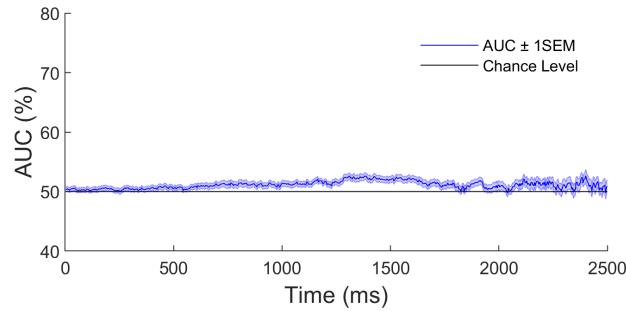


Supplementary Information

Supplementary Note 1. Eye Movement Decoding Analysis

In order to examine whether eye movement data contained sufficient information to distinguish old vs. new faces, we conducted a trial-by-trial decoding analysis using the horizontal (X) and vertical (Y) coordinates of the eye-tracking data from the 84 participants. We used a similar method to the EEG decoding method described in Section “EEG Analysis”. Specifically, for each participant, we first down-sampled the eye position time series data in each trial from 1000 Hz to 250 Hz by averaging data from every consecutive pair of time points, ensuring the sampling rate was the same as our EEG analysis. We extracted features at each time point by collecting the corresponding X and Y coordinates from all trials and the corresponding old/new face labels. We then generated a dataset for each time point and trained a linear SVM classifier with probability outputs, performing 100 repetitions with random sampling (80% training, 20% test). To ensure model robustness, datasets with fewer than 100 samples or with class imbalance exceeding a 2:1 ratio were excluded. Model performance was assessed using the AUC.

To visualize group-level performance over time, individual eye movement decoding performance curves were aligned from 0 to 2500 ms and then averaged. The averaged AUC values of different time points in eye movement decoding are shown in Supplementary Figure 1. We computed the mean AUC at each time point across participants with ± 1 SEM. Overall, the maximum mean AUC across the 0–2500 ms window was only 52.62% (observed at ~1384 ms). We defined the mean AUC value from the first time point (0-second) as the baseline and chance-level performance and pairwise two-tailed *t*-tests were performed between the baseline AUC values and the AUC values from subsequent time points to assess statistical significance. The results suggested that none of these comparisons revealed a statistically significant difference with baseline AUC values (all $p > 0.05$, corrected by the Benjamini & Yekutieli method), indicating that the eye movement features could not reliably predict or distinguish old and new faces in this paradigm. Thus, the eye movement decoding analysis results provide strong evidence that eye movements were unlikely to influence our EEG decoding results in the old/new face recognition tasks.



Supplementary Figure 1. AUC performance curve for eye movement decoding. The purple shading indicates ± 1 standard error of the mean (SEM).

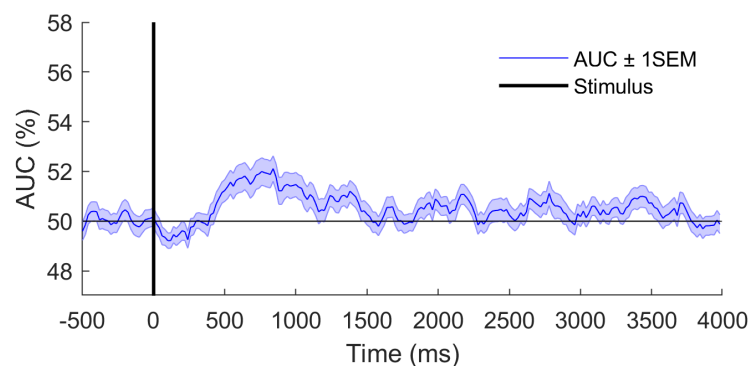
Supplementary Note 2. Eye Movement Data Classification

To further verify that eye movement information did not affect EEG decoding results, we conducted an additional eye movement data classification analysis. Specifically, for each participant we extracted their trial-wise fixation information (horizontal position, vertical position, and fixation duration) from the raw eye movement data, where each trial contained a varying number of fixations. We constructed a long short-term memory (LSTM) model for fixation classification, which is particularly appropriate for modeling variable-length sequential data and capturing both short-range and longer-range temporal dependencies in fixation patterns. Before classification, all fixation data were z-score normalized at the individual level, and each trial was labeled as an old or new face category. The five-fold cross-validation was implemented for each participant. In each fold, separate training and testing sets were constructed, and an LSTM network with 32 hidden units and a final fully connected layer was trained with 200 epochs using the stochastic gradient descent with momentum (SGDM) optimizer. The default learning rate of 0.001 was employed for SGDM. Finally, the individual-level cross-validation mean accuracies were recorded, and an overall mean accuracy of 50.59% was obtained across all participants. A one-sample *t*-test was conducted to assess whether the overall mean accuracy significantly differed from the chance level (50%) across the 84 participants. Before the *t*-test, the data distribution was assessed using the Kolmogorov-Smirnov test, which indicated that the accuracies approximately followed a normal distribution ($p = 0.8531$). The *t*-test revealed that the overall mean accuracy ($M = 0.5059$, $SD = 0.0313$) did not significantly differ from the chance level of 50%, with $t(83) = 1.7246$, $p = 0.0883$. This suggests that raw eye fixations were not predictive of whether the presented face was old or new and thus could not account for the EEG decoding results.

Supplementary Note 3. EOG decoding analysis

In order to examine potential effects of eye movements on EEG, we approximated vertical and horizontal EOG (vEOG, hEOG) signals from the EEG recordings. Following the previous study¹, the Fpz electrode served as the approximation for vEOG, whereas the difference between electrodes F7 and F8 served as the approximation for hEOG. These signals were bandpass-filtered from 0.5 to 5 Hz using a zero-phase, 4-order Butterworth IIR filter, and then segmented into trials ranging from -500 ms to 4000 ms (1125 data points in total). We adopted the same preprocessing and classification procedure described in Section “EEG Analysis”, where each trial was processed with a 5-point moving window to compute the average amplitudes non-overlappingly, yielding 225 amplitude points per trial. Then, a linear SVM was trained to decode old/new faces. Using the same methods as our EEG decoding, each participant’s data were split into a training set (80%) and validation set (20%), repeated 100 times with bootstrapping to stabilize performance estimates. The AUC was used as the decoding performance measure.

The averaged EOG decoding performance is illustrated in Supplementary Figure 2. It revealed that the EOG decoding performance reached a maximum AUC of 52.11% (observed at ~840 ms), with no time point significantly exceeding chance-level performance (all $p > 0.05$, corrected by the BY method). Therefore, isolated ocular artifacts due to eye movements are unlikely to influence the EEG decoding results. These findings are consistent with our eye movement decoding analyses (See Supplementary Note 1) and further demonstrate that the EOG signals do not provide reliable information for distinguishing old faces from new faces.

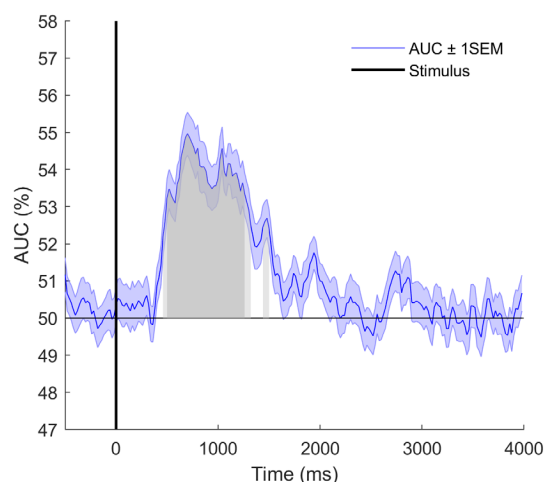


Supplementary Figure 2. AUC performance curve for EOG decoding. The purple shading indicates ± 1 standard error of the mean (SEM).

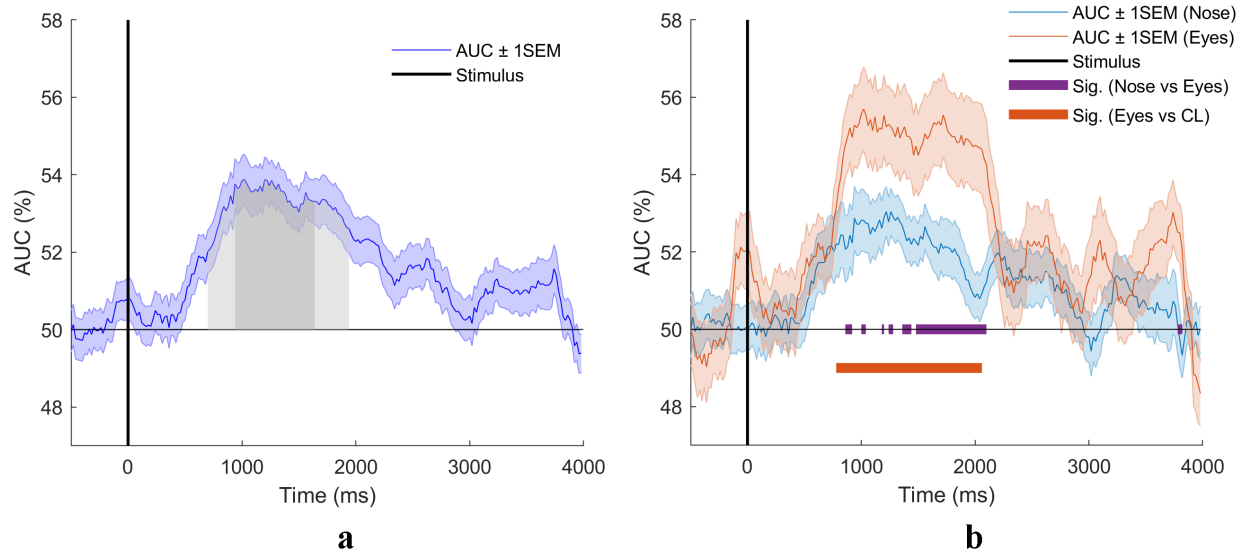
Supplementary Note 4. EEG decoding analysis

Following the previous literature², we used another ICA procedure to discard more potential eye-movement noises in a separate analysis. We incorporated the approximated vEOG and hEOG channels directly into the ICA training data to detect subtle residual ocular signals and more accurately identify ocular-related independent components, resulting in an ICA training dataset with a total of 65 channels (63 EEG + 2 EOG). Concurrently, a 2–100 Hz band-pass filter was applied to the ICA training data to better capture spike potentials that may arise from saccades and other rapid eye movements. We then utilized the ICLabel plugin (EEGLAB toolbox) with a confidence threshold of 90% to automatically detect and remove ICs reflecting blinks or eye movements. The rest of the EEG preprocessing and decoding procedures were the same as described in Section “EEG Analysis”.

The ERP decoding and Alpha band power decoding performance curves are illustrated in Supplementary Figures 3 and 4. It can be observed that the EEG decoding performance obtained with this refined ICA pipeline was nearly identical to those derived from our original approach as shown in Figures 2, 3, and 4 of the main text, indicating that our primary conclusions are robust against different ocular artifact removal methods.



Supplementary Figure 3. AUC performance curve for ERP decoding (0.5-6 Hz). The black horizontal line represents the chance level performance ($AUC = 0.5$), and the black bold vertical line indicates the stimulus presentation onset time. The AUC values in the shaded area are significantly higher than the chance level, where the light gray area indicates the area with corrected $p < 0.05$, and the dark gray area indicates the area with corrected $p < 0.001$. The purple shading indicates ± 1 standard error of the mean (SEM).



Supplementary Figure 4. Alpha band power decoding performance. The AUC performance curve for high-alpha band decoding (10-12 Hz). (a) high-alpha band decoding (10-12 Hz). (b) group-wise decoding performance in AUC in the high-alpha band (10-12 Hz) across time points. The black horizon line represents the chance level performance (AUC = 0.5), and the black bold vertical line indicates the stimulus presentation onset time. The bold purple line marks the time period where the eyes-focused group's performance is significantly higher than the nose-focused group's performance (corrected $p < 0.05$). The bold red line marks the period that the eyes-focused group's performance is significantly higher than the chance level (corrected $p < 0.05$). The blue and orange shading indicates ± 1 SEM, and CL indicates the chance level.

Supplementary Note 5. Eye Movement Data Comparison

We measured the average number of fixations per trial (i.e., number of saccades per trial + 1) and averaged saccade length for old and new faces. We found that these measures of the participants for old and new faces did not differ significantly: Number of fixations, $t(83) = -1.044$, $p = .300$, $d = -.114$; average saccade length, $t(83) = 0.07$, $p = .947$, $d = .007$.

Supplementary References

- 1 Kalaganis, F. P. et al. in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. 395-398 (IEEE).
- 2 Dimigen, O. Optimizing the ICA-based removal of ocular EEG artifacts from free viewing experiments. *NeuroImage*, 207, Article 116117. (2019).