Tracking the Unconscious: Neural Evidence for the Retention of Unaware Information in Visual Working Memory

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Abstract

■ This study investigates the retention of visual information in visual working memory (VWM) when individuals are unaware of it, aiming to provide clear-cut evidence for an unconscious VWM effect. To explore the underlying neural mechanisms, we monitored a critical ERP component, specifically the contralateral delay activity (CDA), which reflects VWM maintenance. Participants performed a change detection task in which to-be-memorized Gabor patches were presented at a visibility threshold, determined to assess subjective awareness using the Perceptual Awareness Scale. Participants performed above chance level in the change detection task even when the visibility of the Gabor patches was subthreshold, indicating retention of visual information without conscious awareness. Notably, in a subsample of participants, a reliable CDA amplitude was observed during unaware trials, in which participants performed correctly, compared to trials with incorrect responses. As a proof of concept, this finding indexed short active maintenance of unaware visual information in VWM, which could be used to perform VWM-based tasks. In conclusion, the results of our study support the existence of an active retention of unaware visual information in VWM. These findings challenge the notion of entirely activity-silent working memory by showing that unconscious information is maintained through active neural firing (CDA), potentially transitioning to activity-silent mechanisms in later phases. ■

INTRODUCTION

Visual working memory (VWM) is a cornerstone of the human cognitive architecture, responsible for the short-term storage and manipulation of visual information, including shapes, colors, and spatial positions (Liesefeld & Müller, 2019; see also Mance & Vogel, 2013). VWM is thought to play a role in a range of cognitive functions, such as attention, decision-making, and problem solving (Luck, 2008) and may even influence early stages of perception. Although our understanding of VWM has advanced significantly, ongoing debate persists regarding the maintenance in VWM of visual information that is outside conscious awareness (Gambarota, Tsuchiya, Pastore, Di Polito, & Sessa, 2022; Persuh, LaRock, & Berger, 2018; Velichkovsky, 2017; Soto & Silvanto, 2014, 2016). The ability of VWM to store unaware information holds profound theoretical and practical implications, as it challenges some of the major traditional cognitive models that consider awareness as a prerequisite for VWM retention (Mashour, Roelfsema, Changeux, & Dehaene, 2020; Dehaene & Changeux, 2011; Baars & Franklin, 2003; Dehaene & Naccache, 2001; Baars, 1988).

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The present study builds on pivotal findings, particularly the influential behavioral work by Soto, Mäntylä, and Silvanto (2011), which suggests that subliminal stimuli can be stored in working memory (WM). Soto and colleagues restricted their behavioral analysis to trials with an awareness score of 1 on a subjective scale of 1–4, where 1 indicated no awareness of the stimulus. Despite this lack of conscious awareness, participants' performance on the WM task was significantly better than chance, suggesting that WM can retain information even when it is not consciously perceived. Subsequent research and a comprehensive meta-analysis (see Gambarota et al., 2022) have further validated the concept of unconscious WM maintenance, prompting adaptations in cognitive models to account for this unconscious dimension (Velichkovsky, 2017; Persuh et al., 2018; Soto & Silvanto, 2014, 2016; Jacobs & Silvanto, 2015).

At present, it remains unclear whether the phenomenon of WM maintenance of unconscious visual information is reflected in neural markers resulting from neurons' active firing specifically tied to visual information retention. This study seeks to fill that gap by examining a key neural response, specifically indexing VWM maintenance, providing compelling evidence that visual information is actively retained in VWM, even when it is outside conscious awareness.

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To this end, we adopted a modified version of the change detection task (Rouder, Morey, Morey, & Cowan, 2011; Rensink, 2002; Pashler, 1988) in which we varied the contrast of Gabor stimuli so that, in some trials, the stimuli remained below the threshold of conscious awareness. Following Soto and colleagues, we used the Perceptual Awareness Scale (PAS; Sandberg & Overgaard, 2015) to assess participants' awareness of the visual stimuli. Critically, we investigated the maintenance of unaware Gabor stimuli in VWM using an ERP component commonly regarded as an index of VWM maintenance, namely, the contralateral delay activity (CDA; Luria, Balaban, Awh, & Vogel, 2016; Vogel & Machizawa, 2004).

The change detection task is a well-known tool for assessing VWM (Vogel, Woodman, & Luck, 2006; Vogel, McCollough, & Machizawa, 2005; Luck & Vogel, 1997). The task requires participants to discern a change between two sequential stimulus arrays, such as colors, oriented lines, shapes, or faces. In our study, participants had to retain Gabor patches in VWM, which were individually calibrated to a 75% visibility threshold. This threshold was selected based on our pilot studies and guided by the "window of subliminal perception" hypothesis (Sandberg, Del Pin, Overgaard, & Bibby, 2022). This approach ensured a balance where participants often did not consciously recognize the stimulus but still performed above the chance level in the VWM task, demonstrating the unconscious VWM effect at the behavioral level of analysis. After the presentation of the Gabor stimulus to be memorized, participants were shown a test Gabor stimulus. They were then asked to compare the orientation of the test Gabor stimulus with their memory of the original Gabor stimulus and indicated whether the orientation was the same or different (50% of the trials each). After responding to the VWM task, participants also provided their subjective evaluations of the visibility of the target Gabor using the PAS (Overgaard & Sandberg, 2021; Sandberg & Overgaard, 2015), a tool designed to capture the nuanced levels of conscious awareness of a stimulus. The PAS is specifically tailored to measure the spectrum of conscious perception, ranging from no awareness to full awareness on a 4-point scale. A strength of the PAS lies in its ability to differentiate between instances of minimal perception and those of no subjective awareness. This distinction is important because brief glimpses or fleeting moments of perception may be categorized by participants as minimal perception, reducing the risk of confounding them with truly unaware trials.[1]

To investigate the neural mechanisms underlying the maintenance of unaware visual information in VWM, we recorded participants' EEG to extract and analyze the CDA, that is, the most investigated neural marker of information maintenance in VWM (McCollough, Machizawa, & Vogel, 2007; Vogel & Machizawa, 2004). This neural activity is characterized by sustained negativity posteriorly over the hemisphere contralateral to the to-be-memorized items, and it is computed by taking the difference in amplitude between the activity recorded at the contralateral electrodes and the activity recorded at the ipsilateral electrodes. The rationale behind this calculation is that the amplitude on the ipsilateral side primarily reflects low-level processing of the to-be-ignored items. In contrast, the amplitude on the contralateral side represents both low-level processing of the to-be-remembered items and activity related to VWM. By subtracting the ipsilateral activity from the contralateral activity, researchers aim to isolate the CDA as a more specific measure of VWM-related activity, thereby removing the influence of low-level processing. The amplitude of this differential waveform increases with the number of objects' visual representations held in VWM, exhibiting a plateau effect at around three or four simple visual items, which is the average individual VWM capacity (Cowan, 2010; Vogel & Machizawa, 2004). Notably, the CDA has emerged as a robust neural correlate of VWM in many studies conducted in the last 20 years (Roy & Faubert, 2023; Chen et al., 2022; Luria et al., 2016).

Further corroborating the involvement of high-order visual processing brain areas, complementary research on the CDA's magnetic counterpart has pinpointed its origins in the superior intraparietal sulcus (IPS), together with the posterior parietal and ventral extrastriate cortices. These magnetic sources undergo temporal shifts, beginning with a bilateral parietal response tied to VWM consolidation before transitioning to a sustained contralateral response from the posterior IPS (Duma et al., 2019; Mitchell & Cusack, 2011; Robitaille et al., 2010; Robitaille, Grimault, & Jolicoeur, 2009).

Previous research has shown that CDA amplitude is higher for correct responses compared to incorrect ones in "conscious" change detection tasks (McCollough et al., 2007). In this study, we extend this finding by investigating whether a similar pattern occurs for stimuli that participants report being unaware of. If the same relationship between CDA amplitude and task performance holds, this would suggest that unconscious stimuli near the threshold of awareness are still actively encoded and maintained in VWM through sustained neural activity. We hypothesize that correct responses, even for stimuli that are inaccessible to conscious awareness, are driven by visual representations maintained in VWM. Accordingly, we expect the CDA amplitude to be higher for correct than incorrect responses, indicating the active retention of these unaware visual representations in VWM. Alternatively, unconscious information could be maintained through activity-silent neural mechanisms (Oberauer & Awh, 2022; Stokes, 2015; Mongillo, Barak, & Tsodyks, 2008). If this were the case, we should not observe differences in CDA amplitude between correct and incorrect responses for unaware stimuli, as such representations would not rely on sustained neural activity. To test our hypothesis, we restricted our analysis of the CDA to trials in which participants were unaware of the target Gabor stimuli (i.e., PAS 1 trials). We then compared the CDA for trials in which participants correctly performed the change detection task (i.e., correctly reported whether the orientations of the two Gabor stimuli were the same or different) with the CDA for trials in which participants provided incorrect responses. The findings from these tests would directly inform whether the online retention of unaware stimuli exists in VWM and whether these representations can be unconsciously accessed and utilized in VWM tasks that require the comparison of stimuli (i.e., the memorized target stimulus with the test stimulus).

METHODS

Participants

We recruited 24 volunteer participants from the University of Padova, comprising 22 women (mean age = 23.6 years, *SD* = 1.71 years) and two men (mean age = 25.5 years, *SD* = 3.54 years). All participants had normal or corrected vision and were in good health. Before the study, each participant provided written informed consent following the ethics guidelines of the University of Padova.

Stimuli and Procedure

The experiment was conducted in a dimly lit room where participants were seated 67 cm away from a 24-in. Asus ROG PG248Q LCD monitor with a refresh rate of 144 Hz. To manipulate stimulus visibility, we employed the change detection task combined with a backward masking paradigm (Breitmeyer & Ogmen, 2000). The trial structure is depicted in Figure 1.

Each trial started with a central fixation cross (0.8°) presented for 500 msec. Subsequently, a left- or right-oriented arrow indicated the task-relevant side of the screen for 500 msec. The memory array consisted of two lateralized Gabor patches (5° horizontal offset and 2° vertical offset from the center) measuring 3.4° each. These patches could be oriented in six different ways (15°, 45°, 75°, 105°, 135°, or 165°), with the uncued Gabor having a random orientation. The Gabors were presented briefly for 33 msec and were immediately followed by masks created using random visual noise, which was displayed for 350 msec. After a 900-msec blank retention interval, another Gabor was presented at the cued location (test array). The cued test Gabor had the same orientation as the memory array in 50% of the trials, whereas it had a different orientation in the remaining 50%. The test Gabor could be tilted clockwise or counterclockwise in trials with different orientations.

Participants were instructed to compare the orientation of the memory and test Gabors using the keyboard and report whether they were the same or different. In cases where the to-be-memorized Gabor was not consciously perceived, participants were asked to make their best guess. We instructed participants to remain engaged, even in trials where stimuli were not consciously perceived. Previous research has indeed highlighted the importance of explicit involvement in tasks involving unconscious stimuli (Pan, Lin, Zhao, & Soto, 2014; Soto & Silvanto, 2014).

After the change detection task response, we employed the PAS to classify each trial based on participants' subjective experiences. The PAS was formulated differently from the original version (Sandberg & Overgaard, 2015; Soto et al., 2011) to suit our purposes. To address the criterion content problem (Michel, 2023), we asked participants to evaluate the experience according to the task-relevant feature, that is, the orientation (see Güldener, Jüllig, Soto, & Pollmann, 2021, for a similar implementation). The PAS levels, translated from Italian, were as follows: 1 = *I did not see the orientation*, 2 = *I saw a brief glimpse of the orientation*, 3 = *I almost saw the orientation*, and 4 = *I clearly saw the orientation*.

To ensure clarity in PAS usage, participants received specific verbal instructions during setup. They were reminded that PAS ratings should reflect their subjective experience of seeing the orientation specifically, not just detecting any visual change. We emphasized that PAS 1 should be used when they had no conscious experience of the stimulus orientation, even if they might have detected some visual event. The exact Italian wording was "1 = Non ho visto l'orientamento, 2 = Ho avuto una vaga impressione di vedere l'orientamento, 3 = Sono abbastanza sicuro di aver visto l'orientamento, and 4 = Ho visto chiaramente l'orientamento."

The trial ended with a black screen lasting 1500 msec to avoid visual aftereffects.

The stimulus presentation time was fixed, and the visibility was modulated by changing the to-be-remembered (i.e., "memory") Gabor contrast using a psychophysical QUEST adaptive procedure (Watson & Pelli, 1983). The distractor Gabor stimulus, presented on the opposite side,

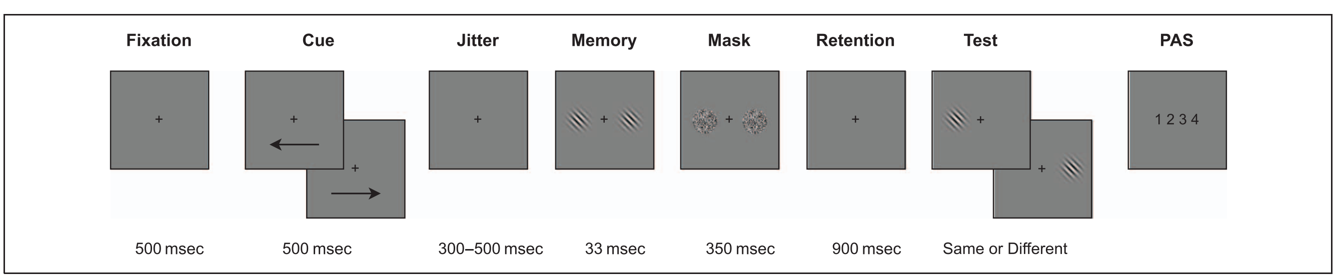


Figure 1. The trial structure.

was subjected to the same adaptation procedure. The QUEST is a widely used Bayesian adaptive procedure that controls a specific stimulus feature (e.g., contrast) trial by trial, based on previous trials and participants' responses. The QUEST is a parametric procedure because it assumes a Weibull distribution as the underlying relationship between the stimulus feature and the detection performance. We used standard values implemented in Watson and Pelli (1983) and PsychoPy (Peirce et al., 2019). The starting contrast value for each staircase was set to 0.5 (ranging from 0 to 1), and the standard deviation was set to 0.2. The slope was fixed to 3.5, and the lower (i.e., false alarm rate) and upper (i.e., lapse rate) asymptotes, respectively, were set to 0 and 0.01, as common for yes/no detection tasks (Watson & Pelli, 1983). We used a target threshold of 75%, based on the "window of subliminal perception" hypothesis (see Sandberg et al., 2022), to ensure an adequate number of PAS 1 trials while maintaining above-chance performance. This threshold was determined through pilot testing and was specifically chosen to create the critical experimental conditions needed to test unconscious VWM. During the experiment, the contrast level was modulated to achieve a 75% subjective report of seen (i.e., PAS > 1) responses, regardless of the accuracy in objective orientation discrimination performance.

The experiment consisted of 432 trials and 90 catch trials, totaling 522 trials. During catch trials, no Gabors were presented. The QUEST respectively reduced and incremented the contrast after PAS 2–4 and PAS 1 responses. We did not apply different contrast reduction depending on the PAS being 2, 3, or 4. The QUEST was not updated during catch trials. We added feedback after catch trials according to the PAS response to control the false alarm rate. PAS 1 responses (i.e., "correct rejections") were followed by positive feedback, whereas PAS 2–4 (i.e., "false alarms") were followed by a warning. The experiment lasted, on average, 60 min, with an additional 40 min for the EEG setup.

Before the main experiment, participants completed practice trials to familiarize themselves with both the change detection task and the PAS ratings. During these practice trials, participants received feedback on their performance and had the opportunity to ask clarification questions about the PAS to ensure proper understanding of the rating system.

Assuming an effect size in terms of accuracy of 0.58 (similar to Soto et al., 2011) for PAS 1 trials (i.e., unseen trials), 75 trials per participants (lower than the expected 25% of PAS 1 valid trials from a 75% QUEST staircase for a more conservative approach) and a by-participant standard deviation of 0.5 (in logit scale); the required sample size to obtain 80% power is approximately 18. The sample size has been estimated using a meta-analytical-based method (see Valentine, Pigott, & Rothstein, 2010), taking into account the number of trials, the number of participants, and the by-participant random effect, comparing the expected proportion (i.e., 0.58) to the chance level (i.e., 0.5). All calculations are performed on the logit scale (Agresti, 2003, p. 74), combining within- and between-participant variability. Refer to the online Open Science Framework repository for more information about the approach.

EEG Recording and Preprocessing

The EEG was recorded during the task by means of 64 active electrodes distributed on the scalp according to the extended 10/20 system, positioning an elastic ActiCAP with reference to the left ear lobe. The high gel viscosity has allowed the impedance to be kept at < 10 KΩ. Signal preprocessing and ERP analysis have been conducted using BrainVision Analyzer 2.1 software (Version 2.1; Brain Products GmbH).

The EEG was rereferenced offline to the mean activity recorded at the left and right ear lobes. The EEG was segmented into epochs lasting 1400 msec (−200/1200). After the baseline correction, trials contaminated by ocular artifacts (i.e., those in which the participants blinked or moved their eyes, eliciting activity higher than ±50 or ±80 μV, respectively) or from other types of artifacts (greater than ±80 μV) were removed.

Finally, the contralateral waveforms were computed by averaging the activity recorded by the electrodes of the right hemisphere when the participants were required to encode and memorize the Gabor stimulus presented on the left side of the memory array (pooling of the electrodes O2, PO8, and P8) with the activity recorded by the electrodes positioned on the left when the participants were required to encode and memorize the Gabor stimulus presented on the right side of the memory array (pooling of electrodes O1, PO7, and P7). The CDA was quantified as the difference in mean amplitude between the contralateral and ipsilateral waveforms in a time window of 300–1200 msec time-locked to the presentation of the memory array for the PAS 1 trials associated with correct and incorrect responses separately.

Behavioral Analysis

The VWM accuracy was assessed using a mixed-effects logistic regression model with the PAS as a predictor, and forward difference contrasts coding was used to test the change detection task accuracy on PAS 1 trials (i.e., the model intercept) and the performance increase as a function of the PAS rating. We used the R software (R Core Team, 2023) with the *lme4* package (Bates, Mächler, Bolker, & Walker, 2015). Given the repeated-measures design, we inserted participants as a random effect (random intercepts). For the signal detection theory (SDT) analysis, we used a mixed-effects probit regression. The probit regression can be used to estimate SDT parameters within a generalized linear model framework (DeCarlo,

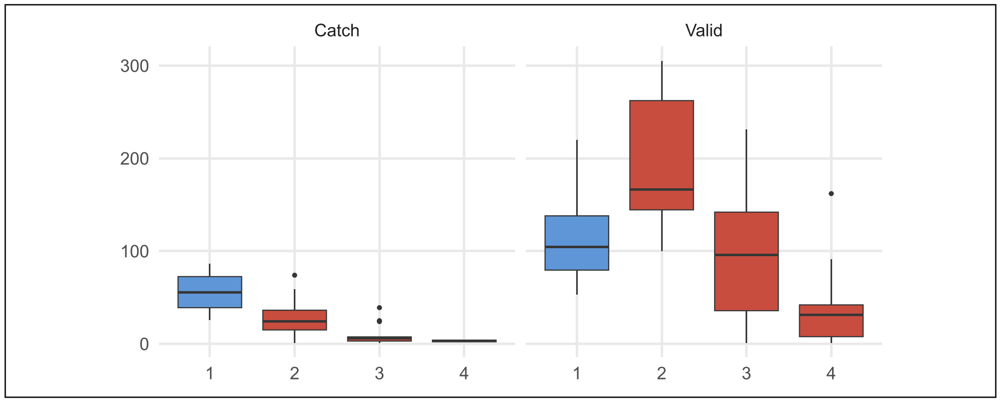


Figure 2. Boxplots for the number of trials across participants for each PAS response and trial type. PAS 1 trials are considered unseen, and PAS 2–4 trials are considered seen.

1998, 2010). Each model parameter is tested using a Wald z test with an alpha level of .05.

ERP Analysis

To ensure reliable CDA computation, we required a minimum of 10 artifact-free trials per condition (PAS 1 correct and PAS 1 incorrect) before the contra-minus-ipsilateral subtraction (based on ERP guidelines; Luck, 2014). This resulted in 14 participants meeting the inclusion criteria for the CDA analysis, whereas 10 participants had insufficient trials in at least one presubtraction condition. For ERP data, we computed the average amplitude of the 300- to 1200-msec time window (i.e., "retention interval"). We evaluated the difference between the CDA amplitudes elicited in the PAS 1 trials when responses at the test were correct and when responses were incorrect using a paired-sample t test (i.e., one-tailed t test). As additional analyses, we compared the CDA amplitude between PAS 1 and PAS 2 (considering only correct responses) and between PAS 1 valid trials (including the stimulus) and PAS 1 catch trials (including only the mask stimulus).

For the t tests, we also reported the Bayes factor (Morey & Rouder, 2011; Rouder, Speckman, Sun, Morey, & Iverson, 2009) using the *BayesFactor* package with the default prior width (scale parameter of the Cauchy distribution as 0.707) on the alternative hypothesis. As the effect size index, we reported Cohen's d_z (i.e., standardized using the standard deviation of differences; Lakens, 2013). The ERP data, ERP analysis pipeline, and statistical analysis scripts are available at the Open Science Framework (https://osf.io/gkmsy/).

RESULTS

Behavioral

Figure 2 depicts the overall PAS distribution according to the trial type (valid and catch) across participants, and Table 1 reports the percentage of PAS responses for valid and catch trials.

We transformed the PAS into a binary visibility scale to compute the overall change detection task parameters, where PAS 1 and PAS 2–4 are unseen and seen trials, respectively. The overall d' is 1.106 (SE = 0.158, z = 7.006, $p < .001$), and the overall criterion is liberal (tendency to say PAS 2–4) but not significantly different from zero ($\beta = -0.126$, SE = 0.073, $z = -1.736$, $p = .083$).

In addition, we analyzed how the participants used the PAS during the experiment. We divided the experiment for each participant into three blocks of 174 trials and fitted a mixed-effects probit regression with an interaction between block and type of trial (valid vs. catch). For the random part, we included a random intercept for participants and random slopes for the interaction.

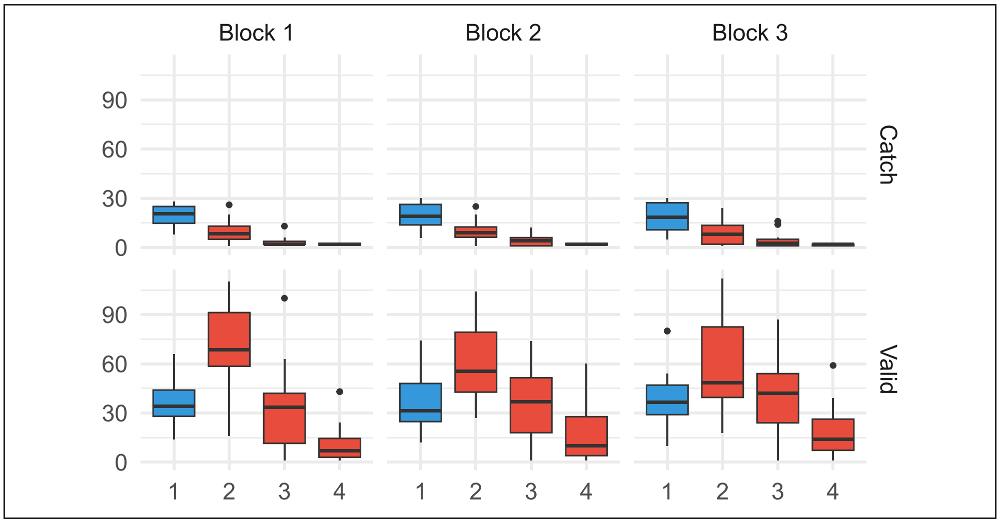
In the first block, the criterion was liberal and significantly different from zero ($c_1 = -0.136$, SE = 0.063, $z = -2.138$, $p = .033$). Then, we contrasted the second block with the first block and the third block with the second block. We found no difference neither in the former ($c_{2-1} = 0.030$, SE = 0.067, $z = 0.447$, $p = .655$) nor the latter ($c_{3-2} = -0.004$, SE = 0.053, $z = -0.082$, $p = .935$) contrast. Figure 3 shows the PAS distribution for catch and valid trials as a function of the experiment block. Figure 4 shows the criterion values for each participant as a function of the block as estimated by the model.

In the SDT analysis of the entire experiment, the number of valid trials substantially exceeds the number of catch

Table 1. Percentage of Trials for Each PAS Response Separately for Catch and Valid Trials

Trial Type	*PAS*	*%*
Catch	1	63.100
	2	29.600
	3	6.430
	4	0.870
Valid	1	25.710
	2	44.410
	3	22.990
	4	6.900

Figure 3. Distribution of PAS responses as a function of trial type and the experimental block for each participant. The y axis is the number of trials for each participant. Blue and red boxplots are respectively considered as unaware and aware trials.



trials (432 vs. 90; a 4.8:1 ratio). This imbalance persists when dividing the data into blocks, maintaining a ratio that is far from optimal for reliable SDT estimates. Therefore, both the overall and block-based SDT analyses should be interpreted as exploratory.

Figure 5 illustrates the accuracy of the change detection task according to PAS ratings, whereas Table 2 presents the results of the mixed-effects model. Performance is above chance for PAS 1 trials, and change detection task accuracy significantly increases from PAS 1 to PAS 2, from PAS 2 to PAS 3, and from PAS 3 to PAS 4.

EEG Results

Given the nature of the comparison (mean CDA amplitude at PAS 1 for correct responses to the test array vs. mean CDA amplitude at PAS 1 for incorrect responses to the test array), it was necessary to have a minimum and comparable number of trials per participant in each condition (i.e., 10). The final number of trials depended on the distribution of responses across PAS levels and the number of trials rejected because of artifact rejection in the EEG analysis. Consequently, this resulted in substantially reducing the initial sample, leaving 14 participants (out of 24) for the statistical comparison between the two relevant experimental conditions. The remaining 10 participants, not included in the CDA analysis, had fewer than 10 trials available for at least one of the conditions. This exclusion criterion was essential to ensure the reliability of the statistical analysis. While excluding 10 participants is significant, it was necessary to maintain the integrity of the data. The excluded participants had an insufficient number of trials per condition, often fewer than five, which would have compromised the robustness of the findings. We aimed to apply a reasonable and consistent criterion without being overly strict, ensuring that the

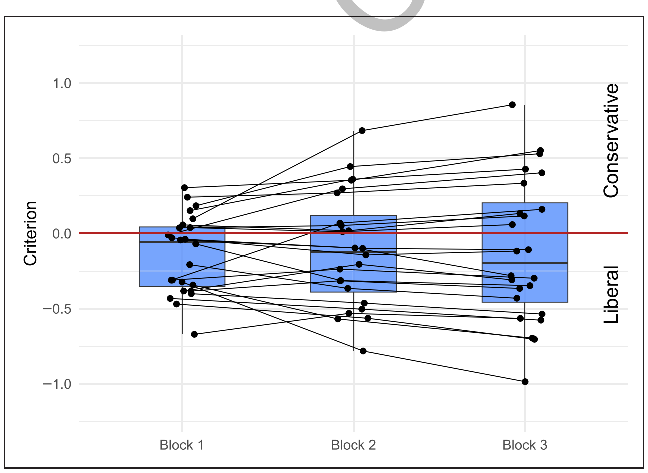


Figure 4. Estimated criterion for each participant with the multilevel probit model. Negative values mean that the criterion is liberal, whereas positive values mean that the criterion is conservative. The red line is the unbiased criterion.

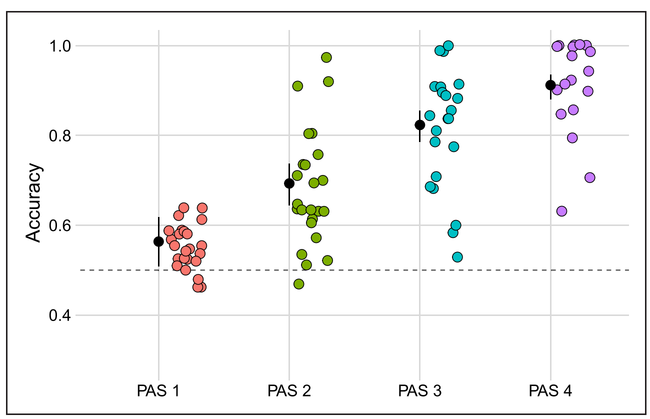


Figure 5. Results from the mixed-effects logistic regression on change detection task accuracy as a function of the PAS. The colored dots represent the average accuracy for each participant. Dots and bars represent the mixed-effects logistic regression estimates and 95% confidence intervals. Two participants had very low accuracy on PAS 3–4 trials; thus, the points were removed from the plot for better visualization.

Table 2. Mixed-Effects Logistic Regression of the Change Detection Task Performance as a Function of the PAS Results

Parameter	*exp(β)*	*SE*	*95% CI*	*z*	*p*
PAS 1 vs. 50%	1.294 ($\hat{p}_{\text{correct}} = .564$)	0.149	[1.032, 1.622]	2.233	$p = .026$
PAS 2 vs. PAS 1	1.755	0.092	[1.584, 1.945]	10.736	$p < .001$
PAS 3 vs. PAS 2	2.072	0.142	[1.812, 2.37]	10.635	$p < .001$
PAS 4 vs. PAS 3	2.233	0.325	[1.678, 2.971]	5.514	$p < .001$
σ_{id}	0.528				

We reported the estimated value, standard error, 95% confidence interval, and Wald-type z test for each parameter. We also reported the estimated accuracy for PAS 1 compared to 50% (i.e., chance-level accuracy).

results are both reliable and interpretable. The final sample of 14 participants (58.3% of the original 24) reflects the inherent challenges of combining unconscious perception paradigms with ERP methodology, where trial distributions across consciousness levels and accuracy conditions cannot be precisely controlled, and the number of artifact-free trials per condition is unpredictable.

Table 3 depicts the results from the multilevel logistic regression for the change detection task accuracy as a function of the PAS for the 14 participants included in the EEG/ERP analysis. The overall pattern is similar to the model, including all participants, but the accuracy of PAS 1 trials is not above chance. However, the absence of a behavioral effect in this subsample of 14 participants does not undermine the rationale for comparing the CDA amplitude at PAS 1 for correct and incorrect responses.

Figure 6 depicts the ERP waveforms for the PAS 1 for correct and incorrect responses to the test array for the subsample of 14 participants. The mean amplitude of the CDA at PAS 1 for correct responses was $\mu V = -0.801$ ($SD = 1.029$) and was significantly more negative than the baseline, $t(13) = -2.915$, $p = .006$, $d_z = -0.779$, $BF_{01} = 9.650$. The mean amplitude of the CDA at PAS 1 for incorrect responses was $\mu V = 0.158$ ($SD = 0.859$). The difference between the two CDA amplitudes was statistically significant (hypothesis-driven one-tailed test: $t(13) = -3.087$, $SE = 0.311$, $p = .004$, $d_z = -0.825$, $BF_{01} = 12.698$).

Beyond our primary analysis comparing CDA amplitude between PAS 1 correct and incorrect trials, we conducted two exploratory analyses to further characterize unconscious VWM maintenance. These secondary analyses, although informative, are necessarily limited by the constraints of our experimental design and should be interpreted as supplementary to our main findings. First, we compared CDA amplitude between PAS 1 correct trials and PAS 1 catch trials. Because catch trials contain only masks without target Gabors, this comparison reveals whether the CDA in unconscious trials reflects target-specific maintenance or visual information retention in VWM useful for the task at hand. Second, we compared CDA amplitude between PAS 1 correct trials and PAS 2 correct trials to investigate whether CDA amplitude reflects objective accuracy rather than subjective visibility.

It is essential to note that our trial-by-trial visibility staircase paradigm, although novel and effective for addressing our primary research question, may inevitably result in variable and unpredictable trial distributions across conditions after artifact rejection. This makes the theory-driven contrast reported in our main analysis—PAS 1 correct versus PAS 1 incorrect—the most powerful and diagnostic test of unconscious VWM.

For the catch trial comparison, we computed mean CDA amplitudes (300–1200 msec) from the pooled lateral–posterior electrode pairs (P8/P7, O2/O1, PO8/PO7). PAS 1 catch trials elicited a significant negative CDA ($M =$

Table 3. Mixed-Effects Logistic Regression of the Change Detection Task Performance as a Function of the PAS Results for the 14 Participants Included in the EEG/ERP Analysis

Parameter	*exp(β)*	*SE*	*95% CI*	*z*	*p*
PAS 1 vs. 50%	1.184 ($\hat{p}_{\text{correct}} = .542$)	0.182	[0.875, 1.601]	1.094	$p = .274$
PAS 2 vs. PAS 1	2.123	0.143	[1.86, 2.423]	11.177	$p < .001$
PAS 3 vs. PAS 2	2.267	0.216	[1.88, 2.733]	8.567	$p < .001$
PAS 4 vs. PAS 3	1.556	0.299	[1.067, 2.268]	2.299	$p = .022$
σ_{id}	0.541				

All other details are the same as in Table 2.

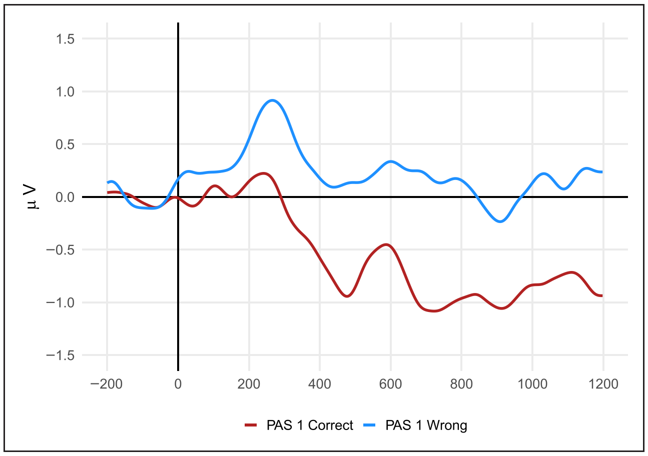


Figure 6. CDA waveforms (pooled from electrodes O1/O2, PO7/PO8, and P7/P8 and filtered at 5 Hz for a graphical representation) for correct responses (red) and incorrect responses (blue) at PAS 1 for the subsample of 14 participants.

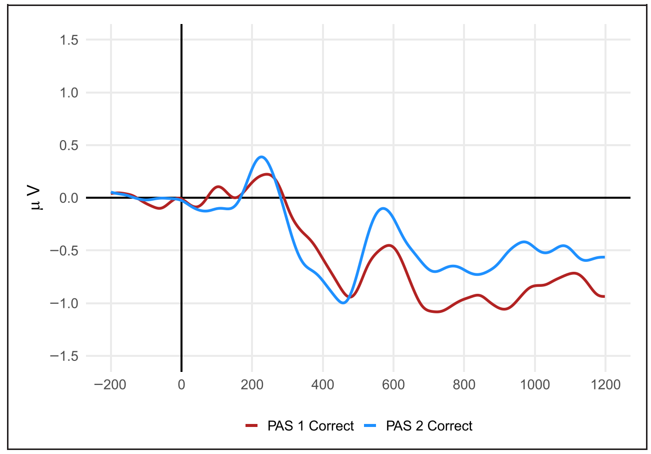


Figure 8. CDA waveforms (pooled from electrodes O1/O2, PO7/PO8, and P7/P8 and filtered at 5 Hz for a graphical representation) for correct responses at PAS 1 (red) and correct responses at PAS 2 (blue) for the subsample of 14 participants.

−0.542 µV, SD = 0.845), t(13) = −2.400, p = .016, d_z = −0.641, BF_{01} = 4.348. PAS 1 correct trials involving Gabors showed a similar effect, t(13) = −2.915, p = .006, d_z = −0.779, BF_{01} = 9.650. CDA amplitude did not differ between PAS 1 correct and PAS 1 catch trials, t(13) = −1.208, p = .248, Cohen's d_z = −0.323, BF_{01} = 2.010 (see Figure 7).

For the comparison between unconscious and conscious correct trials, insufficient participants had analyzable data for PAS 3 (9/14) and PAS 4 (4/14) levels. Therefore, we restricted this comparison to PAS 1 versus PAS 2 correct trials. PAS 1 and PAS 2 correct (M = −0.668 µV, SD = 0.422) trials showed no significant differences between CDA amplitudes, t(13) = −0.884, SE = 0.260, p = .393, d_z = −0.236, BF_{01} = 2.650, providing some evidence that CDA amplitude follows objective

Figure 7. CDA waveforms (pooled from electrodes O1/O2, PO7/PO8, and P7/P8 and filtered at 5 Hz for a graphical representation) for correct responses to the Gabor patches (black) and correct responses to catch trials (red) at PAS 1 for the subsample of 14 participants.

accuracy rather than subjective visibility when performance is matched (see Figure 8).

Although the inherent constraints of our paradigm limit these exploratory analyses, they provide converging evidence that supports—but does not replace—our primary finding. The CDA observed in catch trials, along with the equivalent amplitudes between PAS 1 and PAS 2 correct trials, suggests that CDA indexes goal-directed VWM processes rather than conscious accessibility, reinforcing the theoretical significance of our main result.

DISCUSSION

Although growing evidence supports unconscious processing in WM, to the best of our knowledge, no previous study has focused explicitly on neural markers uniquely associated with VWM. At the neurophysiological level, CDA is a well-established marker of visual information retention, reflecting sustained neural activity at posterior electrode sites. The present study sought to fill this gap by investigating whether unconscious VWM can be maintained through active neural firing, as indicated by the CDA.

Here, we used a modified version of the change detection task to accomplish this, a widely accepted method for assessing conscious VWM capacity and performance. In our adapted task, we presented target Gabor patches with a carefully determined visibility threshold of 75%. We employed a fixed stimulus presentation time while modulating visibility through manipulations of contrast. To precisely control contrast levels, we implemented a psychophysical QUEST adaptive procedure (Watson & Pelli, 1983). Our QUEST procedure ensured 25% of the trials with PAS = 1, corresponding to the phenomenological report of "I did not see the orientation." Within these "unseen" trials, participants demonstrated above-chance performance in the change detection task of the orientation of the Gabor.

To uncover the neural mechanisms underlying the retention of visual information in VWM, we recorded participants' EEG signals and an ERP component, namely, the CDA, as an index of VWM. Of note, in the subsample of participants included in the ERP analysis, we also observed a reliable CDA in those trials where participants performed above chance level in PAS 1 trials, tracking the retention of visual information despite being unaware of it. More specifically, the results showed a significant difference between PAS 1 correct and incorrect responses ($d_z = -0.825$), indicating that correct responses, even when participants were unaware, were associated with a reliable CDA amplitude. This supports the idea that correct responses without awareness of these stimuli are driven by the retention of visual information in VWM. This finding supports the notion that unconscious maintenance of visual information may occur in VWM through the same neural mechanism that characterizes conscious visual information.

Exercising caution, we can confidently rule out the possibility that the neural effects we observed, particularly the noticeable divergence of the CDA from the baseline in the correct trials at PAS 1, are attributable to the VWM maintenance of mere guesses rather than genuine VWM retention of visual information. This is supported by the fact that the CDA reliably indexes the maintenance of visual information in a retinotopic fashion, not guesses (Mössing, Schroeder, Biel, & Busch, 2024).

The results of this study may also contribute to an important discussion in the field regarding the nature of the mechanisms underlying the maintenance of unconscious information in VWM. Specifically, we sought to determine whether this maintenance relies on active neural firing, similar to conscious information, or on activity-silent neural mechanisms. Recent evidence indicates that neural activity during the maintenance phase can be disrupted or even absent when individuals are unaware or inattentive to the information being held (Trübutschek et al., 2017; Wolff, Jochim, Akyürek, & Stokes, 2017; Rose et al., 2016; Wolff, Ding, Myers, & Stokes, 2015). Theoretical frameworks and simulations suggest that activity-silent maintenance, characterized by the absence of accompanying neural firing, may occur through temporary alterations in synaptic connections among neural populations responsible for encoding stored items (Oberauer & Awh, 2022; Stokes, 2015; Mongillo et al., 2008). This view is supported by findings that nonspecific stimulation of these neurons can reinstate the original firing pattern, indicating that short-term synaptic changes enable inactive networks to support the retrieval of information effectively (Rose et al., 2016). Nonetheless, we admit that the observation that the maintenance of unconscious information can be supported by active neural firing (i.e., CDA) does not contradict the idea that an activity-silent mechanism may also exist. In fact, prior research provided some evidence of two distinct successive phases in the maintenance of aware and unaware information, with the initial common stage between the two types of information involving a transient period of approximately 1 sec, during which the representations are encoded through active firing that gradually diminishes. This is followed by an activity-silent maintenance phase, where neural activity intermittently resurfaces for aware stimuli or remains absent for unaware stimuli (Trübutschek, Marti, Ueberschär, & Dehaene, 2019; Trübutschek et al., 2017; King, Pescetelli, & Dehaene, 2016; Salti et al., 2015). In our experiment, visual information was maintained for approximately 1300 msec, which included a 33-msec presentation of the target Gabor stimulus, a 350-msec mask, and a 900-msec retention blank interval. This time frame aligns with the initial active firing phase observed in those previous studies for both aware and unaware information. Within this interval, we observed a reliable CDA for unaware visual information, providing compelling evidence that at least the initial maintenance phase relies on active neural firing. Possibly in line with this interpretation, our previous research on conscious information maintenance (Duma et al., 2019) showed that the early active firing phase reflected by CDA originating from the inferior IPS is supported by ACC activity during later stages, suggesting a distinct role of the IPS in early encoding and storage as well as ACC that could contribute to cognitive control and the safeguarding of information at later stages, possibly indicating a role that requires conscious awareness.

Our exploratory analyses revealed another theoretically important finding: CDA amplitude did not differ between PAS 1 correct and PAS 2 correct trials, despite participants reporting subjective unawareness in the former and awareness in the latter. This equivalence suggests that CDA reflects the objective maintenance of task-relevant information rather than subjective conscious access. These findings collectively suggest that the neural mechanisms supporting VWM maintenance operate independently of conscious awareness, at least during the initial active retention phase captured by the CDA.

We acknowledge that our study provides initial evidence for CDA differences in unconscious VWM, requiring replication. The limited sample size for the ERP analysis (n = 14) reflects the methodological demands of obtaining sufficient artifact-free trials across specific experimental conditions. Future studies should anticipate large exclusion rates when combining consciousness manipulations with ERP recordings and plan recruitment accordingly. Replication with larger initial samples will be important to confirm the robustness of these findings.

In conclusion, this study provides novel insights into the mechanisms underlying unconscious VWM by demonstrating that the CDA can reliably index the retention of visual information, even in the absence of conscious awareness. Our findings provide a proof of concept for unconscious VWM operating through the same neural processes as conscious VWM, specifically active neural firing during the initial retention phase. The significant presence of CDA in the correct responses during PAS 1 trials strongly supports the idea that unconscious visual information is actively maintained in VWM. Ultimately, this study bridges a critical gap in the understanding of unconscious VWM by integrating neural markers such as the CDA with broader theories of memory maintenance. Future research should continue to explore the interaction between active and activity-silent mechanisms, as well as the contributions of different brain regions in maintaining both conscious and unconscious visual information.

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Data Availability Statement

Behavioral and ERP data and scripts for the analyses are available at Open Science Framework (https://osf.io/gkmsy/).

Author Contributions

Filippo Gambarota: Conceptualization; Data curation; Formal analysis; Writing—Original draft. Roy Luria: Conceptualization; Writing—Review & editing. Antonio Maffei: Formal analysis; Writing—Review & editing. Roberto Dell'Acqua: Writing—Review & editing. Naotsugu Tsuchiya: Writing—Review & editing. Paola Sessa: Conceptualization; Formal analysis; Writing—Original draft.

Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .407, W(oman)/M = .32, M/W = .115, and W/W = .159, the comparable proportions for the articles that these authorship teams cited were M/M = .549, W/M = .257, M/W = .109, and W/W = .085 (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance.

Note

1. Although PAS 1 trials indicate the participants' report of no awareness, it is important to acknowledge that this does not necessarily equate to "objective" unconsciousness, as traditionally defined (e.g., $d' = 0$ in a two-alternative forced-choice task).

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