Are Functionally Passive Items in Working Memory More Resistant to Interference?

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Introduction

Human memory is a process of acquiring, storing, updating, and ensuring that information remains consistent with existing memory storage. It is considered one of the most essential skills in human cognition (Baddeley, 1993). This skill set allows humans to succeed in even the most basic daily life tasks, such as grocery shopping, and perform higher functions, such as communicating with each other, making sense of their past, and planning their future.

The architecture of human memory has been discussed since the very beginning of the science of psychology, even before it was considered a legitimate scientific discipline (Roediger & Yamashiro, 2019). Towards the end of the 19th century, the concept of remembering and forgetting was evaluated in an influential book by William James (1890). He distinguished memory systems into two categories based on for how long a piece of information can be stored. His conceptualization of primary and secondary memory was one of the earliest that suggested the distinction between what is now referred to as Long-term memory (LTM) and Short-term memory (STM).

LTM and STM are mainly different in terms of capacity and the duration of information storage (Cowan, 2008). Theoretically, LTM has no limitations, and once the information is successfully stored in LTM, it becomes accessible for a lifetime (Eysenck, 2020). Even if a memorandum is never retrieved after it is initially coded to LTM, it is still considered accessible. This long-term memory property allows humans to travel virtual time (Tulving, 1979) and to wander around in their own past.

Corresponding to James' primary memory concept, STM is responsible for retaining recently perceived information. Without rehearsal, the information in the short-term memory is susceptible to rapid decay. Miller (1956) suggested a limit for short-term memory capacity. He concluded that the limit of STM was 7 ± 2 items. He named his finding “Magical number 7 ± 2”. What was magical about this number is, based on his findings, that this limit was applicable across different paradigms, such as remembering digits, letters, words, or other discrete units of information. Cowan discussed the capacity of STM being 7 ± 2 (Cowan, 2001). He argued that strategies, such as chunking –grouping related information to remember them easily– might have influenced Miller’s findings. He sought to find the *pure* capacity of STM; hence, his tasks were designed to prevent participants from using those strategies. Cowan’s findings, which suggested a lower capacity limit of around four information bits, led the literature to re-evaluate the question of STM capacity (Cowan, 2001; 2004)

Regardless of its exact size, it was widely accepted that STM, as measured, has a limited capacity. This recognition of STM's limited capacity raised significant questions about the adequacy of existing memory models. Baddeley and Hitch (1974) proposed a model that would fill the gap in the current memory models. Early models of STM mostly conceptualized it as a passive storage system, where information was temporarily held without significant change and which was inadequate for explaining complex cognitive tasks requiring active manipulation of information (Miller, 1956; Atkinson & Shiffrin, 1968). Cognitive tasks often require not only the storage of information but also the active manipulation and sequencing of information in a hierarchical order. An example of active manipulation in STM is making a fried lion’s mane sandwich. One must remember the ingredients (bread, cheese, Lion’s Mane Mushroom, tomato, and mustard) and the order of assembly. Preparing the sandwich involves recalling and using this information step-by-step, such as spreading mustard before adding the mushroom. Such a task illustrates the necessity for a memory system that not only stores information but also actively manipulates it, highlighting the limitations of traditional STM models. In response, Baddeley proposed working memory (WM), a more active, online, and dynamic model (Baddeley & Hitch, 1974).

WM is not an entirely different concept from STM. Fundamentally, they are both responsible for retaining information for a short period. However, using the concepts in memory literature is flexible (Aben et al., 2012). It would be appropriate to make the following distinction: WM is an active system and, hence, is responsible for holding and manipulating stored information. In contrast, STM is conceptualized as solely responsible for storing information for a limited time and recall when needed.

The working memory system can be considered a processor responsible for adjusting information flow across memory storages. In the sandwich example above, WM enabled retrieval of the recipe from LTM while keeping the order of ingredients in the focus of attention, making it possible to execute goal-directed behavior. The most dominant model comes from Baddeley's research (Baddeley, 1992; Baddeley & Hitch, 1974), which describes WM as a system that includes multiple storage sub-systems specialized for different types of information. The main sub-systems in the model are the phonological loop, which holds auditory input, and the visuospatial sketchpad, which holds visual input. The model also contains the central executive responsible for operating the sub-systems.

Research has focused on neural regions that enable working memory functions. The prefrontal cortex (PFC) is the human brain region that is formed at the latest (Fuster, 2015) and is the center for the most developed and flexible cognitive skills specific to the human mind, such as abstract thinking, communication, decision-making, planning goal-directed behavior and top-down processing (Funahashi, 2022).

Long-accumulating data showed strong, persistent neural activity in the lateral PFC, dorsolateral parts (dlPFC), during the delay period of WM tasks. For an extended period, it has been assumed that maintenance in WM relies on persistent neural firing (Goldman-Rakic, 1995; Funahashi, 2017; Constantinidis et al., 2018), which means that after the initial encoding of the stimulus, neural firing is continuous keeping the representations of information active during the retention period, even when the stimulus is no longer present in the environment. The persistent activity requirement seems reasonable when looking at working memory's behavioral outcomes, such as using, transferring, manipulating, or combining newly encoded information with previously stored data after a brief retention period.

In one of the pioneer studies on short-term maintenance, Fuster & Alexander (1971) found that specific neurons of primates' PFC exhibited sustained firing during the maintenance and showed spiking during memory delays of WM tasks. This persistent activity was not dependent on external stimuli, suggesting that these neurons were actively maintaining information without sensory input. Moreover, sustained neuronal activity correlated with subjects' task performance, a simple delayed-response task. Furthermore, subjects with PFC lesions showed decreased WM performance (Bauer & Fuster, 1976). The implications of this research were influential on neuronal correlates of short-term maintenance. The results were considered direct evidence of persistent neural activity on STM and influenced the current understanding of the neural basis of transient memory retention.

In the subsequent years, persistent neural activity became synonymous with WM maintenance. However, some researchers have scrutinized the assumed relationship between persistent neural activity and WM maintenance (Sreenivasan et al., 2014; Stokes, 2015). The questions of whether persistent activity in the PFC is exclusively related to WM maintenance, whether persistent spiking in the PFC is necessary for successful goal-directed behavior, and whether the observed persistent activity during WM maintenance is merely a data interpretation have been discussed. Lundqvist, Herman, and Miller (2016) propose that persistent activity observed in working memory tasks may result from averaging the activity of neural populations, with individual neurons exhibiting more dynamic, transient bursts of activity rather than continuous firing. In addition, they proposed a more dynamic and variable model instead of the current persistent-activity model. They hypothesized that WM representations could be maintained by transient bursts of activity, which would be more energy-efficient than continuous spiking (persistent spikes imply elevated energy consumption).

Moreover, they stated that the so-called *activity-silent state* is not only more economical but also less labile in response to ongoing sensory input during maintenance. In other words, it may be more resilient to interference (Kozachkov et al., 2022). Sudden bursts —not persistent but sparse spiking[1]— allow groups of neurons involved in the relevant WM task to store information by protecting it from ongoing sensory inputs. This protection enables the information to be read out more accurately and reliably, which is critical for guiding behavior and task performance.

A synaptic theory has been put forward to underlie the functionally passive maintenance of working memory, which suggests that information is stored during the maintenance process of working memory through transient changes in the strength of synaptic connections between neurons. These changes occur due to the involved neurons' synaptic plasticity (SP). SP refers to the strengthening or weakening of synapses, the connections between neurons, due to the recent activity occurring on neurons (Citri & Malenka, 2008). The type of plasticity that might be supporting transient WM maintenance is known as short-term synaptic plasticity (STSP),

[1] In this context, spiking has been used to refer to the bursts observed in neuroimaging data, which appear as jumps relative to the baseline.

namely, temporary changes in the efficiency of synaptic transmission. These changes could either enhance (short-term facilitation) or reduce (short-term depression) the strength of synapses for a brief period (Zucker & Regehr, 2002; Stevens & Wang, 1995). It has been previously shown that synapses in WM-related neuron populations might be facilitated due to activity-induced residual calcium (Barak & Tsodyks, 2007).

When a neuron fires, calcium ions enter the presynaptic terminal, a specialized region in the neuron's axon filled with vesicles carrying neurotransmitters. If the neuron fires again before calcium levels return to baseline, the increased calcium concentration can enhance neurotransmitter release, thereby strengthening synaptic transmission. This process is known as short-term facilitation. In the context of WM, this synaptic enhancement by residual calcium acts as a temporary trace of the stored information. This 'synaptic trace' means that persistent spiking is unnecessary, as the elevated calcium levels in the presynaptic region maintain the strengthened synaptic connection longer, preserving the information in WM.

Wolf et al. (2017) employed an innovative method in their study. The researchers employed a method they likened to sonar[2], in which they introduced a stimulus to probe the activity-silent states in WM. They used an experimental flow shown in Figure 1 and presented participants with task-neutral and high-contrast stimuli during the WM maintenance period. The aim was to decode activity-silent information from the EEG data after participants were exposed to the impulse. Because this information was stored in an 'activity-silent' manner, it was expected to be undetectable in the EEG data without external stimulation. As proof of this, the researchers reported that decoding accuracy quickly dropped to chance levels after the memory items were

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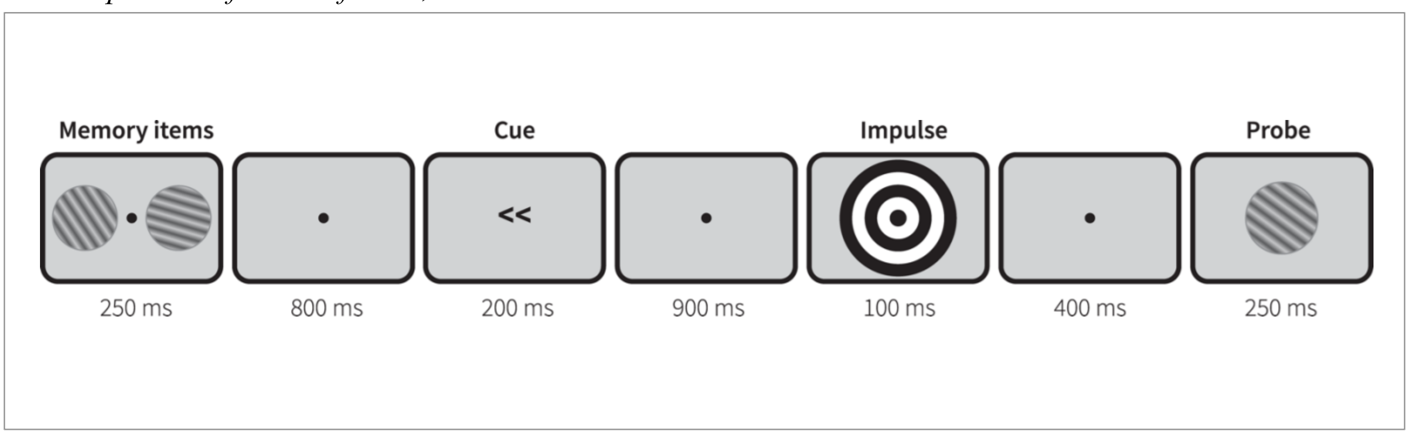
[2] Active sonar works by emitting a sound pulse into the water. When this pulse hits an object, it bounces back as an echo. The sonar transducer then receives this echo and measures the time taken for the pulse to return, which helps determine the object's distance and position. Animated example of how Sonar systems work

presented, indicating a lack of detectable activity. This suggests that the information is maintained in an activity-quiescent state between the presentation of the memory items and the probe.

Furthermore, they demonstrated that the orientation of the cued memory item could be decoded from the EEG data during maintenance in response to the impulse stimulus (Wolf et al., 2019; Pals et al., 2020). Consequently, they introduced the idea that it was possible to decode the content stored in an activity-quiescent fashion by pulsing WM networks through a task-neutral high-contrast stimulus. These findings suggest that WM networks can flexibly shift the functional status of retained information between active and passive states, depending on its relevance to the ongoing task, thereby optimizing cognitive resources.

Figure 1

Main experiment flow Wolf et al., 2017



Pals et al. (2020) used an artificial neural network model to simulate activity-silent processes. A spiking-neuron model of WM was used to assess how short-term synaptic plasticity contributes to information maintenance. The main objective was to build a computational model of WM that could represent the experimental findings of silent state working memories.

Additionally, short-term synaptic plasticity was also considered while modeling the activity-silent WM states. This was achieved by incorporating the calcium kinetics mechanism proposed by Mongillo et al. (2008). By incorporating this mechanism, their model represented the temporary changes in synaptic strength due to neuronal activity, allowing it to account for both active and activity-silent phases of working memory. Their model successfully reproduced the dynamics of STSP in a biologically realistic manner. This allowed the model to simulate how transient synaptic changes could maintain information in working memory without continuous neuronal firing. In line with the previous understanding, Mongillo's model suggests that storing information in short-term synaptic changes rather than persistently firing neuronal representations makes it less dependent on strong interactions between neurons, making it more resistant to distraction and interference.

While computational models provide theoretical support, empirical evidence from transcranial magnetic stimulation (TMS) studies further substantiates the role of STSP in activity-silent WM maintenance. Rose et al. (2016) demonstrated that latent working memory traces, which are not maintained by continuous neural activity, can be reactivated using TMS. Participants were asked to hold two items in working memory. During a delay period, the researchers applied TMS to the brain region associated with WM maintenance (typically the PFC) to see if it would reactivate the latent memory trace. They found that TMS pulses could reactivate the latent memory trace, causing the neural activity associated with the previously latent item to become detectable again. This indicated that the memory trace was not lost but remained in a 'silent' state, capable of being reactivated.

Muhle-Karbe et al.'s (2021) study provides valuable insights into how information might be stored in an activity-silent manner in an experimental setting. In their study, a delayed-response task was employed where participants were asked to hold two stimuli in mind. After presenting the stimuli, a cue indicated which stimulus would be needed shortly afterward, while the other stimulus would be required later in the experiment. The study found that the cued memory item was maintained in an active state, whereas the uncued item was held in an activity-silent state. This suggests that the immediately-needed memory item remains within the focus of attention while the item required later is passively stored. This finding supports the idea that working memory, which guides behavior, may operate hierarchically, prioritizing information based on its immediate relevance.

It is reasonable to suggest that information encoded in an activity-silent state within working memory (WM) populations is less metabolically costly as action potentials account for around 47% of overall ATP usage, and while sustained-activity stored memories are more engaged with sensory processing (Mallett & Lewis-Peacock, 2018), activity-silent memories, stored via short-term synaptic plasticity (STSP), do not have this disadvantage. Neural firing is dynamic and prone to interference, whereas synaptic storage is more stable and requires less continual updating (Kozachkov et al., 2022). As a result, activity-silent memories are likely to be better protected from ongoing sensory input and both task-relevant and task-irrelevant interference. Additionally, this information may be preserved and retrieved more accurately when needed (Atwell & Laughlin, 2001; Stokes, 2015; Oberaur & Greve, 2022; Buschman, 2021; Kilpatrick, 2017; Stokes et al., 2020).

From this perspective, we conducted two experiments in the current study to investigate the role of neural activity-states in WM and their resilience against interference. Activity-silent states refer to a form of memory storage where information is maintained through changes in synaptic strength rather than persistent neural activity. We hypothesized that these states – corresponding to the functionally passive (uncued-unprioritized) items in our task—would be more resilient to interference than the functionally active (cued-prioritized) items stored through ongoing neuronal firing. The experiments employed a 2-item delayed response task, manipulating the similarity between the interference task and the memory items to assess the effects of interference. By cueing which item would be probed first, we induced a functionally active state for that item, whereas the second unprioritized item remained in an activity-silent state. Through these experiments, we aim to clarify how neurally active and activity-silent states in WM correspond to the functionally active and passive items in our design and their vulnerability or immunity to interference

Method

Participants

Participants were recruited through the University of Groningen SONA participant pool website. Some participants joined the study in exchange for SONA credits, while others received a monetary incentive (€12). A total of 52 participants were involved in Experiment 1. The participants' ages ranged from 18 to 42 years (M = 21.9, SD = 4.75). Of these participants, 34 (65.38%) were female. The second experiment involved 44 participants aged 18 to 35 (M = 22.2, SD = 3.71), and 34 (77.3 %) were female. The study was conducted following the Declaration of Helsinki (2008). It was approved by the Ethical Committee of the Faculty of Behavioral and Social Sciences at the University of Groningen (approval number PSY-2122-S-0206). All participants reported normal or corrected-to-normal vision.

Apparatus and Stimuli

OpenSesame v3.3.14, an open-access experimental software, was used for designing and executing this experiment (Mathot et al., 2012). The experiment was conducted on a 19-inch CRT monitor with a resolution of 1280 x 1024 pixels and a refresh rate of 100 Hz. Participants completed the experiment in a sound- and light-isolated booth within the laboratory, with dim lighting controlled by the researcher. The entire experiment was presented on a dark gray background (RGB: 128, HEX: #808080). The Gabor patches were set to 80% contrast relative to the background, with a spatial frequency of 0.05. The colors of the stimuli were selected from the CIE Lab color space (*L = 70, a = 0, b = 0, radius = 38).

Procedure

General Procedure

Participants took part in the experiment at the Behavioral and Social Sciences (BSS) faculty building of the University of Groningen. They arrived at the laboratory on the date and time they selected through the participation platform and were welcomed by the researcher. Participants were taken to sound-attenuated cabinets to begin the experiment. After filling out the consent form, they were given a written document explaining the experiment. Once they had read the document, the researcher briefly explained the experimental flow and answered their questions. The first two blocks were practice blocks, followed by 14 experimental blocks. In total, they completed 384 experimental trials in 16 blocks, lasting approximately 90 minutes. Participants received feedback after each trial in the practice phase but only after each block in the experimental blocks. Participants had the right to withdraw from the experiment at any stage.

Additionally, they were allowed to take a break between blocks. All manipulations detailed below were randomized and counterbalanced.

Experiment 1

Experiment 1 (Figure 2A) aimed to test whether memory items in a prioritized (cued) state are more susceptible to featural interference compared to items in a deprioritized (uncued) state. The experiment was structured into 16 blocks, each beginning with a block cue that indicated the type of memory item (colored circle or Gabor patch) that would be probed first. Once the block cue was given, the cued type of item was consistently probed first throughout that block, making it functionally active.

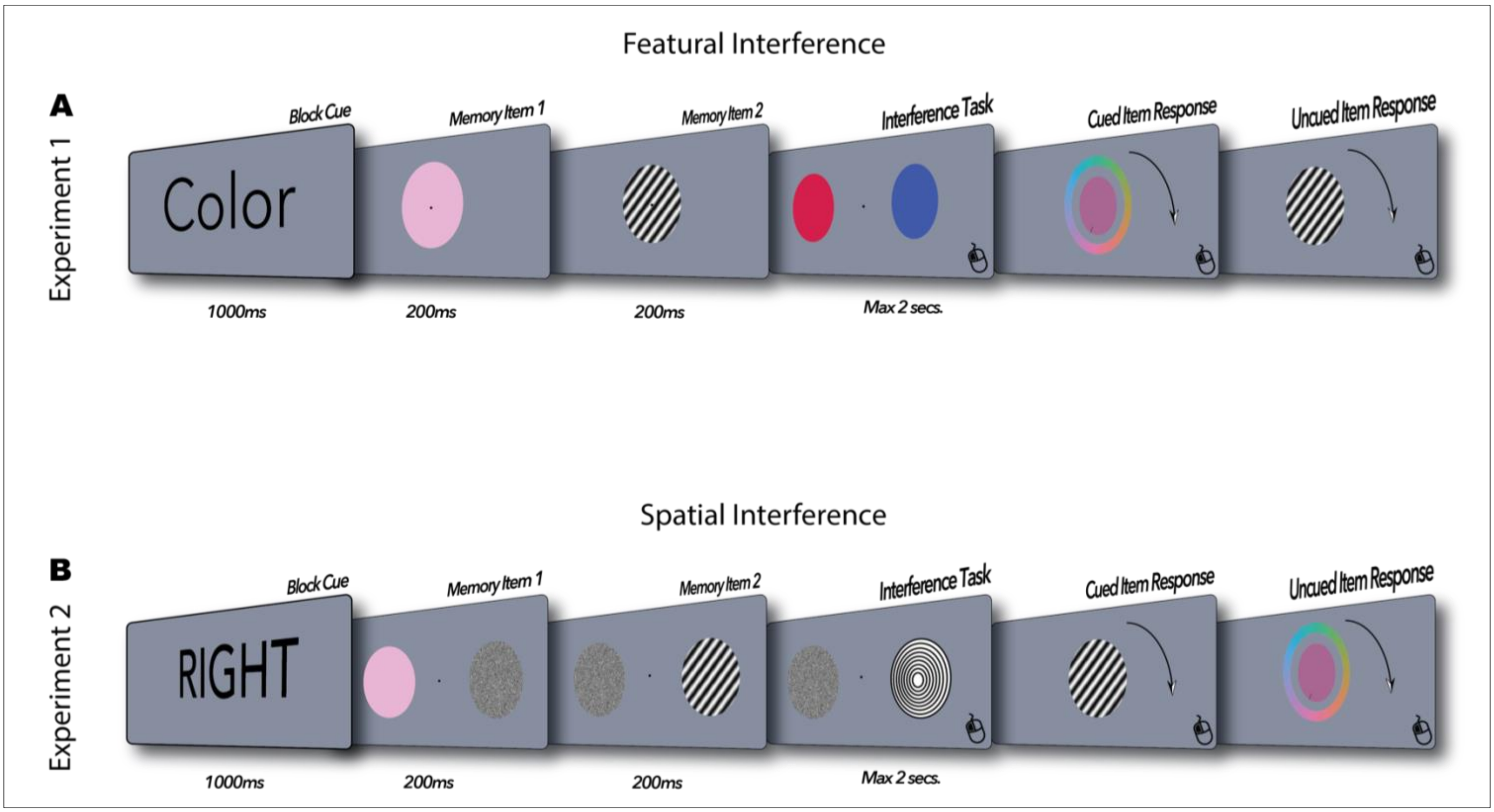
At the beginning of each block, participants received a block cue for 1000 milliseconds. Following the cue, an initial fixation dot between 300 and 500 milliseconds appeared. Then, the first memory item, either a colored circle or a Gabor patch, was presented randomly for 200 milliseconds at the center of the screen. Afterward, a fixation dot appeared and lasted 900 milliseconds, and then the second memory item of the opposite type from the first was presented for another 200 milliseconds.

After two memory items were presented, participants performed an interference task, which could last a maximum of 2000 milliseconds. During this task, participants were required to determine whether the two items on the array were the same or different or, in the baseline condition, participants did nothing; they waited for the probe phase. If the interference task involved colored circles, participants judged whether the two circles were the same color. If the task involved Gabor patches, participants determined whether the orientation of the two patches was the same. The interference trials were counterbalanced to ensure equal representation of 'same' and 'different' conditions, and the order of presentation was randomized across trials.

Additionally, the colors and orientations of the interference stimuli were randomly selected. Interference stimuli were presented on a horizontal axis, with one stimulus positioned at x = -244 pixels (left side of the screen) and the other at x = 244 pixels (right side of the screen), both aligned vertically at y = 0.

Figure 2

Overview of the structure of Experiments 1 and 2



Note. Figure A shows a typical trial from the experiment one. Interference task was also included an orientation and baselineconditions. Figure A depicts a "match trial" as the type of the memory item and the interference task is the same both being colored circles. Figure B shows a typical trial from the experiment two. Interference task was also included a "low spatial frequency" and baseline condtions. Again, Figure B depicts a match trial as the location of the memory item and interference task both located in the same spatial location.

At the end of each trial, participants responded to the memory items by selecting the correct color from a color wheel for the color memory item or by rotating a Gabor patch to match the correct orientation for the orientation memory item.

The interference manipulation was based on whether, in each trial, the feature of the prioritized item matched the feature involved in the interference task. A trial was considered an “interference trial” if there was a match due to the potential for feature-based interference. If there was no match, it was classified as a no-interference trial. The same logic applies to the deprioritized item.

Experiment 2

Experiment 2 aimed to measure the potential interference effects of the similarity between the spatial location of the cued memory item and the interference task. The research question in Experiment 2 was identical to that in Experiment 1; however, in Experiment 2, the effects of location-based interference were investigated instead of feature-based interference.

At the beginning of each block, participants received a block cue for 1000 milliseconds, which specified whether the item on the left or right would be prioritized during the probe phase (Figure 2b). Following this cue, an initial fixation dot between 300-500 milliseconds appeared. Then the first memory item, either a colored circle or a Gabor patch, was presented laterally at an equal distance of 5.93 degrees of visual angle from the fixation dot. Each memory item was presented with a black-and-white noise patch in the opposite, empty location. Afterward, the second memory item of the opposite type from the first was presented with a noise patch for another 200 milliseconds in the same fashion.

After the memory items were presented, participants performed the interference task, which could again last a maximum of 2000 milliseconds. For the interference task, in one location, participants saw a black-and-white ‘bull’s eye’ stimulus, and the task was to judge if the spatial frequency of this item was high or low. The spatial frequencies used were 0.5 (low spatial frequency) and 1.4 (high spatial frequency). The ‘empty’ location was once again filled with a noise patch. At the end of each trial, participants were required to respond to both memory items in the order specified by the block cue. The response involved adjusting a Gabor patch to match the remembered orientation and selecting the right hue from the color wheel to match the remembered color.

Analysis

We identified and excluded outliers using the interquartile (IQR) rule, defining outliers as subjects whose average scores on the first and second memory items fell 1.5 times the interquartile range below the 25th percentile or above the 75th percentile (Exp1: N=6, Exp2: N=2).

The memory items presented in the experiment were probed using a 360-degree color wheel for the color circle and a similarly manipulated 360-degree Gabor patch. Participants' responses were converted into absolute errors in degrees. The difference between the degree of the presented item (color circle) on the color wheel and the degree selected by the participant during the probe phase was defined as the absolute error. The same procedure was applied to the direction of the Gabor patch. The difference between the presented item's direction on the Gabor patch and the direction selected by the participant during the probe phase was also calculated as the absolute error.

The absolute errors for each trial were calculated based on whether the items were cued and the outcomes of match and non-match conditions in the interference task. This calculation assessed the differences in absolute error across these conditions. Paired samples Bayesian t-tests were employed to compare the performance of cued and uncued items based on their match with the interference task.

In the current experiment, the two-component mixture model by Zhang & Luck (2008) was fitted independently to cued and uncued items to compare the items' memory characteristics and examine the nature of the effects of interference on memory items more deeply. The model has two assumptions, with resultant parameters: In a continuous memory task, the participant's response is influenced by how well the memory item aligns with the representation encoded in their working memory. If the memory item is closely aligned with this representation, the participant's response will be near the item's position on the color wheel, which leads to higher precision (κ) values. However, if the working memory representation is weak, noisy, or completely lost, the response will involve random guessing, meaning the participant's selection could fall at any point on the color wheel, increasing the uniformity (Pμ) values.

The pre-processing, model fitting of the mixture model (Grange & Moore, 2022; version: 1.2.1, R Mixtur Package), and the creation of plots were performed using the RStudio software (RStudio Team, 2024, version 2024.4.2.764).

Results

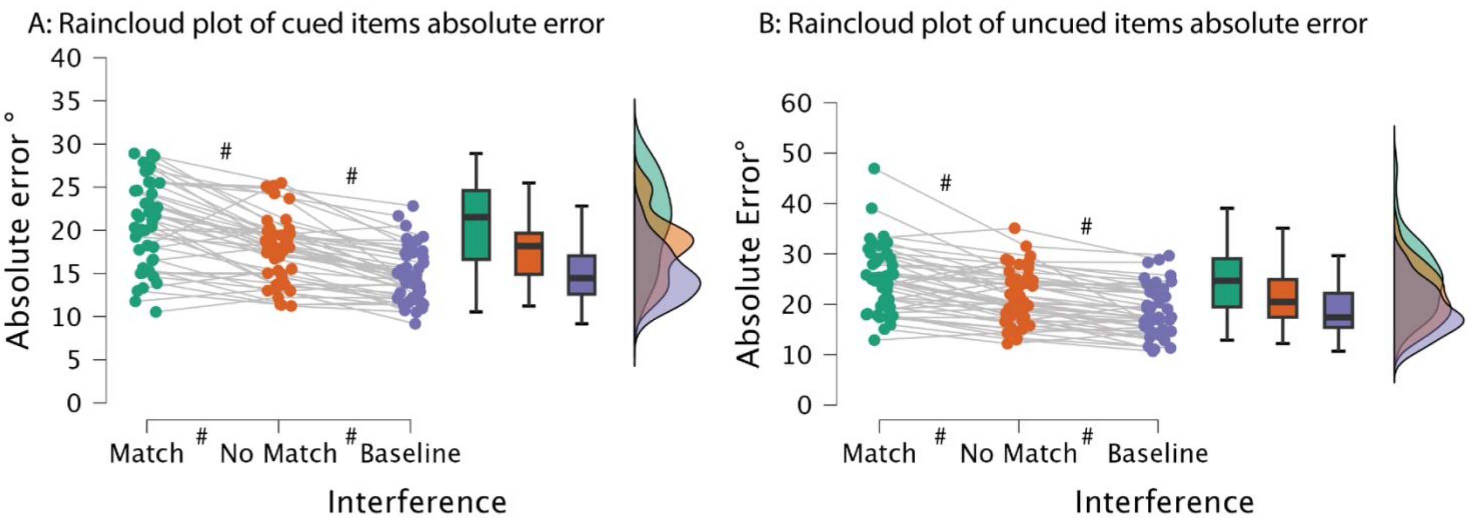
Experiment 1

In Experiment 1, it was examined whether feature-based interference affected the performance of functionally active and passive items equally in working memory. Table 1 shows the average absolute error of all conditions. A binomial test indicated that participants performed significantly above chance level in the interference task, both in the color and orientation, with a success rate of 88.66% sd = 7.59% (95% CI [88.25%, 100%]), *p* <.001. Absolute error rates of cued items (μ = 17.853°, sd = 4.73°) were significantly lower than uncued items (μ = 21.638°, sd

= 6.191 (t_{paired} , BF_{10} = >100) . Note that lower absolute values indicate higher memory performance.

Figure 3

Raincloud plots of the interference conditions



Note. Figure A shows the average absolute errors in degrees for cued items under interference conditions, while Figure B shows the same for uncued items.
#: Significant difference BF10 > 100

Table 1

Descriptive statistics of Exp 1. Absolute error

Item Type	Mean (SD)	Range
Cued Items		
High Interference	20.8° (4.89)	10.5° - 28.9°
Low Interference	17.8° (3.90)	11.2° -25.4 °
No Interference	14.84°(3.11)	9.17° - 22.8°
Uncued Items		
High Interference	24.7° (6.71)	12.8° - 46.93°
Low Interference	21.41°(5.39)	12.1° - 35°
No Interference	18.72°(4.88)	10.6° - 29.6°
Cued Items Overall	17.83°(4.73)	9.1° - 28.9°
Uncued Items Overall	21.63°(6.19)	10.6° - 46.9°

When the feature of the interference task matched the feature of the cued items, the errors for the cued items were higher (μ = 20.8°, sd = 4.89°), compared to when the feature did not match (μ = 17.8°, sd = 3.90°),(t_{paired} , BF_{10} = >100). However, the error rates were even lower in the baseline condition, where there was no interference task at all, compared to non-match trials (μ = 14.84°, sd = 3.11°), (t_{paired} , BF_{10} = >100). The same pattern was observed for uncued items as well. Like cued items, uncued items were also affected by interference, and the effect of interference was substantial when the feature of the interference task matched the uncued item (Table 2).

Table 2

Bayesian Paired Samples T-Test of Absolute error

Measure 1		Measure 2	BF_{10}	error %
Cued Items				
High Interference	-	Low Interference	37898.634	1.179×10^{-10}
Low Interference	-	No Interference	$1.133\times10^{+8}$	7.866×10^{-14}
Uncued Items				
High Interference	-	Low Interference	3022.185	1.701×10^{-6}
Low Interference	-	No ınerference	158067.907	3.735×10^{-11}
HI Cued Item (z-scored).	-	HI Uncued Item (z-scored)	0.162	0.060

Note. HI.: High Interference - Match Conditions

To test the study's central hypothesis, the effect of the interference task on items was measured by comparing the memory performance of cued items with that of uncued items. The scores were standardized to control for the inherent performance advantage of cued items by converting them into z-scores; the higher scores of cued items were controlled for via standardization. This comparison showed no difference between the z-scores of the prioritized and deprioritized items (t_{paired}, $BF_{10} = 0.162$).

As an exploratory analysis, the cued and uncued items' scores were combined across both interference conditions (match and non-match), and the difference between these combined scores and the related baseline scores was calculated. A Bayesian paired t-test conducted on these performance difference scores revealed that the difference was not statistically significant (t_{paired}, $BF_{10} = 0.168$). In other words, this result demonstrated that cued and uncued items were similarly affected by interference, taking their baseline scores into account.

As discussed above, Zhang and Luck's (2008) two-component model was applied to the data to understand better how and to what extent interference affected the memory items' fate. Independent model fitting was conducted separately for cued and uncued items. Table 3 shows the average model parameters for cued and uncued items.

Table 3

A- Mean values of two component model - Cued Items

Item Type	Mean (SD)
Memory Precision – (k)	
High interference	9.051 (4.71)
Low interference	10.365 (3.87)
Baseline	12.181 (3.93)
Guess Rate – (u)	
High interference	0.072 (0.048)
Low interference	0.051 (0.047)
Baseline	0.024 (0.383)

a - Mean values of two component model - Uncued Items

Item Type	Mean (SD)
Memory Precision – (k)	
High interference	7.439 (2.96)
Low interference	8.658 (2.94)
Baseline	9.694 (3.93)

Item Type	Mean (SD)
Guess Rate – (u)	
High interference	0.109 (0.083)
Low interference	0.085 (0.071)
Baseline	0.056 (0.60)

The Bayesian Repeated Measures ANOVA revealed strong evidence that both interference condition and item type (cued vs. uncued) significantly impacted memory precision. The effect of interference conditions, with BF_{10} = >100, indicates that memory performance varies significantly across high interference, low interference, and baseline conditions. A post hoc analysis further confirmed significant differences between all interference levels, with high interference having the most significant impact compared to baseline and low interference.

For item type, the analysis showed a significant difference between cued and uncued items, as indicated by BF_{10} = >100 with cued items consistently showing higher precision. However, the interaction effect between item type and interference condition was not supported , as indicated by BF_M = 0.723, suggesting that both cued and uncued items were similarly affected by interference.

Table 4

Bayesian RM Anova for Memory Precision (k) parameter

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
Null model (incl. subject and random slopes)	0.200	1.646×10^{-11}	6.583×10^{-11}	1.000	
Item type + Interference Condition	0.200	0.847	22.103	$5.145\times10^{+10}$	1.252
Item type + Interference Condition + Item type ✻ Interference Condition	0.200	0.153	0.723	$9.296\times10^{+9}$	3.976
Interference Condition	0.200	2.404×10^{-4}	9.620×10^{-4}	$1.461\times10^{+7}$	1.441

Bayesian RM Anova for Memory Precision (k) parameter

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
Item type	0.200	4.315×10^{-8}	1.726×10^{-7}	2621.619	1.259

Note. All models include subject, and random slopes for all repeated measures factors.

Post Hoc Comparisons - Item type

		Prior Odds	$BF_{10,U}$	error %
Cued	Uncued	1.000	318087.626	2.454×10^{-12}

Post Hoc Comparisons - Interference Condition

		Prior Odds	Posterior Odds	$BF_{10,U}$	error %
High	Low	0.587	67.735	115.314	1.445×10^{-8}
	Baseline	0.587	$1.837 \times 10^{+7}$	$3.127 \times 10^{+7}$	1.821×10^{-10}
Low	Baseline	0.587	100.615	171.289	9.065×10^{-9}

Note. The posterior odds have been corrected for multiple testing by fixing to 0.5 the prior probability that the null hypothesis holds across all comparisons (Westfall, Johnson, & Utts, 1997). Individual comparisons are based on the default t-test with a Cauchy (0, r = 1/sqrt(2)) prior. The "U" in the Bayes factor denotes that it is uncorrected.

The second Bayesian repeated measures ANOVA (Table 5) revealed a significant difference in random guessing rates (Pu) between cued and uncued items. Uncued items displayed higher guessing rates than cued items, as indicated by the strong evidence with a $BF_{10} > 100$, suggesting that uncued items are more susceptible to random guessing.

Additionally, the interference condition substantially impacted guessing rates, with high interference leading to significantly higher guessing compared to low interference and baseline conditions. The baseline condition showed the lowest guessing rates, implying better memory performance when no interference was present.

Table 5

Bayesian RM Anova for Random Guess (P_u) parameter

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
Null model (incl. subject and random slopes)	0.200	1.094×10^{-6}	4.377×10^{-6}	1.000	
Item type + Interference Condition	0.200	0.890	32.351	813216.970	1.783
Item type + Interference Condition + Item type ✻ Interference Condition	0.200	0.076	0.327	69024.141	2.307
Interference Condition	0.200	0.034	0.143	31500.170	1.657
Item type	0.200	2.491×10^{-5}	9.963×10^{-5}	22.758	2.104

Note. All models include subject, and random slopes for all repeated measures factors.

Post Hoc Comparisons - Item type

		Prior Odds	$BF_{10,\,U}$	error %
Cued	Uncued	1.000	227.067	8.705×10^{-9}

Post Hoc Comparisons - Interference Condition

		Prior Odds	Posterior Odds	$BF_{10,\,U}$	error %
High	Low	0.587	12.087	20.577	1.023×10^{-7}
	Baseline	0.587	110490.039	188099.832	2.126×10^{-12}
Low	Baseline	0.587	8.525	14.513	1.504×10^{-7}

Note. The posterior odds have been corrected for multiple testing by fixing to 0.5 the prior probability that the null hypothesis holds across all comparisons (Westfall, Johnson, & Utts, 1997). Individual comparisons are based on the default t-test with a Cauchy (0, r = 1/sqrt(2)) prior. The "U" in the Bayes factor denotes that it is uncorrected.

However, there was no evidence of a significant interaction between item type (cued vs. uncued) and interference condition ($BF_{10} = 0.327$). This means that while both cued and uncued items were affected by interference, the magnitude of the effect on random guessing did not differ significantly between the two types of items. Both item types experienced increased guessing rates with higher interference, but the extent of this impact was similar for both cued and uncued items.

Experiment 2

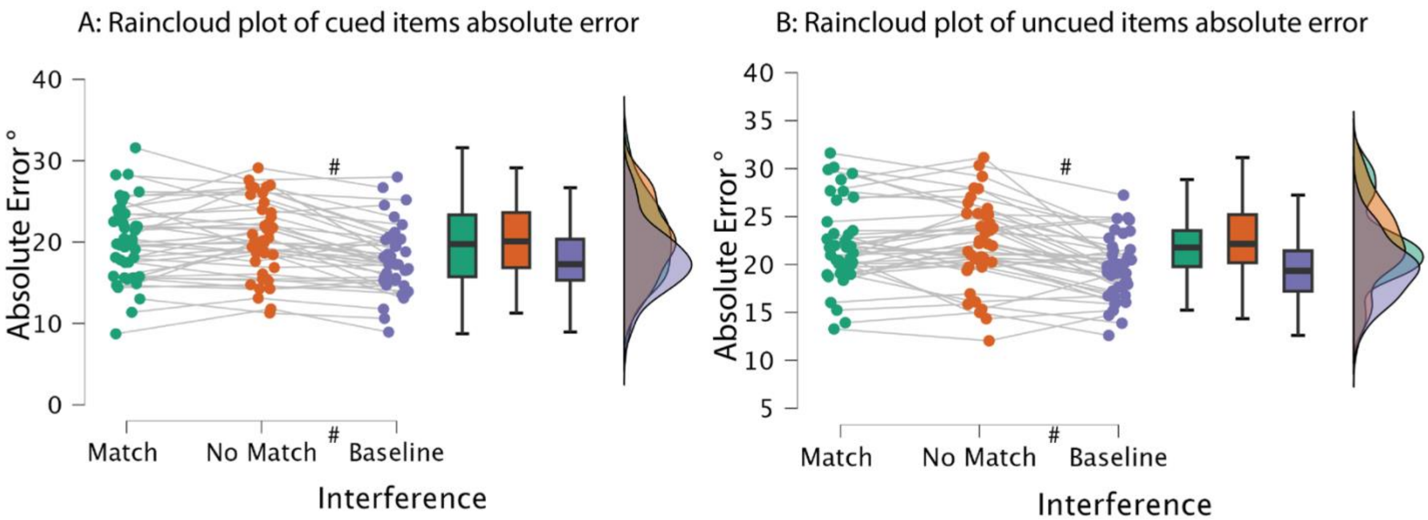
In the second experiment, unlike the first, the effect of the interference task's similarity in terms of spatial location, rather than feature, on both cued and uncued items was examined. Table 5 shows the average absolute error rates of all conditions. Absolute error rates of cued items (μ = 19.36°, sd = 4.31°) were significantly lower than uncued items (μ = 21.26°, sd = 3.64 (t_{paired}, BF_{10} = > 100) in match condition. The absolute error rates of baseline condition in cued items were lower than those of uncued items (t_{paired}, BF_{10} = 21.836). A binomial test indicated that participants performed significantly above the chance level in the interference task, with a success rate of 95.90% (95% CI [95.64%, 100%]), $p < .001$.

Table 6

Descriptive statistics of Exp 2. Absolute error

Item Type	Mean (SD)	Range
Cued Items		
Match	19.90° (4.89)	8.72° - 31.5°
No Match	20.27° (4.65)	11.27° -29.12 °
Baseline	17.90°(4.11)	8.94° - 28.001°
Uncued Items		
Match	22.07° (4.35)	13.27° - 31.62°
No Match	22.17°(4.41)	12.04° - 31.15°
Baseline	18.53°(3.24)	12.60° - 27.23°
Cued Items Overall	19.36°(4.31)	9.82° - 29.07°
Uncued Items Overall	21.26°(3.64)	13.34° - 28.41°

For Experiment 2, no performance difference was found between match and no-match trials for both cued (t_{paired}, BF_{10} = 0.247) and uncued (t_{paired}, BF_{10} = 0.173) items. On the other hand, a significant performance difference emerged between the baseline condition and the no-match condition on both item types with a value of $BF_{10} > 100$. This indicates that interference was effective for both cued and uncued items, but unlike in Experiment 1, the matching of the interference task's properties with the memory items' (match trials) did not affect performance.



Note. Figure A shows the average absolute errors in degrees for cued items under interference conditions, while Figure B shows the same for uncued items.
#: Significant difference BF10 > 100

In Experiment 2, as in Experiment 1, the performance of cued and uncued items under interference was compared. However, since there was no significant difference between the match and no-match conditions, the interference could not be classified as high or low. Therefore, the match and no-match conditions were combined, and the z-score of this combined score was calculated for comparison, instead of comparing the match condition. However, a significant difference between z-scored performance of cued and uncued items did not appear. The effect of both task specific and task unspecific interference on the probe performance of cued and uncued items was similar .

Table 7

Bayesian Paired Samples T-Test of absolute errors

Measure 1		Measure 2	BF_{10}	error %
Cued Items				
Match	-	No Match	0.247	0.046
No Match	-	Baseline	23495.471	2.189×10^{-10}
Uncued Items				
Match	-	No Match	0.173	0.053
No Match	-	Baseline	8004.797	4.405×10^{-6}
Cross Comparison				
Z-score Cued Item I	-	Z-Score Uncued Item I	0.169	0.053
Overall Cued Item	-	Overall Uncued Item	4286.906	2.884×10^{-6}

Note. I: Interference

The two-component model was fitted to the data from the second experiment. Table 8 shows the average model parameters for both cued and uncued items. In terms of memory precision, no significant differences were found between cued and uncued items (t_{paired}, BF_{10} = 0.681) in the match conditions. Additionally, memory precision in the match and no-match conditions was statistically similar for both cued items (t_{paired}, BF_{10} = 0.167) and uncued items (t_{paired}, BF_{10} = 0.403). Likewise, the difference between no-match and baseline conditions was minimal, with BF_{10} values of 1.136 for cued items and 0.177 for uncued items. Thus, overall, interference had no significant impact on memory precision for either cued or uncued items.

However, there was a marginal difference in random guessing between cued and uncued items (t_{paired}, BF_{10} = 1.510). Notably, this difference also appeared in the baseline condition for both item types, suggesting that the observed difference in random guessing was not due to interference.

Table 8

A- Mean values of two component model - Cued Items

Item Type	Mean (SD)
Memory Precision – (k)	
Match	8.211 (4.173)
No Match	8.199 (4.050)
Baseline	9.014 (4.715)
Guess Rate – (u)	
Match	0.054 (0.053)
No Match	0.056 (0.047)
Baseline	0.032 (0.47)

B - Mean values of two component model - Uncued Items

Item Type	Mean (SD)
Memory Precision – (k)	
Match	7.447 (3.237)
No Match	8.042 (3.598)
Baseline	7.919 (3.195)
Guess Rate – (u)	
Match	0.074 (0.058)
No Match	0.091 (0.073)
Baseline	0.047 (0.55)

Table 9

Bayesian Paired Samples T-Test of model parameters

Measure 1		Measure 2	BF_{10}	error %
Precision Cued				
Match	-	No Match	0.167	0.055
No Match	-	Baseline	1.136	0.022
Precision Uncued				
Match	-	No Match	0.403	0.038
No Match	-	Baseline	0.177	0.054

Bayesian Paired Samples T-Test of model parameters

Measure 1		Measure 2	BF_{10}	error %
Random Guess Cued				
Match	-	No Match	0.179	0.054
No Match	-	Baseline	39.731	0.046
Random Guess Uncued				
Match	-	No Match	>100	1.187×10^{-8}
No Match	-	Baseline	>100	3.601×10^{-9}
Across Item Comparisons				
Match Cued Precision	-	Match Uncued Precision	0.681	0.029
Match Cued Random Guess	-	Match Uncued Random Guess	1.510	0.018
Baseline Cued Random Guess	-	Baseline Uncued Random Guess	1.490	0.018

General Discussion

Experiment 1 demonstrated that the interference condition affected both cued and uncued memory items as expected. Furthermore, the effect of interference varied depending on the match with the memory items. As the level of interference increased, its impact grew, leading to a decline in performance. This finding aligns with the finding that task-related information following target information is more contaminating than task-unrelated information (Kliegl & Bauml, 2021). The significant results of the interference task validated that the interference task in Experiment 1 was successful.

Interference not only increased the absolute error but also systematically affected memory precision and random guessing. For both cued and uncued items, memory precision varied depending on the level of interference. As the level of interference increased, precision decreased, and the rates of random guessing increased.

Cued items consistently exhibited better memory performance compared to uncued items. While the feature-based interference task affected both items, the magnitude of this effect did not differ between cued and uncued items. Uncued items did not demonstrate resilience to interference.

In Experiment 2, the interference task affected both cued and uncued items. However, this time, the effect did not vary with the level of interference. No significant difference in the impact of interference was found between the match condition and the no-match condition. It was found that the overlap in spatial location between the interference task and the memory items did not produce a significant difference, but the presence of interference task itself did. This may suggest that if location is not an inherent part of the task, overlapping locations do not interfere with working memory.

The performance of cued items was higher than uncued items both under interference and in the baseline condition. However, memory precision did not differ between cued and uncued items. In conditions where interference was present, the precision of both cued and uncued items was similar.

On the other hand, random guessing was higher for uncued items. Although random guessing did not vary based on the levels of interference for uncued items, the difference in random guessing between cued and uncued items persisted, even though their precision remained the same. In Experiment 1, the performance difference between cued and uncued items was accompanied by changes in both precision and guessing rates. However, in Experiment 2, the performance difference was accompanied only by changes in the guessing rate.

Neural correlates of WM

There is increasing evidence in the literature that information retention in working memory can occur both in active and activity-silent forms (Stokes, 2015; Kozachkov et al., 2022; Mongillo et al., 2008). This may depend on the task relevance, relative importance, and other characteristics of the stored information. Both types of retention may have their advantages and disadvantages. In this study, we tested the resilience of information with the potential for activity-silent retention (a potential driven by the item's task relevance and functional priority status) to proactive interference. This resilience could be one of the functional advantages of activity-silent retained information as the STSP account of activity-silent states suggests (Stokes, 2015).

In this study, we aimed to manipulate the neural states of working memory items by prioritizing them. We hypothesized that prioritized items would be stored in an activity-dependent state, while non-prioritized items would be encoded in an activity-silent state. However, this study did not collect any neural data; therefore, we did not provide data on the neural correlates of memory item representations. We did not have data on the neural states in which prioritized and unprioritized items were stored. Studies that collect concurrent neural data during the task could reveal how successfully items are encoded into active or silent states.

The performance difference between cued and uncued items might indicate that different neural systems maintain these two types of items. On the other hand, one of our findings was that cued items were equally resistant, if not more, to interference but also stored with higher precision and lower random guessing. Our prediction that functionally passive items in working memory would have an advantage against interference was not supported.

There could be several reasons for this. The current study used a pre-cueing (block-cueing) method, which indicates which item will be probed before the working memory items are even presented, allowing participants to encode the memory items with this knowledge. Although participants showed reasonable performance for uncued items, they may have allocated disproportionately more attention to the cued items, which could have substantially weakened the representations of the uncued items, even though a response was always required for them as well. Such a difference between the allocation of internal focus on items might have hindered any possible protection against distraction for uncued items. The affected representations of uncued items could explain the elevated random guess rates between cued and uncued items. A study using a retro-cue design could measure the effectiveness of interference by balancing the focus of attention across items, while still prioritizing items during WM maintenance.

The interference task used in our study consisted of two conditions besides the baseline condition, in which no task was present. These two conditions were match and no-match. In the no-match condition, which did not overlap with the cued item's content, the interference task still overlapped with the uncued item. In summary, the interference task used in our study was not qualitatively different from the memory items. This could have created a ceiling effect for the interference impact, potentially obscuring any protective effect.

Lastly, it might be argued we were not able to sufficiently represent functionally active WMs in active states. In that case, this may suggest that functionally passive items were not subjected to relatively activity-silent encoding either. This situation could lead to competing representations, in which cued items would always consume more of the focus of attention's resources; therefore, they would exhibit a more accurate readout.

Additionally, state-based working memory theories argue that the difference between prioritized and unprioritized items should lie in their functional properties but not their precision. In contrast, resource-based theories suggest that shifting priority could impair the precision of uncued items (Muhle-Karbe et al., 2021). Our findings support the latter, since we found a significant difference in precision between functional states.

Conclusion

Working memory retention is maintained by dynamic processes. During the retention period, some representations require sustained firing, while others may be retained through sparse spikes and relatively silent activity. Although we demonstrated that functionally passive items in working memory perform worse compared to active items, we did not find any additional protection against interference for these items. Studies conducted with different designs could provide further insight into the neural correlates of functionally passive working memories and the advantages of these networks.

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Supplemental Resource

The data from the experiments, R scripts, and other materials are available at the following link: https://github.com/muratcanboyva/L-autodidacte.