentangle the relationship between anticipatory gaze and explicit report, we collected verbal reports in all four experiments. For Experiment 1, 3 and 4 we asked after each movie "*Have you seen this movie before?* (“Yes” or “No”)," and collected their confidence rating. In Experiment 2, five retrieval tasks were presented: i - movie recognition, ii - free recall, iii - object recognition, iv - location recall, v - temporal recall.

Anticipatory gaze and explicit report

For the anticipatory gaze analysis in relation to the explicit report, we computed the MEGA score for each movie. To estimate the difference between the first and the second viewing, we averaged the MEGA score over all movies for each participant (‘new’ movies were excluded) and then tested the MEGA score against chance. To estimate the subsequent memory effect, we computed the MEGA score according to the explicit report. That means, for example, we aggregated the MEGA score once for all movies that were recognized and all movies that were not recognized, according to the answer to the question “Have you seen this movie before?”. Next, we compared the average recognized and unrecognized MEGA score (via the Wilcoxon signed-rank test and a binomial test, respectively). This was done for naturalistic and animated movies. Moreover, we used the same procedure to compare the sleep and the wake groups.

Anticipatory gaze and event-specific recollection. In Experiment 2, after extracting raw responses to each separate question (available in Supp. Figure 1), responses were combined into an integrated measure as follows:

Based on the four forced-choice tasks (i - recognition, iii - what, iv - where, v - when) and the defined three labels of remembered memory content: (A) Context and event recollection: movies where participants accurately recall the context and the surprising event. Namely, a correct answer for the movie recognition, object recognition, and event location recall. (B) Context recognition: recognition of the movie's setting without specific recollection of the event. Namely, a correct answer for the movie recognition but an incorrect answer for the object recognition and spatial recall, and (C) not recognized: when participants did not recognize the movie at all. Namely, indicating that they do not recognize the movie, independent of the retrieval performance in

object recognition and event location recall. Temporal recall was not further analyzed since retrieval performance was at chance (p=0.81, chance=50%, see Discussion). The free recall (ii) was analyzed separately. A movie was labeled as successfully recalled if a participant could recall the object of the surprising event before any visual cue of the object itself was presented.

Single-Trial Decoding with Machine Learning

To analyze the eye-tracking data, we employed various machine learning algorithms to identify the most effective model for our data. Initially, we experimented with several binary classification algorithms, including logistic regression, support vector machines (SVM), decision trees, and random forests. Logistic regression, being a linear model, estimates the probability of a binary outcome and is often used as a baseline model due to its simplicity and interpretability. SVM is a powerful classifier that finds the optimal hyperplane to separate classes in the feature space, effective in high-dimensional spaces with different kernel functions. Decision trees partition the data into subsets based on feature values, resulting in a tree-like model of decisions, which are easy to interpret but can be prone to overfitting. Random forests, an ensemble method, construct multiple decision trees and combine their outputs to improve predictive performance and reduce overfitting. After extensive evaluation, we found that the XGBoost classifier outperformed the other models in terms of accuracy and robustness. XGBoost (Extreme Gradient Boosting) is an advanced ensemble method that builds multiple trees sequentially, with each tree correcting the errors of its predecessors. Its ability to handle high-dimensional data and prevent overfitting through regularization made it the best choice for our analysis.

Feature engineering for machine learning (ML) analysis. Our ML analysis relied on the extraction and transformation of raw eye-tracking data into a set of features. We calculated a total of 243 eye-tracking features. These features were broadly categorized into four groups: Fixation, Saccades, Blinks, and Pupil. Each category encapsulated different aspects of the participants' eye movements and responses. The features were primarily computed using the time interval leading up to the event onset in each movie clip. Of these 243 features, 87 features were related to the event: where the event was about to appear (“event-Based Features”). These features leveraged the location and timing of the event, offering a more nuanced view of how

participants' gaze interacted with specific elements of the visual stimuli. A comprehensive list and description of the features can be found in Supp. Table T4.

XGBoost Classifiers. ML employed an ensemble of XGBoost (Extreme Gradient Boosting) classifiers, operating through the construction of multiple decision trees in a gradient boosting framework, where each tree is sequentially built to correct the errors of its predecessors. The optimization of node splits and tree structure is driven by gradient statistics of a loss function, aiming to minimize prediction errors. Our implementation adhered to the standard specifications of XGBoost, as delineated by Chen and Guestrin[28]. The algorithm was implemented by its application to each fold in our leave-one-subject-out (LOSO) cross-validation (CV) framework, ensuring robust and generalizable findings. LOSO iteratively trains the model on the dataset excluding data from one subject, which is then used as the test set. This approach mitigates potential biases and accounts for inter-individual variability, enhancing the model's applicability to new, unseen data. To optimize parameters, we used a grid search process to pinpoint optimal hyper-parameters within predefined ranges: 'learning_rate' (0.001-0.5), 'max_depth' (2-4), and 'n_estimators'(100-150). Final average hyperparameters used were 'learning_rate': 0.058, 'max_depth': 3.26, and 'n_estimators': 118.52, were instrumental in fine-tuning our models to achieve optimal performance.

Performance evaluation. We quantified model performance via several metrics: A) Classification Accuracy: the proportion of correctly predicted viewings, capturing the model's ability to accurately differentiate between 1st and 2nd viewings. B): Average Confusion Matrix: a more nuanced breakdown of model predictions separating true positives, true negatives, false positives, and false negatives. The average confusion matrix extends this analysis across all the models we created, providing precision and recall capabilities. C) Receiver Operating Characteristic (ROC) Curve: The ROC curve shows the trade-off between the true positive rate and false positive rate across different thresholds, with the Area Under the Curve (AUC-ROC) providing a summary measure of model performance. Finally, presentation of individual and average ROC curves for each model facilitates a deeper exploration of the model's sensitivity and specificity.

SHAP Analysis. Understanding the intricate decision-making processes of our ensemble XGBoost classifiers necessitated the integration of SHAP (SHapley Additive exPlanations) analysis grounded in cooperative game theory[29], to interpret the contribution of each feature to individual predictions. SHAP analysis was implemented in Python 3.9 Anaconda, with the shap package version 0.42.1.

Statistical analysis

The error probability of 5% was chosen for all statistical tests. For hypothesis testing, we used mainly nonparametric statistics. Most data distributions approximate normality, suggesting that parametric tests could be adequate; however, to ensure methodological consistency across all comparisons, we opted for the Wilcoxon signed-rank test for testing whether the GAD values were different between first and second viewings (Figures 2C, 4A, 4B, 4D, 4F, 4G, 5C, 5D, and). In our analysis of gaze anticipatory scores (Figures 4B, 5D, and 6C), we tested the statistical significance of the observed changes between the first and second viewings of each subject using a binomial test. To compare wake and sleep data, the MEGA score was compared between two groups (Figure 6B) using the Wilcoxon rank-sum statistic for two independent samples of unequal sizes. The statistical significance of ML classification was quantified by applying a one-sample t-test to the ROC AUC score compared to the chance level (50%). Lastly, we employed Cohen's d (Cohen, 1988) to assess the magnitude of effects observed in the study.

Behavioral data were analyzed in R (https://www.r-project.org/, version 2022.07.0) and Python 3.9 Anaconda, with Scipy version 1.7.1. The sleep EEG data and eye tracking analyses were conducted using Python 3.9 Anaconda.

Code and stimuli availability

Code used to preprocess and analyze the gaze data in this study is available at: https://github.com/dyamin/MEGA

The experiment code is available at: https://github.com/dyamin/MEGA-Experiment

The movie clips used in the experiments are available at: https://yuvalnirlab.com/

Results

We constructed the Memory Episode Gaze Anticipation (MEGA) paradigm with the aim of capturing memory retrieval in its raw form, without the additional layer of verbal reports. Participants viewed short (3-26s) movie clips in two sessions conducted a few hours apart while gaze was monitored using an infrared video-based eye tracking system (see Methods). Each movie contained a surprising event that saliently occurred in an unexpected location and time (e.g., an animal suddenly appearing behind a rock, Figure 1A; see A1 for the full movie). The movie clips were custom-designed animations depicting simple ecological scenarios. Precise event timings and their locations were equally distributed across the movie length and screen space (see methods). We hypothesized that in the first viewing, gaze patterns before the event occurs ('pre-event') would be exploratory, whereas in the second viewing after the formation of memory, gaze patterns would anticipate the event and preferentially occur around the event location (Figure 1B). Accordingly, the memory for the surprising event may manifest as a difference between the 1st and 2nd viewings at pre-event intervals around the anticipated location of the event (red rectangle and heat maps in Figure 1B). To test this, the first experiment included 34 participants who viewed 65 movie clips in two viewing sessions separated by a two-hour break (Figure 1C and see detailed methods). In the 2nd viewing session, verbal reports and confidence measures were collected after each movie, to allow comparison with standard explicit reports.

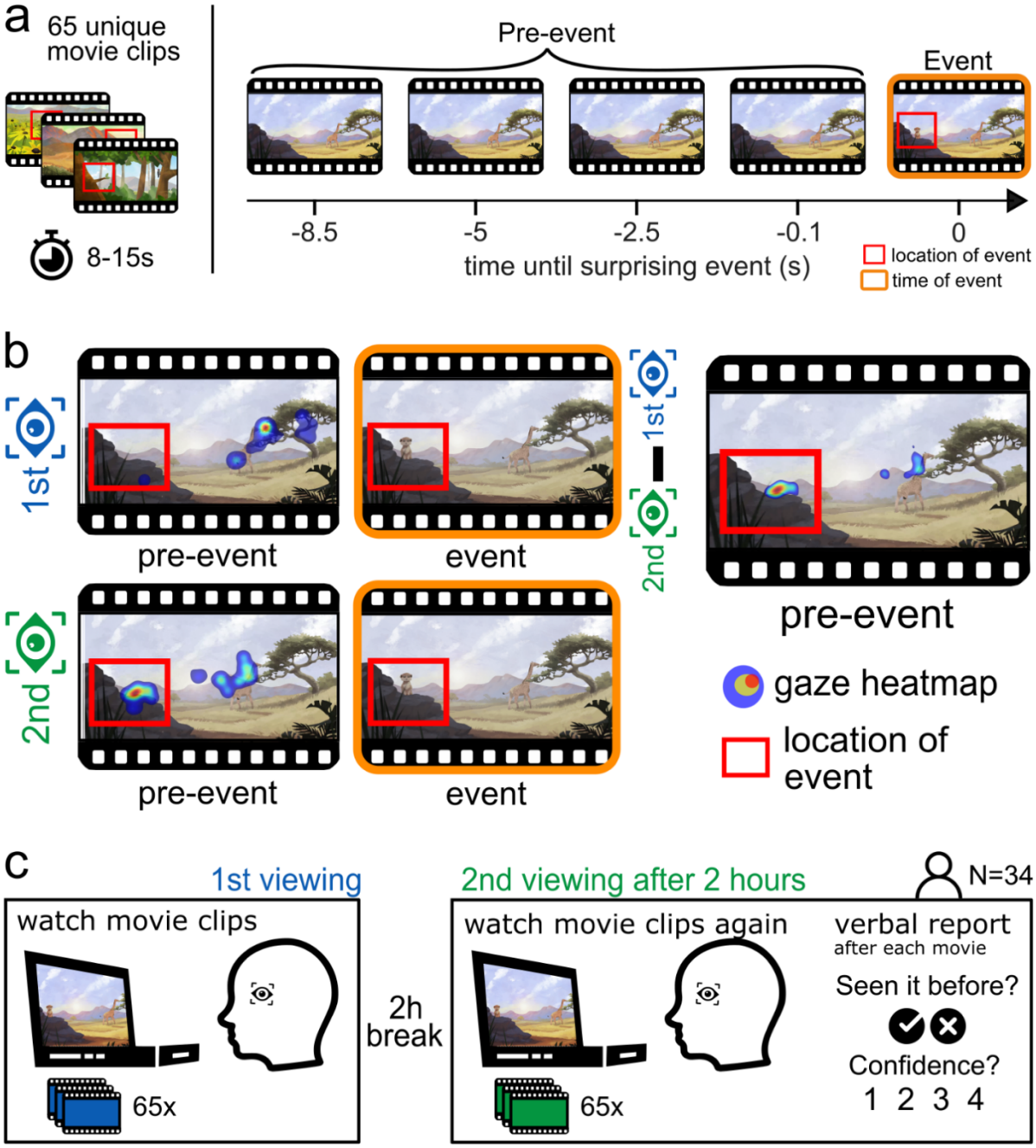


Figure 1. MEGA paradigm. (a) Visual Stimuli. 34 Participants watched 65 custom-made movie clips, each featuring a distinct surprising event. Each surprising event included a specific object at a specific location (red square) at a specific time (orange square). (b) Analysis rationale: gaze patterns during the 1st and 2nd viewings were compared to uncover memory retrieval. Top row: the average gaze location during 1st viewing (blue); Middle row: the same average gaze during the 2nd viewing (green). Bottom row: the difference between the gaze during 1st and 2nd viewings before the event appears on the screen. Participants were expected to gaze more often toward the location of the upcoming event, indicating their memory of the event. Heat maps represent gaze locations of a single move, averaged over time. (c) Experimental design: 65 movie clips were presented twice in randomized order, with a consolidation interval of 2 hours between viewings. Eye tracking data was collected during both viewings. During the 2nd viewing, after each movie participants reported whether they recognized the movie clip from the first session and rated the confidence of their response.

Gaze anticipation indexes memory for events

To quantify anticipatory gaze towards the remembered location in each movie viewing, we assessed, for each time point separately, the Euclidean distance from the gaze location to the event location (apriori defined by the animation studio that compiled the movies, Methods). Figure 2A illustrates this calculation, which utilized all data points (not only fixations) to transform the multivariate eye tracking data into a single time-series that encapsulates anticipatory gaze behavior. During the 1st viewing, the distance from the event location was mostly large, but upon 2nd viewing, we observed that the gaze gravitated toward the expected location of the event before its onset (see representative example of a single movie in Figure 2B). We quantified this by the Gaze Distance (GAD) — the mean distance from each gaze point to the event location from the movie's beginning until the event onset. GAD is a simple indicator that can reveal a tendency to gaze closer to the event location before its onset. Computing the GAD across all movies for each participant (Figure 2C) revealed a significant convergence to the event location upon 2nd viewing, observed in 31/34 (91%) of participants (mean GAD 1st viewing=18.13±0.62° vs. mean GAD 2nd viewing=16.91±1.05°; $t(33)=583$, $p=4.07e-09$; Cohen's $d = 1.4$). Next, to observe the temporal dynamics of anticipatory gaze, GAD was averaged across all movies and participants without averaging across time (Figure 2D). This analysis revealed a closer gaze towards the event location in the 2nd viewing that was present throughout the seconds leading to its appearance (Figure 2D, green time-course), followed by a sudden drop in GAD after-event appearance (reflecting gaze towards the surprising event once it occurred).

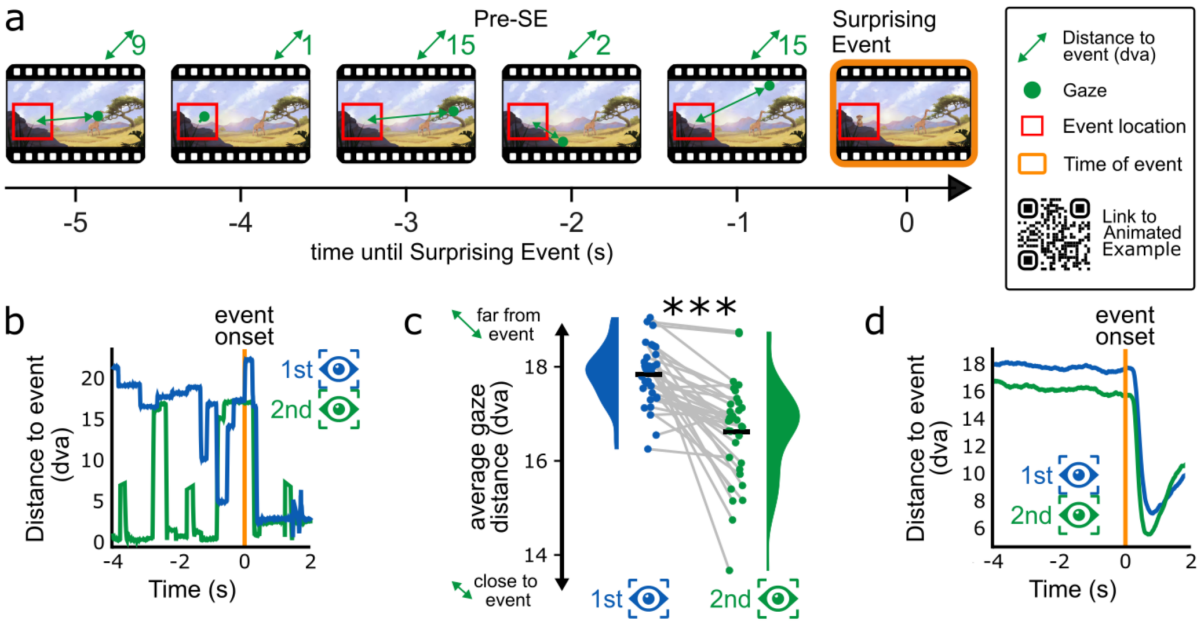


Figure 2. Anticipatory gaze effect. A) Gaze Proximity Measurement: participant's gaze trajectory while watching a movie clip. The Euclidean distance to the location of the surprising event center point is calculated at each time point in Degrees of Visual Angle (DVA). The QR code leads to an animated illustration of the methodology (example movie with superimposed eye-movements and gaze distance measure). B) Temporal Gaze Distance of a single participant during first (blue) and second (green) viewings of a clip. The SE's onset is marked by an orange line, serving as a temporal marker for gaze behavior. C) Gaze averaged distance (GAD) comparison within participants across two viewings. The gaze average distance is calculated relative to the event center prior to its appearance on the screen and averaged across movies. GAD significantly decreases during the second viewing compared to the first viewing indicating memory for the location of the event. Black horizontal line: group average, colored area: density estimate of GAD distribution, dots: individual participant average, line connects 1st and 2nd viewing of the same participant. D) Averaged gaze temporal dynamics: An aggregate view of gaze distance from the event across all participants and movies, time-locked to the event onset. The distances as a function of time for the first (blue) and second (green) viewings show the participants' anticipation of the event based on their prior viewing experience. Participants were surprised and looked at the surprising event immediately after its appearance, which can be seen in the steep slope after the event onset (orange line). *** = p<0.0001

Machine learning discriminates first and second viewings at a single trial resolution

We tested to what extent machine learning (ML)-based classification of multiple eye tracking features could extend the intuitive GAD metric and accurately identify memory traces at the single-trial level. First, we focused on reducing gaze distance as captured by the GAD metric (above). We employed the XGBoost classification algorithm[28] at the single-trial level, complemented by a leave-one-subject-out cross-validation method (Figure 3A). Models achieved an average correct classification of 69±10%

(chance: 50%), demonstrating the model's ability to distinguish, based only on GAD, whether a single trial's data represented the first movie viewing or whether it had been viewed before (1st or 2nd viewing), based on data of a participant not included in the training dataset (Figure 3B). The Receiver Operating Characteristic (ROC) curves for each subject-specific model and the average ROC curve indicated consistent model performance across subjects (Figure 3C). Accordingly, the area under the ROC curve (AUC-ROC) was 0.75±0.26, quantifying the model's overall effectiveness ($t(33) = 10.76$, $p = 2.47e\text{-}12$ via 1-sample t-test). In 32/34 of the participants (94%), model accuracy was greater than chance levels, with an average accuracy of 0.69±0.1, attesting to its reliable prediction of identifying memory traces (Figure 3D).

Next, we employed an exploratory 'bottom-up' ML strategy by broadening our analytical scope to encompass a wider array of eye-tracking features, irrespective of our initial GAD metric. We manually engineered multiple features from eye-tracking data centered around the event location, thereby minimizing potential session-specific confounds such as differences in time-of-day and cognitive load due to tasks and reports in 2nd viewing (Methods). Such features (87 in total) included aspects such as fixation count ratios relative to the event location, the velocity and visual angle of saccades directed towards the event, and the change in pupil radius during fixations within the event location compared to prior fixations, thereby capturing event-related eye tracking spatial and temporal features. With these features, models achieved an average classification accuracy of 71±11.73% and 70±12.34% for 1st and 2nd viewings, respectively. Associated AUC-ROC metrics exhibited an average of 0.75±0.26 ($t(33) = 10.85$, $p = 1.98e\text{-}12$ via 1-sample t-test). In 32/34 of the participants (94%), model accuracy was greater than chance levels, with an average accuracy of 0.7±0.11. Remarkably, our initial analyses based solely on the GAD metric already captured nearly all variance within the dataset and showed comparable performance to the extensive 87-feature model, attesting to GAD's potent predictive value and showing that distance metrics alone are sufficient for precise identification of episodic-like memory traces in the MEGA paradigm.

To further understand which eye-tracking features are most effective in capturing event memory, we incorporated SHAP (SHapley Additive exPlanations) feature importance analysis, a game theory-based method to distill and quantify each feature's

influence on the model's output[29]. SHAP provides an average impact of each feature on model prediction by examining its performance with and without the presence of each feature across all possible feature combinations. This analysis identified distance-based features as particularly informative, with GAD ranking as the top feature (Figure 3E). Along the same lines, a waterfall plot of a representative trial illustrates how individual features (especially GAD) cumulatively influence the model's decision-making process for a single trial, highlighting the predictive power of GAD in indexing memory in the MEGA paradigm (Figure 3F).

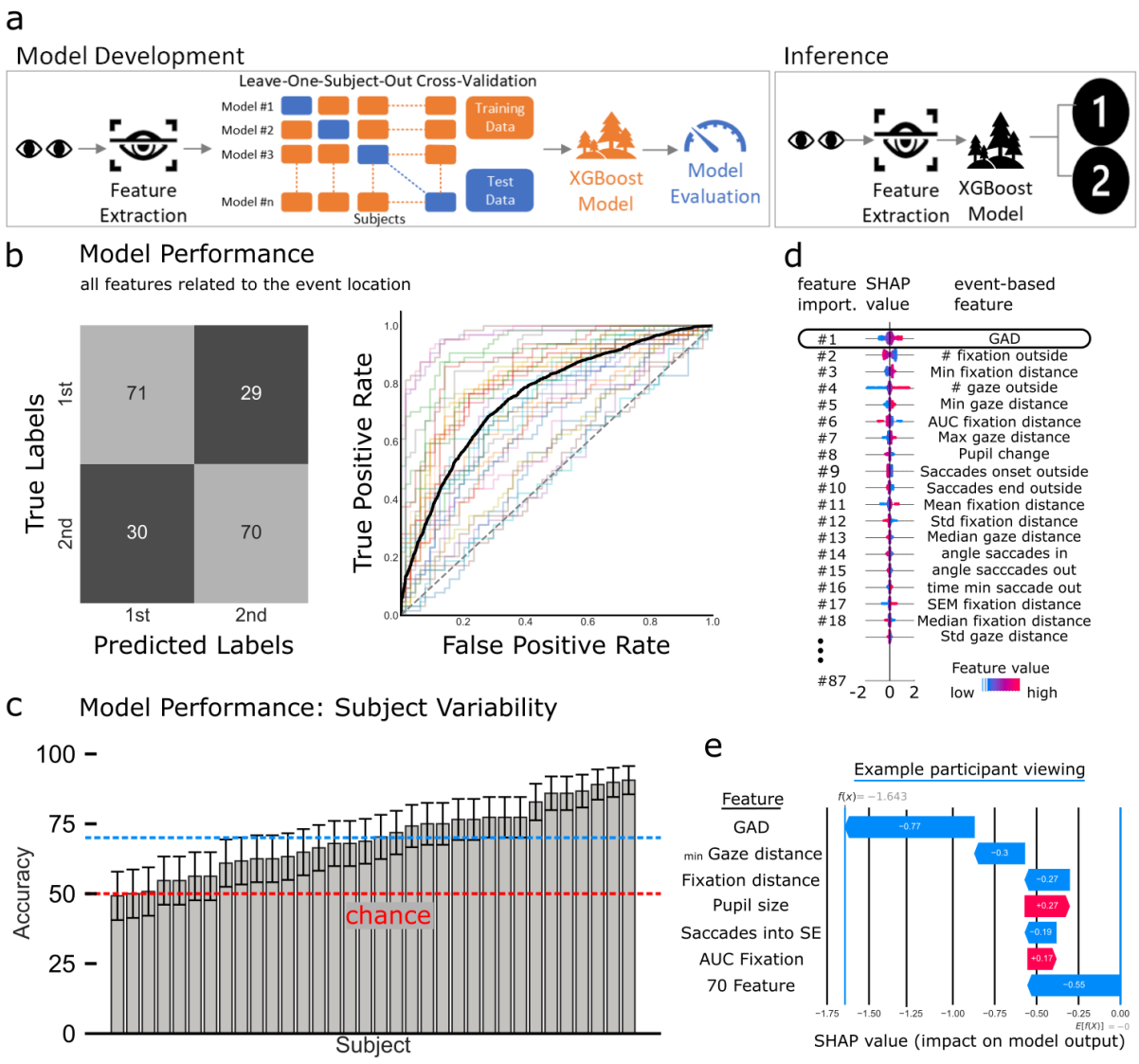


Figure 3. Single-trial Predictive Modeling Using Machine Learning of Eye Tracking Data Features (a) Model Development and inference: We utilized an XGBoost classifier, leveraging 87 features derived from the event location and timing to perform single-trial level classification. The model's robustness was ensured through a leave-one-subject-out cross-validation technique, where the algorithm was iteratively trained on the dataset excluding one subject, which was then used for testing. (b) Confusion Matrix: The average confusion matrix across all subjects, summarizing the classification performance of XGBoost models. Values along the diagonal (top left and

bottom right) entries (71%,70%) represent the percentage of correct classifications, indicating true positives and true negatives, respectively. Off-diagonal values (bottom left to top right) entries (30%, 29%) denote misclassification probability. The Receiver Operating Characteristic (ROC, on the right) curves for XGBoost models, each tested on a distinct subject within our study cohort. These curves plot the true positive rate (TPR) against the false positive rate (FPR) at various decision threshold levels. Each trace represents the ROC curve for a subject-specific model (different color for each participant), delineating the trade-off between sensitivity and specificity. The black line denotes the mean ROC curve across all models. (c) Performance across individual participants (bottom left): bar chart displaying the classification accuracy for each subject, with the average accuracy across all subjects (blue, 70%) and chance-level (red, 50%). Error bars signify confidence intervals reflecting the precision of the model for each subject. (e) SHAP feature analysis: ranking of the influence of various gaze metrics on the model's predictions. Out of 87 SE-based features, the distance-based features, particularly GAD emerged as the most important feature. (f) A waterfall plot provides an example of how individual features contribute to a single trial's classification.

Anticipatory gaze marks event recollection whereas pupil size indexes context recognition

What aspects of memory does anticipatory gaze capture? To what degree does it reflect episodic-like memory for the event versus familiarity with the general context? To address these questions, we first tested how MEGA relates to simple verbal reports ('Have you seen this movie before?'). We compared GAD scores in movies reported as 'seen before' vs. 'not seen before', focusing only on trials with reports associated with high confidence ratings (Methods, Figure 1B). We found a significant reduction in GAD upon 2nd viewing for movies that were reported to be seen before ($GAD_{1st\ v.}$= 17.97 ± 0.72, $GAD_{2nd\ v.}$= 16.7 ± 1.13, t(33)=572, p=3.72e^{-08}, Cohen's D = 1.34, Figure 4A) but also a significant effect for movies that (incorrectly) reported as 'not seen before' ($GAD_{1st\ v.}$= 18.35 ± 1.93, $GAD_{2nd\ v.}$= 17.44 ± 1.78, t(33)=556, p=4.4e^{-07}, Cohen's D = 0.49, Figure 4A). To directly compare the difference between the first and second viewings of the explicitly recognized and not-recognized movies, we computed the normalized decrease of GAD from 1st to 2nd viewing ($GAD^{1st\ viewing}$ - $GAD^{2nd\ viewing}$ / max($GAD^{1st\ viewing}$, $GAD^{2nd\ viewing}$), Figure 4B). Higher values reflect an anticipatory effect during the second viewing and thus reflect memory-guided behavior. This score exhibited a trend towards higher values for movies that were subsequently recognized than for not-recognized movies ($M_{MEGA\ recognized}$=0.07 ± 0.07, $M_{MEGA\ not\ recognized}$=0.05 ± 0.05, paired t-test: t(66)=1.7, p=0.093, Cohen's D = 0.41, Figure 4B).

To better understand what aspects of memory are captured by anticipatory gaze beyond 'have you seen this movie before?', a second experiment was conducted to evaluate multiple dimensions of memory reports in detail, aiming to distinguish between event recollection and context recognition (Figure 4C). Participants watched 48 animated movies depicting similar surprising events. After a four-hour break, they again watched these movies with 12 novel movies in a randomized order. However, in this experiment, the 2nd session included the exact same movies, except the surprising event was omitted. Because the surprising event was not presented during the 2nd viewing, we could follow up with an array of retrieval tasks immediately after each movie. These tasks aimed to provide additional sensitivity to better investigate the relationship between explicit memory and anticipatory gaze. We collected the following five verbal reports: recognition, free recall, object recognition, event location recall, and temporal recall (for details, see Methods).

Results reliably replicated the anticipatory gaze effect with a new group of participants. 30/30 of participants (100%) demonstrated significantly greater gaze proximity to the event location during the second viewing ($M_{MEGA\text{-}score}$=0.086 ± 0.037, t(29)=12.8, p=2e^{-13} , Figure 4D). Next, we analyzed the GAD of each movie based on its explicit report in three categories (Methods): event recollection (correct movie recognition, as well as object recognition and event location recall), context recognition (scenery was recognized, but the object recognition or event location recall was incorrect), and unrecognized movies (incorrect recognition task, independent of the answer in event location recall or object recognition). Temporal recall (when precisely the event occurred) was not further analyzed because retrieval performance was at chance (p=0.81). Behaviorally, retrieval performance for movie recognition, object recognition, and location recall were all significantly above chance (all p<2e^{-09}, Figure S1).

Analyses revealed that MEGA scores were significantly higher for movies where participants recollected the event in full, highlighting the sensitivity of MEGA to episodic-like recall (Figure 4E & 4F). Accordingly, ANOVA with the dependent variable MEGA score and the factor memory content (event, context, and no memory) revealed a significant main effect (F(2,87)=14.11, p=4.9e^{-06}). Post-hoc pairwise comparison revealed a significantly higher MEGA-score for full recollection of the event compared to MEGA-scores of movies where only context was recognized (M_{event}=0.12 ± 0.06,

$M_{context}$=0.08 ± 0.04, p_{Tukey}=0.002) or compared to unrecognized movies (M_{event}=0.12 ± 0.06, $M_{no\text{-}recognition}$=0.05 ± 0.05, p_{Tukey}=0.000004), but the latter two conditions did no differ significantly (context vs. no-recognition: p_{Tukey}=0.2). Moreover, the MEGA score of each movie correlated with participants' precision in reporting the event location such that stronger anticipatory gaze effects are associated with higher proximity to the event location (pearson r = 0.22, $p<2.2e^{-16}$, 1438 movies). Accordingly, in each trial, the higher the precision in explicitly reporting the event location, the closer the anticipatory gaze was to that location before it occurred on the screen. Accordingly, the MEGA score of participants correlated with the number of trials categorized as event recollection (pearson r=0.37, p=0.043, N=30) but did not correlate with the number of trials that were not recognized (r=-0.046, p=0.81). Correlation with the number of trials where only the context was recognized exhibited a marginally significant negative correlation (r=-0.36, p=0.05). To further examine the participants' event recollection and anticipatory gaze, we examined anticipatory gaze in the light of the free recall of the surprising event instead of object recognition and location recall. (in contrast to the forced-choice task in the object recognition task)

Finally, we investigated anticipatory gaze within the context of participants' free recall of surprising events rather than location recall and forced-choice object recognition. As expected, the MEGA score was bigger if the object of a surprising event was explicitly recalled, compared to movies for which participants could not remember the event's object (free recall: MEGA score $_{recalled}$=0.14 ± 0.08, MEGA score $_{not\ recalled}$=0.07 ± 0.03, paired t-test: t(28)=5.46, p=7.8e^{-06}, Cohen's D =1.22). Furthermore, this difference in anticipatory gaze linearly increased for the participants' ratio of objects recalled and forgotten (pearson r=0.56, p=0.0016, N=29).

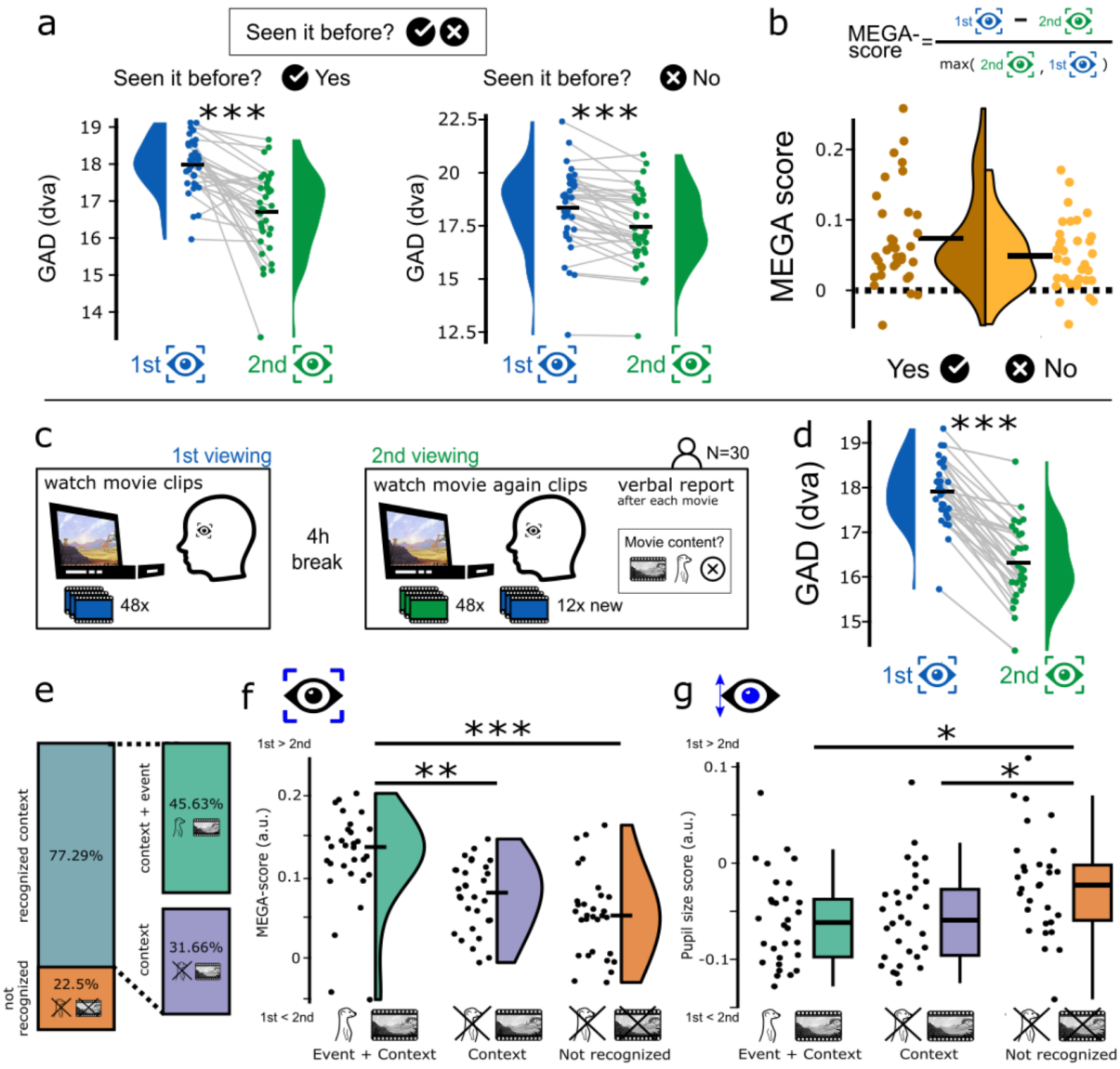


Figure 4: The relationship between anticipatory gaze and explicit memory reports A) First experiment: gaze in the second viewing of movies explicitly reported as "seen" (green) showed greater proximity to the event location compared with the first viewing (blue) for both recognized and unrecognized movies, signifying memory retrieval. B) The MEGA score quantifies the change in GAD between the first and second viewings, calculated using the formula above. This MEGA score is higher for movies that were explicitly remembered versus not remembered. C) Procedure of the second experiment: Participants completed a similar task, except surprising events were omitted from the second viewing, followed by an extensive explicit memory report. Memory was assessed to determine what exactly participants remember. D) Replication of the anticipatory gaze effect: consistent with experiment 1, anticipatory gaze appears in the second viewing (green) and not in the first viewing (blue) across all naïve 30 subjects. E) Categorization of explicit report. Participants did (i) not recognize the movie clip at all (orange), (ii) recognize the context alone (violet), or (iii) recognize the context and recollected the event (green). F) The MEGA score is higher for movies where participants fully remembered the event, compared to those with only scenery memory or completely forgotten movies. There is no significant difference between movies with scenery recognition and those without recognition. G) Pupil size variation and memory: Examines the decrease in pre-event pupil size from first to second viewing in relation to scene recognition and event recollection, highlighting smaller changes (1^{st} vs 2^{nd} viewing) in unrecognized cases. * = p<0.05, ** = p<0,01, *** = p<0,001

To further distinguish MEGA from context recognition, we focused on pupil dilation as an index of familiarity upon repeated stimulus presentation[30–33]. Specifically, previous findings suggest that pupil dilation is increased for recognized words compared to unrecognized words[34,35]. In line with this literature, we also found that pupil size was larger for the second viewing compared to the first viewing (pupil size $_{1st\ v}$=4436. 25 ± 378.12, pupil size $_{2nd\ v}$=4647.57 ± 378.12, t = 59, p-value = 1.974e^{-05}). Next, we compared changes in pupil size across repeated movie viewings in relation to the verbal report. To this end, we computed a normalized pupil size score using the same formula used for the MEGA score (1st viewing - 2nd viewing / max(1st viewing, 2nd viewing), negative values reflect larger increase in pupil size, Methods). We found a larger increase in pupil size for movies that were recognized compared to movies that were not recognized (higher pupil size score for 'not recognized' in Figure 4G). ANOVA with pupil dilation score as the dependent variable and the explicit memory questions as a factor revealed a significant main effect ($F(2,87)=5.05$, $p=0.008$). Post-hoc pairwise comparison revealed a significantly higher pupil score for movies where the event was recollected in full (M_{event}=-0.059 ± 0.048, $M_{no\text{-}recognition}$=-0.021 ± 0.054, p_{Tukey}=0.013) and for movies where the context was recognized ($M_{context}$=-0.054 ± 0.049, $M_{no\text{-}recognition}$=-0.021 ± 0.054, p_{Tukey}=0.033) compared to unrecognized movies. Crucially, pupil dilation score did not differ between the movies with event recollection and context recognition, suggesting no specific relationship with event memory (event vs context: p_{Tukey}=0.93). These findings suggest that while the pupil is indicative of recognition of the context alone, anticipatory gaze is guided by a richer memory that includes recollecting event details such as its location within the context.

Anticipatory gaze is Replicated in Naturalistic Movies

To what extent can anticipatory gaze be revealed using other movies, not necessarily animations compiled specifically for scientific research? We set out to test the degree to which anticipatory gaze captures episodic-like memory recall in settings that closely mimic real-world experiences, with the aim of bridging laboratory research and everyday memory. To this end, we performed a third experiment, where 32 naïve participants viewed 100 YouTube videos (Figure 5A). First, it was necessary to define the surprising event location and timing since these were not defined a-priori as in the

tailor-made animations. A group of 55 independent participants marked the spatial and temporal coordinates of the surprising event. The event location and timing were defined for each movie as the median (X, Y, t) of their choice of coordinates. 48 movies that exhibited a minimal level of consensus (within one standard deviation of the median time or location, Methods) were used for subsequent analysis. Once again, analysis of GAD preceding the surprising event replicated the anticipatory gaze effect, with a completely different set of stimuli and a different group of subjects. A significant increase in gaze proximity to the event location was observed upon 2nd viewing in all participants but one, robustly indexing memory without report ($t(31)=495$, $p=9.3e^{-10}$; W-SRT, Cohen's d = 1.52, Figure 5C). Increased proximity of anticipatory gaze to the event location was evident throughout the seconds leading to the event (Figure 5B). GAD declined upon the event onset in both 1st and 2nd presentations, reflecting gazing towards the event once it occurred, but this drop was less steep and interestingly began already *prior* to event onset, arguably since the gaze of participants was already "drawn" towards the event location by narrative cues in real movies compared to the highly unexpected event appearance in tailor-made animations. Analyzing GAD and MEGA computed separately for recognized and unrecognized movies (according to verbal report, Figure 5A), showed that MEGA score significantly exceeded chance-level for both remembered and forgotten movies, replicating the observation in the previous experiments ($M_{1st\ v.}=10.96$ +-0.46, $M_{2nd\ v.}=10.04$+-0.72, $t(31)=560$, $p=2.5e-7$, for explicitly remembered trials; $t(31)=539$, $p=3.6e-6$ for explicitly forgotten events, Figure 5D). Together, the results show that the anticipatory gaze effect robustly replicates with naturalistic movies, attesting to the utility of this approach in diverse contexts, including real-life situations.

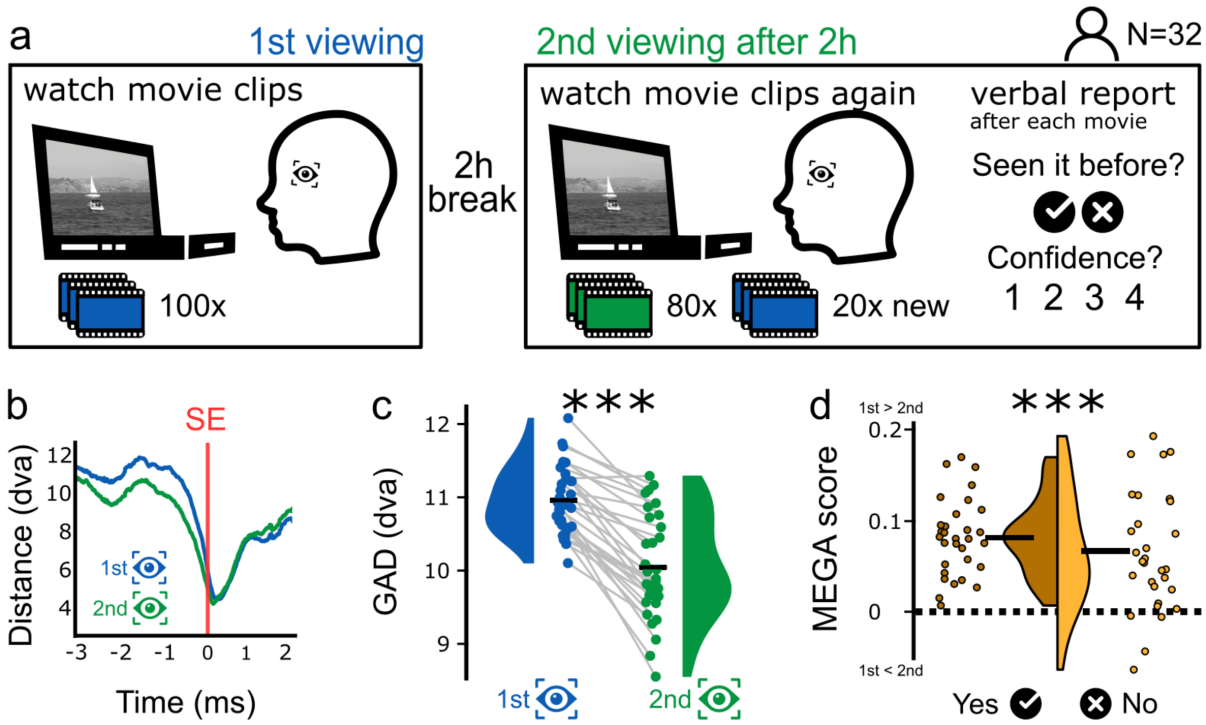


Figure 5: Naturalistic (YouTube) videos replicate the anticipatory gaze effect. (a) Experimental procedure: 32 participants viewed 100 YouTube movies in two sessions spaced 2 hours apart. In the 2nd session, 20 novel ('lure') movies were included along with 80 of the original movies, and verbal reports were collected after each movie. (b) Gaze Average Distance to the surprising event for 1st (blue) and 2nd (green) viewing. A drop in gaze distance that already begins before event timing shows some anticipation of the surprising event in naturalistic movies, probably due to narrative and camera movements. (c) GAD decreases in 2nd viewing (green) compared to 1st viewing (blue): p = 9.3e-10, Wilcoxon Signed-Rank Test). (d) MEGA scores as a function of explicit memory reports, showing a higher MEGA score for movies that participants remember (p<0.0001).

Anticipatory gaze reveals sleep's benefit for memory consolidation without report

We demonstrate one potential application of the MEGA paradigm regarding sleep benefits for memory consolidation. Naïve participants were recruited for a fourth experiment (Figure 5A), viewing naturalistic videos (identical to experiment 3) in two sessions separated by a 2h break that included either a nap opportunity for some individuals (n=19) or an equally long interval of wakefulness for other individuals (n=32, same data as in "naturalistic" experiment 3 shown in Figure 5). First, regardless of sleep or wake, we replicated the anticipatory gaze effect with a new group of participants. We observed significantly lower GAD reflecting anticipatory gaze (Figure 5B) in 16/19 of participants (84%), substantiated by statistical analysis ($M^{1st\ v.}$=11.3±0.62, $M^{2nd\ v.}$=10.12±0.87, t(18)=184, p=2.67e-5; W-SRT; Cohen's d = 1.54).

This constitutes a third successful replication of the anticipatory gaze effect, reinforcing its reliability in capturing memory. Next, comparing sleep and wake, we found that MEGA score in the nap condition was 23.6% higher than in the awake condition (M_{wake}=0.069 ± 0.043, M_{nap}=0.09 ± 0.048, W=1.7, p=0.0439, Cohen's d=0.48). This indicates that the nap positively impacted memory consolidation as reflected in anticipatory gaze, demonstrating the potential of MEGA as a no-report paradigm for studying the relation between sleep and episodic-like memory consolidation.

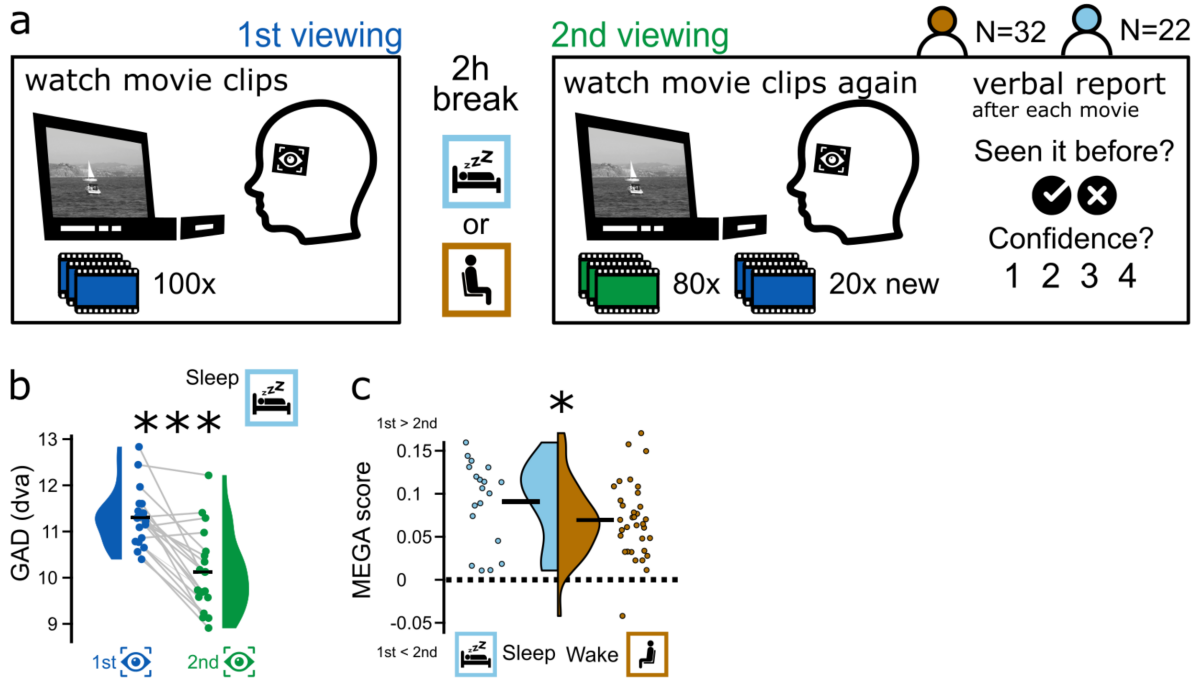


Figure 6. MEGA scores improve after sleep compared to wakeful rest. (a) Experimental design: participants (N = 19 for nap condition; N=32 for wakeful rest condition) watched naturalistic videos as in a "naturalistic" experiment with YouTube videos. The 2h interval between the 1st and 2nd viewing included either a nap opportunity or wakeful rest. (b) GAD in 1st (blue) and 2nd (green) viewing for the nap condition participants reveals a significant decrease in GAD during 2nd viewing (p = 9.3e-10, Wilcoxon Signed-Rank Test) (c) A comparison of MEGA scores (normalized difference in GAD between 1st and 2nd viewings) in the wake (brown) and sleep (cyan) conditions reveals greater MEGA after a nap (Mann-Whitney U test, p = 0.0439)

Discussion

This study shows that tracking gaze during repeated viewings of movies with surprising events constitutes an effective method for investigating memory without verbal reports. The results establish that the gaze gravitates towards the event location during the second movie viewing, exhibiting memory-guided prediction that anticipates its occurrence. Gaze distance (GAD) can be used as an intuitive metric to capture the degree of this predictive anticipation, showing significantly higher proximity to the event location during the second viewing. The anticipatory gaze effect was captured before changes were visible in the movie and even when the surprising event was entirely absent in the second movie viewing. This establishes that it corresponds to memory-guided prediction irrespective of the visual cues that mark it. Anticipatory gaze is a highly robust effect that is consistently observed and replicated several times across multiple stimulus types and in different naïve groups of participants (N=126) - attesting to its versatility and utility across settings. Machine learning classifications of features extracted from gaze data identify memory traces at a single-trial level in new participants. In a separate experiment where we collected verbal reports about the movie events, we found that anticipatory gaze effects are largest when the surprising event was fully recalled, showing dissociation from pupil size measures associated only with recognition of the movie's context. Finally, we illustrate how applying MEGA without verbal reports can effectively replicate the classical beneficial effect of sleep on declarative memory[20,36,37]MEGA can be successfully employed using either naturalistic movies or custom animations specifically designed for this purpose, a resource made available for any future follow-up study (https://yuvalnirlab.com/).

The current study extends the growing literature on studying memory with eye-tracking[10,11]. Most previous studies in this domain probed familiarity, i.e., how the recognition of still images influences viewing patterns[11,12,14–16,33]. By contrast, inspired by research in great apes[19], our anticipatory gaze approach captures memory-guided predictions in the absence of the encoded item (when it is not presented), a phenomenon that is distinct from cue-induced recall. Importantly, MEGA captures single-shot memory of events in a way that requires knowledge about their properties (e.g., location) and correlates with explicit reports about event content. Strikingly, the

anticipatory gaze effect is very sensitive, as it even detects memory when it cannot be consciously recalled. Thus, MEGA represents important new features of memory retrieval that go above and beyond eye-tracking memory research.

Two complementary approaches were used to quantify the anticipatory gaze effect. The first and intuitive metric, GAD, captures the average Euclidean distance to the location of the surprising event from the beginning of the movie presentation until the event occurs and enables identification of memory-guided gaze in ~90% of participants. A second machine learning approach using the XGboost classification algorithm is aimed at the predictive power of single-trial gaze. Surprisingly, machine learning applied on merely seven-second intervals of gaze data during pre-event movie viewing - without any averaging across movies or participants - was sufficient to significantly identify whether this viewing was associated with memory for the event (first or second viewing). Strikingly, classification performance was maintained even when we only used gaze distance instead of a comprehensive set of 87 gaze distance-related eye-tracking features. A post-hoc comparison of all features' importance confirmed that GAD was most informative.

What is the added value of estimating memory without verbal reports? This approach entails several distinct advantages. First, MEGA can provide memory measures in clinical settings where verbal communication is challenging. For instance, individuals with cognitive impairments, such as those with aphasia or developmental disorders, often struggle with complex instructions or language comprehension and production. Along the same line, a stroke patient may be unable to speak yet we would like to estimate their memory capacity. Second, MEGA provides higher sensitivity than the reports typically collected, as is evident by the presence of significant effects even in cases when participants reported not recognizing movies they had seen before. Such heightened sensitivity may hold significant promise for detecting early signs of preclinical Alzheimer's disease, where subtle memory deficits may go undetected by conventional questionnaire-based assessments. Third, MEGA can enhance consistency in memory research by increasing generalizability across participants who speak different languages. Finally, from a basic science perspective, current research employing reports confounds memory itself with the ability to articulate it. In this

context, MEGA can help distill the brain activities and diseases affecting memory per se beyond its access and report.
Another important advantage of MEGA is that it goes beyond a binary ‘recognized’ vs. ‘non-recognized’ report to represent memory as a continuous quantitative variable. The MEGA-score metric is sensitive to various anticipatory behaviors—whether through a few prolonged fixations at the event location, multiple fixations around it, or even subtle proximity to the event location. This granularity allows us to reveal a linear relation between the anticipatory gaze scores and the individual precision in reporting the event's location for single movies. Accordingly, the degree of event recollection per participant correlates with the participant's MEGA score.

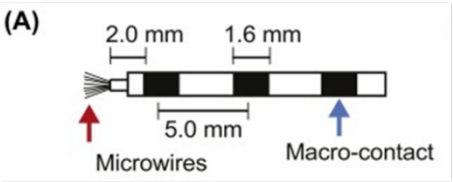
The findings broaden the discourse on unconscious memory as captured by eye tracking[10] by extending the results from still images to dynamic videos. While lower than when consciously reported, we nevertheless find a significant anticipatory gaze score even in cases where participants confidently report they haven’t seen the movie before. This suggests that, even without conscious indication, memory processes are at play to an extent that is sufficient to modulate eye-movement behavior. While previous studies[11,38–40] have demonstrated unconscious relational memory in eye-movements, MEGA leverages dynamic videos to detect unconscious memory effects without the object about to appear being visible on the screen. Because this effect can reveal whether a stimulus has been encoded – despite explicit indication of not remembering it, MEGA opens new avenues for research investigating why some memories transcend into explicit recall while others remain implicit.

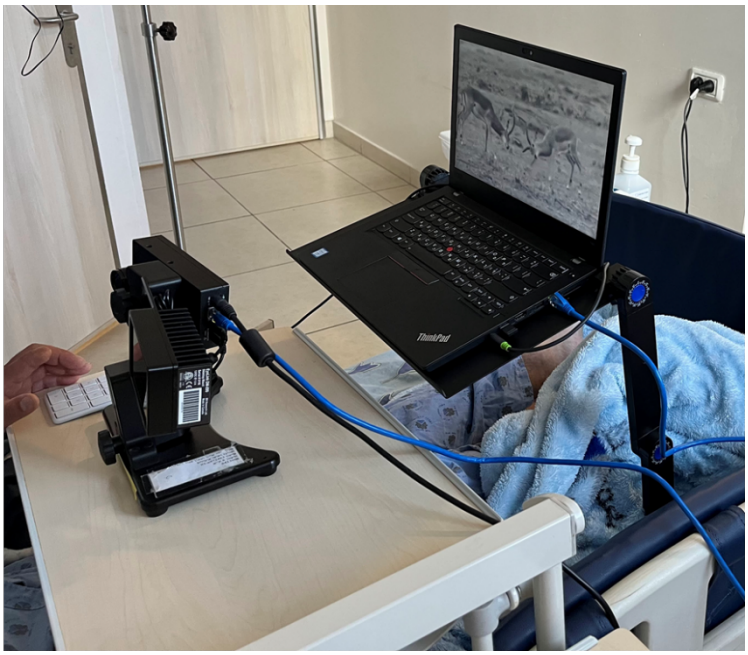
Future studies can compare this memory-guided behavior beyond explicit reports with established measures of unconscious memory. This can disentangle to what extent the above-chance performance in “not recognized” scenarios stem from nuanced memory activation compared to mere exploratory behavior or attentional diversion. The fact that MEGA emerges independently of conscious recognition highlights its potential to uncover unconscious memory independent of traditional explicit memory reports.

Future research can expand and further develop MEGA across several domains. A natural question concerns the neuronal underpinnings associated with anticipatory

gaze, and the extent to which it depends on activity in the hippocampus and the medial temporal lobe (MTL). Studies could further illuminate the neural circuits engaged during anticipatory eye movements and memory encoding[44] by using functional magnetic resonance imaging (fMRI)[45], electroencephalography (EEG)[46], and intracranial research[47], offer complementary insights by measuring the electrical activity associated with anticipatory behaviors and memory processes at high temporal resolutions.

We have already begun to explore these mechanisms by collecting intracranial data from epilepsy patients undergoing treatment at the Tel Aviv Sourasky Medical Center. N=10 patients were implanted with Behnke–Fried depth electrodes primarily targeting the hippocampus and other limbic regions. This setup allowed us to record single-unit neuronal activities synchronized with eye-tracking data as patients engaged with both animated and naturalistic movie clips during Experiments 1 (animation) and 3 (naturalistic movies). This setup can pave the way for a deeper understanding of the intricate links between neural activity, eye movement patterns, and episodic memory recall, potentially influencing both clinical practices and cognitive neuroscience research.





Future studies could also test the utility of anticipatory gaze in entirely passive viewing conditions without any instructions. It should be acknowledged that the current results involve a task where participants were required to report if the movies were previously

seen or not, thereby introducing an additional layer of cognitive processing that could influence the natural recall of events.

Another application lies in research on memory consolidation. The present results already bear important implications in suggesting that sleep's benefits for memory consolidation extend beyond the mere ability to report memories, and such research can be developed further. MEGA can also be applied across diverse populations, including infants[48] and the elderly[49] to study memory development across the lifespan.

In clinical settings, MEGA holds promise in several domains, for example, for early diagnosis of memory disorders in mild cognitive impairment (MCI) and for monitoring Alzheimer's disease progression beyond standard cognitive and neuropsychological assessments like the MMSE[50] or the MoCA[51] that are limited in detecting preclinical memory deficits.

In an additional aspect of this study not covered in the results section, we investigate the extent to which anticipatory gaze could differentiate between healthy elderly individuals, those with mild cognitive impairment (MCI), and Alzheimer's disease (AD) patients. In this fifth ongoing experiment, we replicate the methodology of Experiment 3, with 42 elderly (~70 year old)_ participants who viewed 100 YouTube videos, followed by clinical assessments including Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA). The cohort comprised healthy elderly participants, MCI patients, and AD patients. Interim findings suggest that anticipatory gaze effects, as measured by gaze proximity to the event location before its occurrence, are consistently observed in healthy elderly individuals. Notably, similar effects were robustly present in MCI patients and exhibited a notable trend in AD patients, with all but one showing increased gaze proximity during the second viewing. This suggests that anticipatory gaze might serve as a subtle indicator of episodic memory retention across different stages of cognitive decline. As a further step, we are currently exploring the use of machine learning algorithms to predict cognitive performance scores (MoCA, MMSE, and d-prime) from eye-tracking data gathered during these experiments. This ongoing work aims to develop predictive models that could potentially enhance diagnostic and monitoring capabilities in clinical settings.

Beyond degeneration, MEGA can be used for assessing memory upon damage to the medial temporal lobe (MTL)[52]. It is often unclear to what extent damage affects mnemonic systems or their interface with other brain systems that enable conscious report. To investigate these dynamics, we have initiated a preliminary study involving subjects with varying degrees of MTL damage. Future experiments will explore how such damage impacts the MEGA scores and the subjects' ability to report memories. This direction is vital for understanding the differential effects of MTL impairment on memory systems and could lead to more tailored therapeutic strategies.

Another clinical application pertains to patients suffering from motor or language disorders that limit verbal report, such as those with aphasia[53,54], offering a non-verbal means of assessing memory integrity.

The findings from the machine learning analysis highlight the potential of single-trial assessments in memory research. However, several avenues for further development could enhance this approach's practical utility and robustness. The current study employed XGBoost classifiers using a set of manually engineered features derived from eye-tracking data. While this approach achieved a significant level of accuracy, incorporating larger datasets could further improve model performance. Future research should consider expanding the dataset to include a more diverse range of participants and stimuli, enhancing the generalizability of the models. Moreover, exploring various machine learning models could provide insights into the most effective algorithms for this data type. For instance, deep learning models such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) might capture more complex patterns in the data, particularly if they can incorporate temporal dynamics and the spatial layout of the stimuli. Including features derived from the stimuli themselves as input to the models could also enhance performance. By analyzing the content and structure of the movies, models could potentially identify patterns that are predictive of memory retrieval. For example, features such as visual complexity, scene changes, and the presence of surprising events could be integrated with eye-tracking data to improve the accuracy of memory assessments. The MEGA paradigm, enhanced with advanced machine learning techniques, holds significant promise for assessing memory performance across different populations.

Combining eye-tracking data with neural data could provide a powerful tool for both basic science and clinical applications. Neural correlates of memory retrieval could offer additional layers of information, allowing for more precise assessments and a better understanding of the underlying mechanisms. This multimodal approach could lead to breakthroughs in identifying early signs of cognitive decline and understanding the neural basis of memory processes. In summary, the development of single-trial assessment methodologies using machine learning has the potential to revolutionize memory research and clinical practice. By leveraging larger datasets, diverse models, and integrating stimulus and neural data, future studies can enhance the accuracy and applicability of these tools. This approach not only offers practical benefits for assessing memory in various populations but also provides a robust framework for exploring the neural mechanisms of memory at a fundamental level. These advancements will pave the way for more sensitive, non-verbal memory assessment tools, ultimately improving our ability to diagnose and treat memory disorders and contributing to broader cognitive neuroscience understanding.

In conclusion, the MEGA paradigm introduces a significant advance in memory research. Utilizing eye tracking to study memory without verbal reports offers wide implications for both basic research in cognitive neuroscience and in clinical fields.

Supplementary

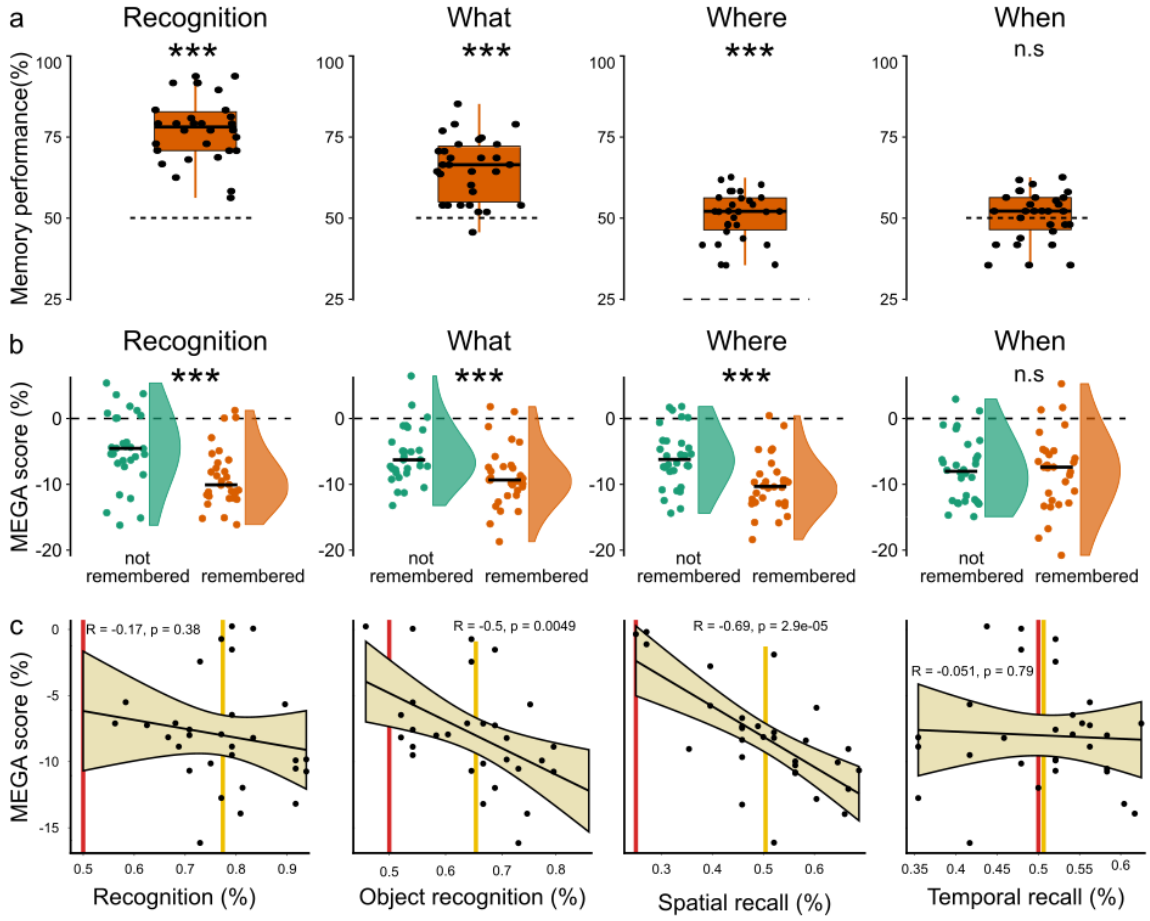


Figure S1. The relationship between MEGA and explicit memory reports – original retrieval questions A) verbal report: Participants' retention rate for each retrieval task independently. Tasks from left to right: movie recognition, object recognition, spatial recall, temporal recall. B) Memory task and MEGA-score: Comparison between the MEGA score of correct (orange) vs incorrect (green) answers, according to each retrieval task. The MEGA score is higher for movies that were recognized and higher if participants recalled the object and the location of the SE. C) Correlation of individuals' MEGA-score and their verbal reports, indicating more object recognition and higher spatial recall relates to the MEGA-score. * = p<0.05, ** = p<0,01, *** = p<0,001, dotted lines mark chance-level performance.

Event-Based Eye-Tracking Features

* SEC- Surprising Event Center Point

Category	Feature	Description
Raw Gaze	In SEC Gaze Count	Total number of gaze points within the SEC.
	Out SEC Gaze Count	Total number of gaze points outside the SEC.
	In/Out Gaze Ratio	Ratio of in SEC data points to out SEC data points.
	Gaze Entry Count	Number of entries the gaze made into the SEC.
	Gaze Entry Rate	Frequency of gaze entries into the SEC per unit of time.
	Mean Euclidean Distance to SEC	Average Euclidean distance from gaze points to the center of the SEC.
	Median Euclidean Distance to SEC	Median Euclidean distance from gaze points to the center of the SEC.
	Minimum Euclidean Distance to SEC	Smallest Euclidean distance from any gaze point to the SEC.
	Maximum Euclidean Distance to SEC	Largest Euclidean distance from any gaze point to the SEC.
	STD of Euclidean Distance to SEC	Variability of Euclidean distances from gaze points to the SEC.
	SEM of Euclidean Distance to SEC	Standard error of the mean of Euclidean distances to the SEC.
	AUC for Euclidean Distance to SEC	Area under the curve for Euclidean distance measurements to SEC.
Fixations	SEC Fixation Count	Total number of fixations within the SEC.

	Out SEC Fixation Count	Total number of fixations outside the SEC.
	In/Out Fixation Ratio	Ratio of in SEC fixations to out SEC fixations.
	Fixation Entry Count	Number of times fixations entered the SEC.
	Fixation Entry Rate	Frequency of fixation entries into the SEC per unit of time.
	Mean Fixation Duration	Average duration of fixations within the SEC.
	Median Fixation Duration	Median duration of fixations within the SEC.
	Max Fixation Duration	Longest single fixation within the SEC.
	Min Fixation Duration	Shortest single fixation within the SEC.
	STD of Fixation Duration	Variability in the duration of fixations within the SEC.
	SEM of Fixation Duration	Standard error of the mean of fixation durations within the SEC.
	AUC for Fixation Duration	Area under the curve for fixation durations within the SEC.
Saccade	Saccade-start SEC Count	Number of saccades that started within the SEC.
	Out SEC Saccade-start Count	Total number of saccades that started outside the SEC.
	In/Out Saccade-start Ratio	Ratio of in SEC saccade-starts to out SEC saccade-starts.
	Saccade-end SEC Count	Number of saccades that ended within the SEC.
	Out SEC Saccade-end Count	Total number of saccades that ended outside the SEC.

	In/Out Saccade-end Ratio	Ratio of in SEC saccade-ends to out SEC saccade-ends.
	Number of Saccades to First Fixation within SEC	Number of saccades before the gaze first fixates within the SEC.
	Mean Saccade Peak Velocity to SEC	
Average peak velocity of saccades moving towards the SEC.		
	Min Saccade Peak Velocity to SEC	Minimum peak velocity of saccades moving towards the SEC.
	Max Saccade Peak Velocity to SEC	Maximum peak velocity of saccades moving towards the SEC.
	STD of Saccade Peak Velocity to SEC	Variability in the peak velocity of saccades towards the SEC.
	SEM of Saccade Peak Velocity to SEC	Standard error of the mean of saccade peak velocities towards the SEC.
	AUC for Saccade Peak Velocity to SEC	Area under the curve for saccade peak velocities towards the SEC.
Visual Angle	Mean Visual Angle from SEC	Average visual angle from the SEC.
	Minimum Visual Angle from SEC	Smallest visual angle from the SEC.
	Maximum Visual Angle from SEC	Largest visual angle from the SEC.
	STD of Visual Angle from SEC	Variability in the visual angle from the SEC.

	SEM of Visual Angle from SEC	Standard error of the mean of visual angle measurements from the SEC.
	AUC for Visual Angle from SEC	Area under the curve for visual angle measurements from the SEC.
	Mean Visual Angle to SEC	Average visual angle to the SEC.
	Minimum Visual Angle to SEC	Smallest visual angle to the SEC.
	Maximum Visual Angle to SEC	Largest visual angle to the SEC.
	STD of Visual Angle to SEC	Variability in the visual angle to the SEC.
	SEM of Visual Angle to SEC	Standard error of the mean of visual angle measurements to the SEC.
	AUC for Visual Angle to SEC	Area under the curve for visual angle measurements to the SEC.
Pupil	Pupil Radius Difference When Looking at SEC- min, max, avg, media, std, sem, auc	Difference in pupil radius when looking at versus away from the SEC, indicating cognitive or emotional response.
	Pupil Radius Difference When First Looking at SEC	Difference in pupil radius for the first fixation inside versus the previous outside the SEC.

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תקציר

זיכרון אירועי (זיכרון אפיזודי), היכולת לשחזר אירועים מהעבר עם ההקשרים המרחביים והזמניים שבהם התרחשו, היא אחת מאבני היסוד בקוגניציה האנושית. עם זאת, התלות המסורתית בדיווחים מילוליים להערכת זיכרון אירועי מערבבת למעשה בין תהליכי הזיכרון האמיתי לבין היכולות הלשוניות. מצב זה לא רק מקשה על הבנת המנגנונים המוחיים הבסיסיים העומדים מאחורי יצירת זיכרון והשחזור שלו, אלא גם מסבך את חקר הזיכרון האירועי באנשים או באוכלוסיות שבהן התקשורת המילולית פגומה או לא מפותחת, כמו אצל פעוטות, אפאזיים או בעלי חיים אחרים. בנוסף לכך, השיטות המקובלות נתקלות בקשיים בהבחנה בין זיכרון אירועי מפורט לבין זיכרון הכרתי בלבד (familiarity), אתגר שאף מתעצם במחקרים המשתמשים בתמונות סטטיות בלבד שלא בהכרח מכילות את הרכיבים הכלולים בזיכרון אירועי (מה, מתי, איפה).

על מנת לנסות להתמודד עם האתגרים הללו, אנו מציגים בעבודה זו גישה חדשנית המשתמשת בטכנולוגיית מעקב אחר תנועות עיניים וניתוח המאפיינים שלהם למדידה של זיכרון אירועי ללא שימוש בדיווח מילולי. תנועות העיניים נותחו בזמן צפייה בסרטונים דינמיים המדמים אירועים מהעולם האמיתי, כאשר בצפייה החוזרת של הסרטונים ניתן להבחין שבדפוסי תנועות העיניים קיימת ציפייה (anticipation) למה שעומד להתרחש בסרטון. את הציפייה לאירוע ניתן לכמת ע"י פירוקה לרכיב המרחבי ולרכיב הזמני (טמפורלי) שלה ובהתבסס עליהם ליצור מאגר של מאפיינים. היעילות של הפרדיגמה שלנו הוכחה דרך סדרה של ניסויים שונים עם 126 משתתפים, סוגי גירויים שונים כולל אנימציות מותאמות אישית וסרטים ריאליסטיים שנאספו מ- youtube.com, ומגוון גישות אנליטיות. הממצאים שלנו מדגימים את האפשרות של שימוש מעשי בגישה המשתמשת במאפיינים של תנועות העיניים למדידת זיכרון אירועי, הן באמצעות ניתוח סטטיסטי והן באמצעות שימוש בלמידת מכונה. ראשית, ניתן להבחין באופן מובהק בין צפייה של סרטון בפעם הראשונה, בה לנבדק אין זיכרון, לבין צפייה חוזרת, בה לנבדק יש זיכרון אודות האירוע שהתרחש בסרטון. שנית, בכלים של למידת מכונה הצלחנו להראות שגם ברמת צפייה בודדת של סרטון אחד של נבדק אחד, ניתן לנבא האם זו הפעם הראשונה בה צפה בסרטון, או שמדובר בצפייה חוזרת. זאת גם כאשר לאלגוריתם למידת המכונה לא היה מידע מקדים כלל עבור אותו נבדק (הוא אומן על נבדקים אחרים). כמו כן, השוואה מפורטת של התוצאות לדיווחים מילוליים מראה כי המאפיינים של תנועות העיניים המבוססות על ציפייה אכן מקושרות לזיכרון אירועי בעוד שמאפיינים אחרים שבחנו כמו התרחבות האישון מקושרים לזיכרון הכרתי.

לבסוף, הדגמנו אפליקציה אחת של שימוש בתנועות עיניים, אשר מראה את ההשפעות החיוביות של שינה על זיכרון אירועי ללא דיווח. המבט הצופני מייצג כלי חדשני ועמיד שאינו תלוי בשפה להערכת שחזור והתמצקות זיכרון אפיזודי עם יישומיות רחבה במחקר הקוגניטיבי ובתחומים קליניים.

בית הספר סגול למדעי המוח

הפקולטה למדעי הרפואה והבריאות

לצפות את העתיד:
תנועות עיניים כסמן של זיכרון

מאת

דניאל ימין

החיבור בוצע בהנחייתו של

פרופסור יובל ניר

מאי 2024