Exogenous spatial attention selects associated novel bindings in working memory

Á. Fuentes-Guerra, F. Botta, J. Lupiáñez, P. Talavera, E. Martín-Arévalo [*,1], C. González-García [*,1]

Department of Experimental Psychology, and Mind, Brain, and Behavior Research Center (CIMCYC), University of Granada, Granada 18071, Spain

ABSTRACT

Real-world environments are complex, demanding a diverse set of cognitive functions such as attention and working memory (WM) to perform adaptive behaviors. However, exogenous attention, characterized as automatic and involuntary, has primarily been studied by focusing on spatial perception. In particular, the ability of pure exogenous *retro*-cues to select and prioritize not only spatial locations, but also novel stimulus–response (S-R) bindings held in WM remains largely unexplored. Here, in two experimental series, we provide evidence that pure exogenous non-predictive *retro*-cues can select not only space, but also associated S-R bindings held in WM. Additional evidence from a drift–diffusion model hinted at the possibility that the mechanisms through which exogenous attention selects and prioritizes WM contents depend, at least partially, on the hierarchical relevance of the different dimensions encoded within a specific representation. These results highlight the relationship between pure exogenous attention and complex WM contents and shed light on current theoretical debates about the interaction of attention, memory, and action.

Introduction

Imagine someone driving through a busy street to find a parking spot. As they maneuver through the different roads, they keep checking out for signs of a parking spot nearby. Suddenly, a loud noise automatically catches their attention. Consequently, their foot is quickly shifted from the gas pedal to the brake to be able to stop if the situation demands so. As illustrated in this example, humans shape, influence, and interact with the environment through their own actions (Kunde, Weller & Pfister, 2018). In doing so, a set of diverse cognitive operations, such as selective attention and working memory (WM), help us to successfully adapt to the various demands of everyday situations.

In particular, the person in the example was exerting two types of attentional selection: on the one hand, they were looking for the parking signal voluntarily, differentiating the diverse signals, focusing on the color, shape, etc., to complete the desired action with maximum efficiency. This is commonly referred to as endogenous/voluntary attention (Jonides, 1981; Corbetta, Patel & Shulman, 2008), and it is assumed to be exerted in a top-down/goal-directed fashion (Chica, Bartolomeo, &

Lupiáñez, 2013). On the other hand, in parallel, just like the loud noise, any salient stimuli in the environment will likely capture their attention as well. This form of automatic and involuntary selective attention is usually described as exogenous attention (Jonides, 1981; Posner & Cohen, 1984), and it is characterized by its bottom-up/stimulus-driven nature. Importantly, to achieve their goal of finding a parking spot, the person in the example will additionally have to maintain certain information about the environment available, like remembering the directions she saw in a traffic sign. This is afforded by WM, commonly defined as the ability to store, and manipulate information in an online fashion independently of sensory stimulation (Baddeley, 1992; Souza & Oberauer, 2016; Nobre & Stokes, 2020).

This example represents how the convergence of these cognitive operations is critical in executing everyday actions, as well as many other complex tasks. However, relative to research dedicated to externally directed attention for perception, research on internally directed attention to WM contents remains less well understood (Awh, Jonides & Reuter-Lorenz, 1998; Awh & Jonides, 2001) and has largely focused on visual memories (Downing, 2000; de Fockert et al., 2001). Specifically,

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* Corresponding authors.

E-mail addresses: aguedafgt@ugr.es (Á. Fuentes-Guerra), fabianobotta@ugr.es (F. Botta), jlupiane@ugr.es (J. Lupiáñez), pedro_talavera@ugr.es (P. Talavera), emartina@ugr.es (E. Martín-Arévalo), cgonzalez@ugr.es (C. González-García).

[1] Equal contribution

several studies have evaluated the mechanisms underlying internal attention (Kiyonaga & Egner, 2013; Myers, Stokes & Nobre, 2017; Nobre & Stokes, 2020; Zokaei et al., 2019; van Ede, 2020; van Ede & Nobre, 2023; Huynh Cong & Kerzel, 2021), which refers to the selection and modulation of internally generated information, such as the contents of WM, long-term memory, task sets, or response selection (Chun, Golomb & Turk-Browne, 2011). Essentially, these studies have primarily assessed the effects of endogenous attention on visual WM contents (Landman et al., 2003; Griffin & Nobre, 2003; Gazzaley & Nobre, 2012; Rerko, Souza & Oberauer, 2014; Souza, Rerko & Oberauer, 2014, 2015; Gunseli, van Moorselaar, Meeter, & Olivers, 2015; Gunseli et al., 2019). In this line, these and other studies have provided important evidence that *retro*-cues (i.e., cues presented between the offset of a memory array and the onset of a probe) can select and prioritize visual WM contents (Souza & Oberauer, 2016; Shepherdson, Oberauer & Souza, 2018; Rerko, Souza & Oberauer, 2014), even with bottom-up (although predictive) *retro*-cues (Berryhill et al. 2012). In parallel, recent research in the area of novel stimulus–response (S-R) associations has revealed that endogenous attention can also affect how more complex memoranda, such as planned actions, are represented in WM (González-García et al., 2020; Formica, González-García & Brass, 2020; Formica et al., 2022; Formica et al., 2023).

Conversely, exogenous attention studies have traditionally neglected the role of WM representations, focusing primarily on the perceptual spatial domain by implementing variations of the Posner (1980) classical cue-target orienting paradigm (see Chica et al., 2014, for a review). Although it could be the case that WM contents are irrelevant to the mechanisms of exogenous attention, recent evidence suggests otherwise. For instance, it has been shown that some attentional costs (i.e., slower reaction times (RTs) and/or lower accurate responses for uncued vs. cued target locations) might be at least in part due to a disruption of episodic cue-target integration processes (Spadaro, He, & Milliken, 2012) or by the encoding of the cue (Chen & Wyble, 2018; see also Lupiáñez, Martín-Arévalo, and Chica, 2013). Moreover, some other studies have shown that repetition of non-spatial attributes such as color and shape can lead to attentional costs as well (Hu & Samuel, 2010; Hu, Samuel, & Chan, 2011). More directly, several experiments point to a systematic difference in the effects of endogenous and exogenous attention on visuospatial WM contents (Botta et al., 2010; Botta & Lupiáñez, 2014). In this regard, recent evidence suggests that symbolic (central) non-predictive *retro*-cues can select visual WM contents (van Ede, Board, and Nobre, 2020).

However, although this emerging evidence of exogenous attention effects on WM contents has recently gained significance, it has largely focused on visual memories of simple stimuli such as squares, circles, bars, etc. (Hu & Samuel, 2010; Hu et al., 2011; Berryhill et al., 2012; van Ede et al., 2020; Chao, Hsiao, & Huang, 2022). Nevertheless, real life environments are more complex than that, and an infinite number of stimuli of different nature catch our attention involuntarily on an everyday basis. In this context, attention, memory and perception tend to be intertwined with the main aim of executing behaviors (Hommel, 2019; Frings et al. 2020). In this context, studying whether fully exogenous (non-predictive and peripheral) cues can select WM representations that go beyond visual memories, such as S-R associations, is essential and it would allow to better conceptualize exogenous attention as a broader phenomenon, not just related to perceptual information.

Although untested, the hypothesis that exogenous cues should be able to select complex WM contents such as S-R associations fits well with recent theoretical frameworks of action control. The Binding and Retrieval in Action Control framework (BRAC) put forward by Frings and collaborators (2020) proposes that stimulus features, response, environment, and its subsequent effects are integrated into a "mental representation" in which all the elements related to that specific event are included (Frings et al., 2020). Such mental representation is referred to as an *event file,* as coined by Hommel, Müsseler, Aschersleben, and Prinz (2001); Hommel (2019) in his Theory of Event Coding (TEC).

Importantly, it is assumed that the latter repetition of any of these elements triggers the retrieval of the previous event-file as a whole, comprising codes of the same features, which can impact current performance (Frings et al., 2020). Thus, if we consider the BRAC and TEC frameworks, when encoding some content in a *retro*-cueing paradigm, the event file of a trial will contain all information pertaining that event (e.g., stimulus, response, the encoding location, the laterality of the response, task demands, etc.). If a spatial *retro*-cue, even if non-predictive, later flashes on the location where the event was encoded, then the entire event file should be retrieved.

Consequently, here, we aimed to address whether a purely exogenous/automatic *retro*-cue could effectively select S-R representations held in WM. We hypothesized that in an exogenous *retro*-cueing task pertaining S-R associations, exogenous cueing would be able to retrospectively select content in WM, and this would be reflected as a facilitatory effect: faster and/or higher accurate responses in cued object vs. uncued object trials. In the first two experiments, we tested this hypothesis along a series of preregistered manipulations of the cue-target onset asynchrony (CTOA), given its central role in the classical exogenous cueing effects on perception (Gabay & Henik, 2010; Chica et al., 2013; Martín-Arévalo, Botta, De Haro & Lupiáñez, 2021). In a third experiment, we explored whether exogenous attention interacts similarly with different elements of the event file or whether it prioritizes spatial components. In all experiments, and, in line with our hypotheses, we observed facilitation in cued object vs. uncued object trials, suggesting that non-predictive/peripheral cues can automatically select novel S-R associations held in WM.

Experiment 1A

Data availability

Raw data, experimental files and analyses' scripts for this experiment can be found at (https://osf.io/r8fks/?view_only=ca3358b6251b49d3bc4aa558d4429175). The hypotheses and analysis plan were preregistered prior to data collection and can be found at https://aspredicted.org/blind.php?x=Z29_Y5K. Specifically, we hypothesized that exogenous *retro*-cues would select and prioritize not only space, but also its associated WM contents. This would be evidenced by faster and/or higher accurate responses in cued object vs. uncued object trials.

Methods

Participants

Twenty-three naïve volunteers participated in this experiment (4 males, mean age of 21.1 years, SD=2.96). Sample size was determined a-priori by a sequential Bayes Factor approach (see preregistration).[2]

Participants were recruited through the experiments' website of the Centro de Investigación Mente, Cerebro y Comportamiento (CIMCYC). The prerequisites for participation in the present study were to be between 18 and 35 years old, normal, or corrected to normal vision, and to give written consent. Moreover, participants were monetarily compensated (5€ per half an hour) after completing their partaking. The experiment was conducted in accordance with the ethical guidelines laid down by the Department of Experimental Psychology, University of Granada, in conformity with the ethical standards of the 1964 Declaration of Helsinki (last update: Brazil, 2013). The experiment was part of a larger research project approved by the University of Granada Ethical Committee (1816/CEIH/2020).

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[2] Note that the final sample size deviated from the preregistered one due to practical issues with the participants' recruitment method. Nevertheless, 20 participants were enough ($BF_{10} = 22.783$).

Apparatus, stimuli, and procedure

We conducted the experiment on a computer with an Intel Core i7-3770 CPU @ 3.40 GHz x8 processor, connected to a 24 in. Benq XL2411T monitor with a 1920x1080 (16:9) pixel resolution and 350 cd/m^2 of brightness. Participants sat at a viewing distance of approximately 65 cm. The presentation of stimuli and data acquisition were controlled with PsychoPy 2021.2.3 throughout the whole experiment.

The experimental display consisted in the presentation of two placeholders, one on each side of the fixation point, which was presented right in the middle of the screen (position [relative to the center] of x = 0, y = 0). Each placeholder box had a size of 200 x 200 pixels, and the border of the box comprised an extra 10 pixels. The left box was in the position (x = -250 pixels, y = 75) and the right one in (x = 250, y = 75). Inside of each placeholder an image of 200 x 200 pixels appeared at the beginning of each trial. These images of animate (non-human animals) and inanimate (vehicles and instruments) items were compiled from different available databases (Brady et al., 2013, 2008; Brodeur et al., 2014; Griffin, Holub, & Perona, 2022; Konkle et al., 2010), creating a pool of 1550 unique pictures (770 animate items, 780 inanimate). To increase perceptual distinctiveness and facilitate recognition, the background was removed from all images, items were centered in the canvas, and images were converted to black and white. Additionally, we created peripheral cues by increasing the outline of one of two placeholder boxes from 10 to 30 pixels.

The experiment consisted of a choice-reaction task embedded in an exogenous cueing paradigm, with a 500–700 CTOA, which has already shown reliable exogenous cueing effects (Martín-Arévalo et al., 2013, 2016, 2021). The sequence of events in each trial is illustrated in Fig. 1. Each trial began with the presentation of the encoding display, containing the fixation point, two placeholders, and two novel images, for a duration of 1000 ms. Participants were instructed to create two S-R

associations in which they had to associate each stimulus with a certain bimanual response depending on its location on the screen. Specifically, participants were instructed at the beginning of the experimental session to associate stimuli to the left of the fixation point to bimanual index finger responses, and stimuli to the right to bimanual middle finger responses. The location-response contingency was constant during the experiment but counterbalanced across participants. Bimanual index and middle responses were used to fully orthogonalize the location of the stimulus on the screen with the associated response hand. Importantly, in each trial, the stimuli pair was completely novel, with stimuli that would never repeat again throughout the experiment. Next, an interval, composed by the two empty placeholders and the fixation point, appeared for 500 ms (see Souza & Oberauer, 2016). Immediately after, the peripheral non-predictive cue was presented for 50 ms in one of the two possible locations with equal probability (50 %). This cue was completely non-predictive of which of the two stimuli would be later probed nor of the location of the target. After the peripheral cue had disappeared, a fixation display was presented for a jittered duration of 450–650 ms. Then, a target image was displayed for 1200 ms in the center of the screen without placeholder (x = 0, y = 75). Participants were instructed to provide the associated response learned at the encoding stage of the trial. Specifically, they had to simultaneously press the "S" and "L" keys on the keyboard with both middle fingers if the target was associated with middle fingers' responses, and "D" and "K" with both index fingers simultaneously if index fingers responses were required. For the response to be considered correct, both key presses ("S" and "L"; "D" and "K") were required; if only one of them was pressed or if it was a mixture of the two, the response was considered incorrect. RTs from both fingers were collected, although only the fastest one was selected for the analysis. In 15 % of trials, a completely new picture, different from the two displayed in the encoding screen, and never seen
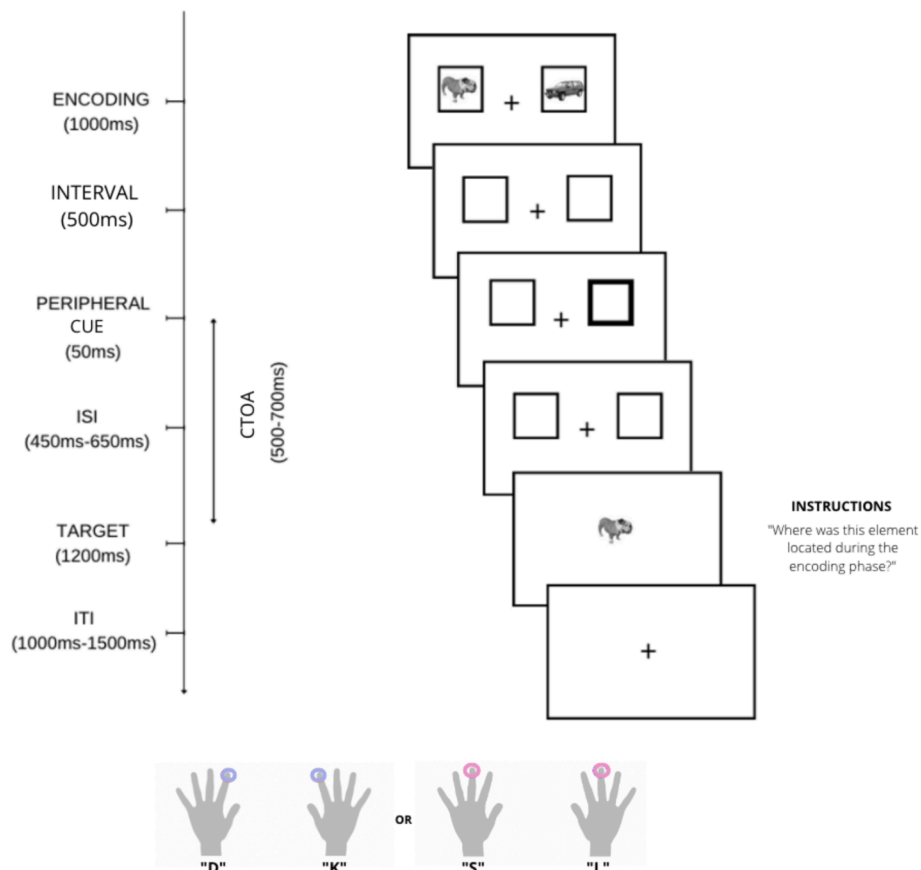
Fig. 1. Sequence of events in a given trial. Note. ISI: inter-stimulus interval. ITI: inter-trial interval. CTOA: cue-target onset asynchrony.

before, was shown as the target. In those cases, which we labeled "catch trials", participants were instructed to press the spacebar with their thumbs. These trials were included to prevent participants from adopting strategies to reduce the WM load (e.g., encoding just the left item and then treating the target as a go-no go task). The inter-trial interval, in which the screen remained empty, lasted 1000–1500 ms.

Participants completed two runs of 161 trials each (137 regular, 24 catch). Therefore, the full experiment was composed of a total of 322 trials. In the middle of each run and between runs, participants could take a break. Prior to the main task, participants performed a practice phase with a similar task that did not include cues. This practice phase consisted of one block of 16 trials (14 regular, 2 catch), which participants repeated until they achieved an accuracy of at least 85 %. The images used in the practice phase were not used during the main task. The total duration of the experiment was around 40 min.

Design

The experiment consisted of one within-participant factor with two levels. Two dependent variables were measured: RTs and accuracy, and one independent variable was manipulated throughout the experiment, object cueing (manipulated within trials), with two levels: *cued object* (the target was the object associated with the location where the cue appeared) and *uncued object* (the target was the object associated with the uncued location).

Statistical analyses

To test our hypothesis, we performed a Generalized Linear Mixed Model (GLMM) (see e.g., Lo & Andrews, 2015). The GLMM included the factor object cueing as a fixed effect. The best structure for the random component was obtained by comparing all possible models appearing from the combination of the intercepts and slopes of object cueing, in the random factors of participants and trial. The model with the smallest Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) was chosen as the most suited model for our data. Within this model, we performed the preregistered analysis of deviance on RTs since it is the most sensible variable for studying exogenous cueing effects in perception across the vast majority of studies (see e.g., Martín-Arévalo, Chica, & Lupiáñez, 2013; Martín-Arévalo et al., 2016; 2021). Before performing the analysis of deviance, trial rejection was conducted for each participant by selecting only correct trials and by filtering out catch trials. Lastly, p values in post-hoc comparisons were corrected with the Holm-Bonferroni method. Importantly, the model selection process was conducted independently of subsequent hypothesis testing. All data processing and analyses were carried out with RStudio 2022.02.3 and JASP 0.14.0.0. B. We also performed an additional equivalent exploratory analysis of accuracy scores since the effect of exogenous attention is not so pronounced on accuracy scores, although it is usually considered in WM literature (see e.g., Souza & Oberauer, 2016; Shepherdson, Oberauer & Souza, 2018; Rerko, Souza & Oberauer, 2014).

Results

After comparing the 11 computed models, the best-suited model for our data, which included the random intercept and slope of object cueing in the random factors of participants and trial (AIC=72345; BIC=72404) was selected, and an analysis of deviance was performed within this GLMM. This analysis revealed a statistically significant difference between cued and uncued object trials on RTs [$X^2(1, N=23) = 6.69$, p $= .01$], with faster responses for cued (M=712 ms; SD=81 ms) than uncued object trials (M=730 ms; SD=80 ms) (See Table 1. and Fig. 2; cueing effect (uncued-cued object trials) = 18 ms; see Fig. 5, left panel). In fact, the Bayesian scores obtained from the BIC index, provided strong evidence for this model (BF$_{10}$ = 2.13e + 5).

Additionally, the selected glmm model for accuracy scores (AIC=4781.8; BIC=4822.4, p < .001) which included the random

Table 1
Descriptive statistics of Reaction Times (RTs) and Accuracy Scores for Experiment 1A and 1B.

		Reaction Times (RTs)		Accuracy Scores	
		Mean	Standard Deviation (SD)	Mean	Standard Deviation (SD)
Experiment 1A	Cued Object	712 ms	81 ms	.87	.07
	Uncued Object	730 ms	80 ms	.87	.1
Experiment 1B	Cued Object	714 ms	106 ms	.86	.09
	Uncued Object	749 ms	110 ms	.83	.08

intercept of participant and trial revealed that object cueing was not statistically significant when considering accuracy scores [$X^2(1,N=23) = 0.133$, p = .720] (See Table 1.).

Discussion

This first experiment provided initial evidence that purely exogenous non-predictive/peripheral *retro*-cues can automatically select S-R associations held in WM. This was shown by faster responses in non-predictive cued trials compared to uncued object trials. In line with the TEC (Hommel, 2019), these results suggest that in our task, the event file would encompass all the elements of the trial. Critically, when the non-predictive cue is presented in one of the locations, the corresponding event file would be updated with that information, thus activating the whole event file with all the content in WM.

Experiment 1B

In Experiment 1B, we aimed at replicating and validating these results under a shorter CTOA (250–350 ms) to test whether, akin to the perceptual domain, the exogenous cueing effects on WM contents would be boosted (Chica et al., 2013; Martín-Arévalo et al., 2013).

Data availability

Raw data, experimental files and analyses' scripts for this experiment can be found at (https://osf.io/r8fks/?view_only=ca3358b6251b49d3bc4aa558d4429175). This experiment was not preregistered.

Methods

The method was like Exp.1A except in the following:

Participants
A total new sample of twenty-one naïve volunteers participated in this experiment (1 male, mean age of 20.7, SD=6.22). Sample size was determined by a sequential Bayes Factor approach as in the previous experiment.

Apparatus, stimuli, and procedure
The task only varied in the implemented CTOA (250–350 ms instead of 500–700 ms).

Results

After comparing the 11 computed models, the best-suited model for our data, which included the random intercept and slope of object cueing in the random factors of participants and trial (AIC=64121; BIC=64179) was selected, and an analysis of deviance was performed within this GLMM. This analysis revealed a statistically significant
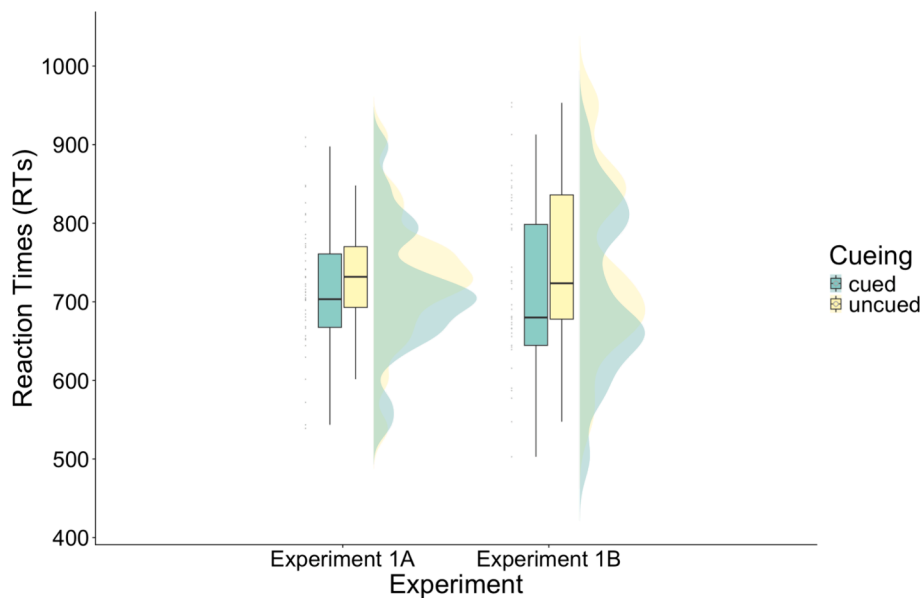
Fig. 2. Effects of object cueing on Reaction Times (RTs) in Experiment 1A and 1B. Note. The maximum and minimum Reaction Times' (RTs) values are represented in the whiskers of the box plots. The Interquartile range (IQR) is displayed in the boxes by portraying the lower quartile, median and upper quartile. The half-violin plots represent the distribution of RTs across conditions.

difference between cued and uncued object trials on RTs [$X^2(1,N=21)$ = 25.47, p < .01], with faster responses for cued trials (M=714 ms; SD=106 ms) compared to uncued object trials (M=749 ms; SD=110 ms) (See Table 1. and Fig. 2 and Fig. 5 (left panel); cueing effect (uncued-cued trials) = 35 ms). Just like in Experiment 1A, the Bayesian scores obtained from the BIC index, provided strong evidence for this model (BF_{10} = 1.84e + 4).

Moreover, selected glmm on accuracy scores (AIC=4855.4; BIC=4888.8, p = .04) which included the random intercept of subject revealed that the effect of object cueing was statistically significant [X^2 (1,N=21) = 15.29, p < 0.001] (See Table 1.), with higher accuracy scores in cued (M=.86; SD=.09) vs. uncued object trials (M=.83; SD=.08).

Lastly, in order to test our assumption of stronger exogenous cueing effects with a shorter CTOA, we computed two exploratory repeated measures ANOVAs combining the datasets from Experiment 1A and 1B. In these analyses, object cueing was set as a within-participant factor and experiment as a between-participant factor. The dependent variables were RTs and accuracy scores. Regarding RTs, the interaction between object cueing and experiment didn't reach significance [F (2,44) = 3.86, p = .056], but there was a numerically higher difference between cued and uncued trials in Experiment 1B than in Experiment 1A (35 ms vs. 18 ms, respectively). Furthermore, this analysis revealed a significant interaction between object cueing and experiment in accuracy scores [F(2,44) = 6.00, p = .019], with higher differences between cued and uncued object trials in Experiment 1B than in Experiment 1A (.03 vs..01, respectively).

Discussion

This second complementary experiment replicated the previous pattern of results under a shorter CTOA, providing further evidence that exogenous cues can select automatically complex WM contents. This experiment further revealed higher cueing effect as the CTOA is reduced, in line with classical exogenous experiments in perception where a facilitatory effect (i.e., faster RTs and/or higher accuracy for cued vs. uncued trials) tends to be found at shorter CTOA (Chica et al., 2013; Lupiáñez et al., 2013; Martín-Arévalo et al., 2013).

After carrying out the first two complementary studies, a few new questions emerged. First, it could be argued that participants may have

learned to generalize the rule under which they had to encode the stimuli; that is, the location and the corresponding response. Consequently, the exogenous cue may just activate the motor rather than the S-R association. Additionally, the weighting mechanisms assigned to the different elements of the event file remained unexplored in these two previous studies. According to the updated version of the TEC (Memelink and Hommel, 2013; Hommel 2019), task demands affect the processing of event files during the retrieval stage.

Hence, in our final experiment, we assessed whether exogenous *retro*-cues interacted with all components of the event file (i.e., an object with a specific color, at a specific location, to be responded to with a specific response, etc.) equally or there were rather differences in the weights associated with each component, while ensuring that stimuli were being encoded and retrieved together with the response, namely, the S-R association. Here, we manipulated task demands by asking participants to respond based on location (as in previous experiments) or based on another additional element, namely, color. We expected exogenous prioritization of WM content independently of the task to be performed. Still, the effect should be more pronounced when the location was a relevant dimension of the task compared to other dimensions (like color), showing a more nuanced effect when not relevant. This hypothesis was based on the long empirical trajectory that associates exogenous attention with the spatial domain (Posner, 1980; Lupiáñez et al., 1997, 2013; Martín-Arévalo et al., 2013, 2016, 2021; Hu & Samuel, 2010; Hu et al., 2011). This experiment used the same CTOA (250–350 ms) as in Experiment 1B, given that results were stronger with this setting.

Experiment 2

In Experiment 2, we aimed at testing whether the presentation of a spatial non-predictive *retro*-cue would activate and prioritize a representation held in WM which was initially encoded according to a non-spatial feature (color). We expected to find faster RTs and/or more accurate responses for cued object trials compared to uncued object trials both when the binding was created based on the location, and similarly, when it was created according to a non-spatial feature such as the color, although with more pronounced effects for the former.

Data availability

This study was preregistered (https://aspredicted.org/LV3_TL8) and raw data, experimental files and analyses' scripts can be found at https://osf.io/r8fks/?view_only=ca3358b6251b49d3bc4aa558d4429175.

Methods

The method was similar to Exp.1B except in the following:

Participants

A new sample of twenty-one naïve volunteers participated in this experiment (5 males, mean age of 22.4 years, SD=3.84). Sample size was determined by a sequential Bayes Factor approach (see preregistration).[3]

Design and Procedure

In this experiment, each participant performed two different sessions (of 30 min each one). They were carried out on different days, with the order of the sessions counterbalanced between participants. Each session was composed of two runs of 92 trials each (80 regular, 12 catch), giving a total of 184 trials per full session. Just like in the previous experiment, participants underwent a 16 trials practice phase (14 regular, 2 catch) before performing the experiment, which participants repeated until they achieved an accuracy of at least 85 %. Participants were allowed to rest in between runs.

In one of the sessions, participants executed a choice-reaction task very similar to the one in the previous experiments, but with an additional feature (i.e., color). In this experiment, the two lateralized stimuli appeared either in an orange or green background (randomly assigned and changed from trial to trial). Still, participants were instructed to perform an S-R association based on the location of the stimuli, just like in the previous experiments, and to ignore the color of the stimuli which was effectively irrelevant. In contrast, during the other session, the same task display was presented, but the instructions were altered. The S-R associations, in this case, were defined according to the color of the stimuli, not the location. Participants had to associate an image with a specific background color (orange or green) to a certain response (middle or index fingers; counterbalanced across participants), regardless of its position (See Fig. 3). Consequently, the design was a 2 within-participants factor with 2 levels: object cueing (target is the cued object vs. uncued object, which changed trial-by-trial) x task (location relevant vs. color relevant, which was manipulated between sessions).

Statistical analyses

Preregistered analysis

To test our hypothesis, we performed a GLMM with the factor object cueing and task as fixed effects. The best structure for the random component was obtained by comparing all possible models appearing from the combination of the intercepts and slopes of object cueing, in the random factors of participants, trial, and session order. The model with the smallest AIC and BIC was chosen as the most suited model for the random component of the model. Afterwards, the fixed component was obtained by comparing p values between the different models which were achieved by altering the possible interactions between the independent variables. Within the selected model, we performed an analysis of deviance on RTs. Before performing the analysis of deviance, trial rejection was conducted for each participant by selecting only correct trials and by filtering out catch trials. All data processing and analyses

were carried out with RStudio 2022.02.3 and JASP 0.14.0.0. B.

Exploratory analyses

Similar to Experiment 1, we also performed additional exploratory analyses regarding accuracy scores, and a hierarchical drift diffusion model (HDDM; Wiecki et al., 2013).

Results

After comparing the 42 computed models, the best suited model for our data was selected. This model included the random slope and intercept of the interaction between object cueing and task in the random factor participant and trial (AIC=73348.17; BIC=73514.19; p < 0.001). Consequently, an analysis of deviance was performed within this GLMM. Critically, this analysis revealed a significant main effect of object cueing [$X^2(1,N=21) = 19.18, p < .001$] with faster responses in cued (M=715 ms; SD=108 ms) compared to uncued object trials (M=752 ms; SD=106 ms; cueing effect: uncued-cued trials = 36 ms; see Fig. 5, left panel). In contrast, neither the main effect of task [$X^2(1, N=21) = 2.78, p = .096$] nor the interaction between task and object cueing were statistically significant [$X^2(1,N=21) = 0.1499, p = .699$] (See Fig. 4).

Additionally, the selected glmm on accuracy scores, which included the random intercept of participant and the random slope of task in the factor participant with the interaction between object cueing and task as fixed effects (AIC=5678.3; BIC=5732.8), revealed that both object cueing [$X^2(1,21) = 19.18, p < .001$] and task [$X^2(1,21) = 9.04, p < .05$] were statistically significant, with higher accuracy scores in cued (M=.86; SD=.07) than uncued object trials (M=.83; SD=.09), and higher accuracy scores in location (M=.87; SD=.06) than color task (M=.81; SD=.11). Further, the interaction between these factors was also statistically significant [$X^2(1,21) = 4.50, p = .03$]. Post-hoc comparisons revealed a significant difference between cued and uncued object trials only in the color task [$X^2(1,21) = 4.43, p < .001$] and a statistically significant difference between the color task and the location task only in uncued object trials [$X^2(1,21) = -3.24, p = .02$] (See Fig. 6).

Hierarchical Drift Diffusion Model

To disentangle the possible mechanisms underlying this difference between tasks with the exact same cue, we carried out an exploratory HDDM analysis of our data. HDDM treats two-alternative decision-making as a process of evidence accumulation towards one of two decisional boundaries over time (Ratcliff & Rouder, 1998). It has the advantage of considering the available data in its entirety, thus retrieving parameters to fit both correct trials and errors RTs distributions. Crucially, such parameters can be mapped onto psychologically meaningful processes, making it possible to infer which cognitive operations are affected by the experimental manipulations. In its simplest formulation, the decision process can be described by 4 parameters: the *drift rate (v)*, reflecting the pace and efficiency of evidence accumulation; the *non-decision time (*t_0), encompassing all cognitive processes not directly associated with the decision itself, such as perceptual and motor operations; the *decision threshold (a)*, referring to the amount of evidence required to reach a specific decision; and the *starting point (z)*, indicating whether there is a systematic bias towards one of the two options. The HDDM is considered hierarchical insofar as it first uses data from all the participants to estimate group-level mean parameters, and then it uses these group-level priors to constrain the estimation of the participant-specific parameters. Consequently, it allows for more stable results, even with fewer data per participant with respect to the traditionally used algorithms (Lerche et al., 2017). Based on previous studies with similar tasks (see e.g. Formica et al., 2024), we first established a cut-off so that RTs below 200 were discarded. Moreover, the analysis was performed only on regular (non-catch) trials. Finally, when estimating the models, we used the HDDM command "p_outlier" to specify a
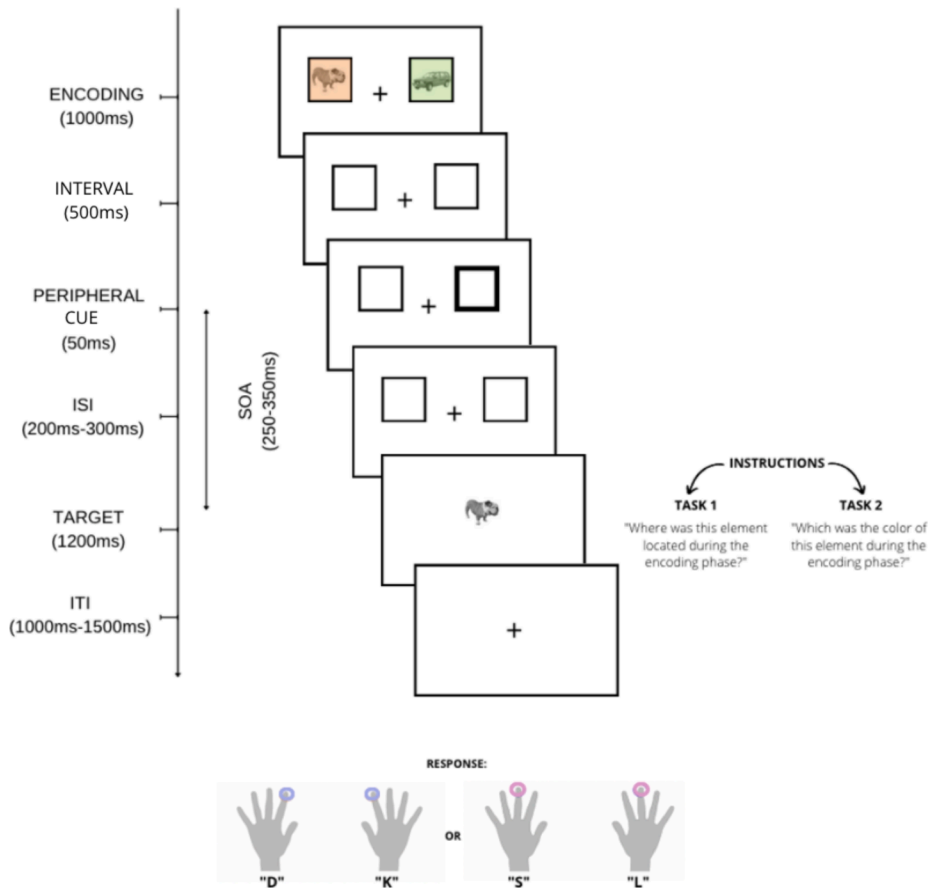
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[3] Note that the final sample size deviated from the preregistered one due to practical issues with the participants' recruitment method. Nevertheless, 20 participants were enough ($BF_{10} = 12.227$).

Fig. 3. Sequence of events in a given trial. Note. ITI: inter-trial interval. CTOA: cue-target onset asynchrony.
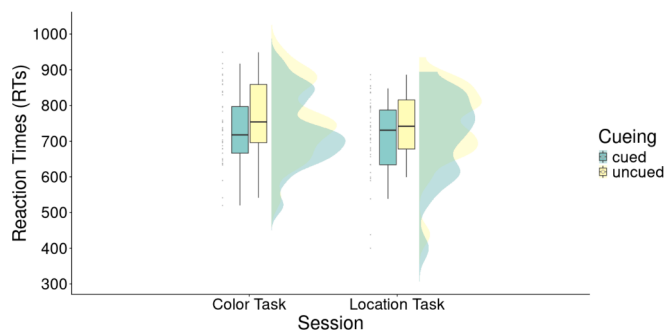

Fig. 4. Effects of object cueing and task on RTs. Note. The maximum and minimum Reaction Times' values are represented in the whiskers of the box plots. The Interquartile range (IQR) is displayed in the boxes by portraying the lower quartile, median and upper quartile. The half-violin plots represent the distribution of RTs across conditions.

mixture model that assumes outliers come from a uniform distribution, with a fixed probability of 0.05 (therefore, 5 % of trials would be considered outliers). Estimating model parameter distributions within the HDDM toolbox relies on a Markov-chain Monte Carlo sampling procedure (Gamerman & Lopes, 2006). We used a chain with 10,000 samples; the first 1000 samples were discarded as burn-in, allowing the sampling procedure to settle around a value after an initial more exploratory sampling. To reduce autocorrelation in the retained samples, we additionally discarded every second sample.

We hypothesized our two independent variables (object cueing and task) to impact both the rate of evidence accumulation (v) and/or the non-decision time (t0). This rationale is partly based on recent literature

that relies on drift rate to model congruency effects (Ulrich et al., 2015; White et al., 2018). In addition, Shepherdson and colleagues (2018) showed an increase in drift rate and a reduction in non-decision time when *retro*-cues benefit memory performance. Thus, if object cueing and/or task impact drift rate, it would imply a decrease in the quality of the evidence entering the decision process. In contrast, a modulation of t0 would reflect a slowing in the non-decision phase that could encompass perceptual, retrieval, and motor processes associated with the decision (Formica et al., 2023).

We thus compared two models that differed on whether the threshold parameter would also differ across tasks. Importantly, r-hats values for both models were below 1.05 which is interpreted as adequate convergence within each model (Makowski et al., 2019).

Model fitting was assessed based on the Deviance Information Criterion (DIC), where lower values indicate better fit of the model to the empirical data. In this case, the evidence for a difference in DIC between two models was not strong (considering the traditional minimal difference of 5, see e.g. Cain & Zhang, 2019). Hence, we decided to go for the simpler model (see Table 2.) and therefore, here we report the results of such model.

After evaluating model fit, the best model was the one where both object cueing and task were mapped onto drift rate and non-decision time. Regarding drift rate, we found a main effect of object cueing (b = -0.22, 95 % HDI=[-0.35, −0.1], pd = 100 %) and task (b = -0.21, 95 % HDI=[0.08, 0.34], pd = 100 %), suggesting that evidence accumulation was faster in cued, compared to uncued object trials, and in the location, compared to the color task. Interestingly, we also observed an object cueing x task interaction in drift rate (b = -0.22, 95 % HDI=[-0.35, −0.1], pd = 100 %). This interaction revealed that participants accumulated evidence faster in cued, compared to uncued object trials, when performing the color task but not in the location task (See Fig. 7).
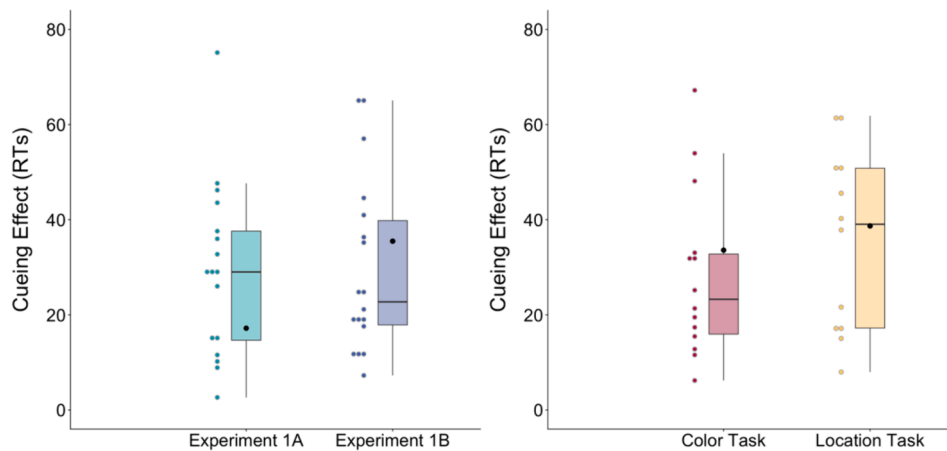
Fig. 5. Cueing effects on RTs on the full experimental set.Note. The maximum and minimum Reaction Times' values are represented in the whiskers of the box plots. The Interquartile range (IQR) is displayed in the boxes by portraying the lower quartile, median and upper quartile. The mean is represented as a black dot.
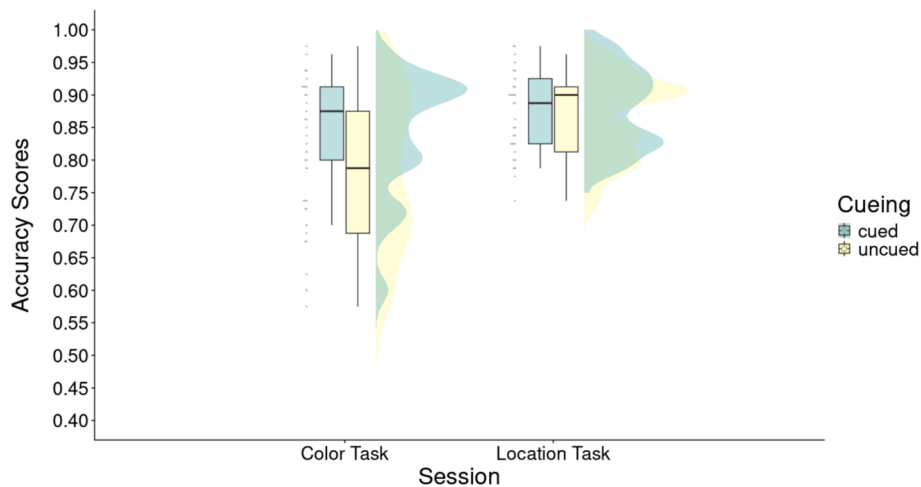
Fig. 6. Effects of object cueing and task on Accuracy Scores. Note. The maximum and minimum Accuracy Scores' values are represented in the whiskers of the box plots. The Interquartile range (IQR) is displayed in the boxes by portraying the lower quartile, median and upper quartile. The half-violin plots represent the distribution of Accuracy Scores across conditions.

Table 2
Model fitting between the two proposed drift diffusion models.

Model #	Object Cueing	Task	DIC
1	v, t0	v, t0, a	1656.96
2	v, t0	v, t0	1654.77

Note. v: drift rate; t0: non-decision time; a: decision threshold; DIC: Deviance Information Criterion

When looking at non-decision time, we again found evidence for a main effect of object cueing (b = 0.03, 95 % HDI=[0.02, 0.04], pd = 100 %). In contrast, the effect of task was not significant (b = 0.0006, 95 % HDI=[-0.01,0.01], pd = 56.3 %), suggesting faster encoding of sensory information and/or execution of motor responses in cued compared to uncued object trials, regardless of the task. Importantly, the interaction between these two factors was significant (b = 0.04, 95 % HDI= [0.02, 0.05], pd = 100 %), revealing a greater difference between cued and uncued object trials during the location task, compared to the color one (See Fig. 8).

Discussion

The second experiment showed once again that an exogenous non-
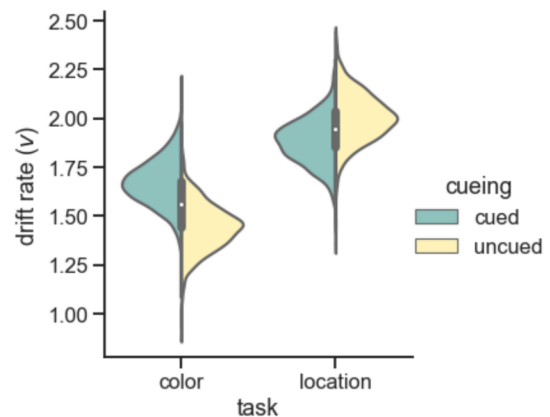
Fig. 7. Drift rate of the object cueing factor in the two tasks.

predictive, peripheral *retro*-cue was able to automatically select and prioritize complex representations held in WM, as shown by both in RTs and accuracy scores. Moreover, in RTs, it also provided evidence that this effect was maintained even when the task demands were altered and the S-R association in retrieving was ensured. These results fit well with
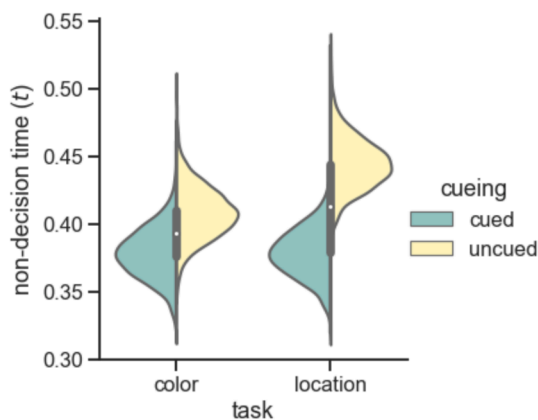
Fig. 8. Non-decision time of the object cueing factor in the two tasks.

the conceptualization of event files (Hommel, 2019): the exogenous *retro*-cue was able to interact with WM through space but also with other non-spatial dimensions, such as color (Hu & Samuel, 2010). Additionally, in accuracy scores, this experiment provided evidence for a significant difference in task, with higher accuracy scores on the location task compared to the color task, which supports previous findings that stress the weight of the location dimension when studying exogenous attention in perception (see Posner, 1980; Lupiáñez et al., 1997, 2013; Martín-Arévalo et al., 2013, 2016, 2021; Hu & Samuel, 2010; Hu et al., 2011). However, the accuracy difference between cued and uncued object trials was only significant in the color task. On top of that, the difference between the two tasks was only significant in uncued object trials. These exploratory findings highlight the importance of considering task demands when evaluating exogenous effects on WM contents and stress the fact that there are certain discrepancies in the different dependent variables (RTs and accuracy scores). Consequently, more sensitive complementary analyses like HDDM appear to show that the cost attached to uncued object trials in the location task loads mainly in non-decision time, while in the color task, it seems to be related to drift rate. These results, in addition to evidence with mainly accuracy scores, raise the intriguing possibility that, on the one hand, a ceiling effect might be present on accuracy scores in the location task and on the other, that the mechanisms through which exogenous attention interacts with WM contents depend on the relevant characteristics through which these contents have been encoded. Nevertheless, it is still difficult to determine whether the different results are due to the relevance (the spatial dimension was less relevant in the color task compared to the location task) or to the specific feature by which the binding was coded (color-R mapping vs. location-R mapping). Future studies will shed light on this matter.

General Discussion

This research had a two-fold aim: first, it intended to test whether pure exogenous attention as in perception can select and prioritize complex WM contents by evaluating its implications in action control. Additionally, it also aimed at assessing whether this effect is present throughout different task settings with complex stimuli and demands. This was achieved by implementing an exogenous *retro*-cueing paradigm that capitalized on S-R associations held in WM, across two different tasks.

In two experimental series, over three different experiments, we observed a general facilitatory effect: faster RTs and/or more accurate responses in retrieving from WM the content of cued compared to uncued objects (see Souza & Oberauer, 2016; Shepherdson, Oberauer & Souza, 2018; Rerko, Souza & Oberauer, 2014). These results constitute initial evidence that pure exogenous attention interacts with S-R associations held in WM, which aligns with previous literature (Gazzaley &

Nobre, 2003, 2012; Myers, Stokes & Nobre, 2017). Recent studies (e.g., van Ede et al., 2020) have reported converging evidence that not only endogenous but also symbolic, central, non-predictive *retro*-cues can select simple visual WM contents. Here, we extend previous findings by showing that 1) purely exogenous/automatic lateralized cues can induce similar facilitatory effects; 2) these effects go beyond visual WM and can operate on complex and ecological stimuli that require the execution of S-R associations. This result is especially important given that the majority of studies that are starting to conceptualize the automatic selection of WM contents through exogenous cues employ simple stimuli with low ecological validity (see Hu & Samuel, 2010; Hu et al., 2011; Berryhill et al., 2012; van Ede et al., 2020; Chao, Hsiao, & Huang, 2022), especially compared to real-world meaningful stimuli (Brady, Strömer, & Alvarez, 2016; Brady & Störmer, 2020; Asp, Stömer, & Brady, 2021; Chung, Brady, & Strömer, 2023). Hence, our results provide more applied, further insight into conceptualizing the interaction between pure exogenous attention and WM. A critical aspect here is that – as neutral cues were not included – we cannot entirely rule out a potential cost from uncued trials rather than a benefit from cued trials in our results. Future studies should properly disentangle between these two possibilities.

We departed from Hommel's (2019) conceptualization of *event files* to understand the mechanisms under which exogenous attention can automatically select space and its associated WM content. This idea of feature binding in attentional selection is also shared by Manohar and collaborators (2019) under a more biological perspective. These authors propose that persistent neuronal activation serves as the focus of attention that encodes recent activity patterns into synapses. Additionally, rapid plasticity in flexibly-coding neurons allows features to be bound together into objects, with an emergent property being that the last item is maintained actively. Moreover, recent previously attended items are preserved instead in synaptic traces, therefore, they are in a non-privileged state but, importantly, can be reactivated by partial information (Manohar et al., 2019). In this regard, the Experiment 2 suggested that not all the same features of the *event file* have the same weight, and that some might be more easily accessible by spatial *retro*-cues than others (Memelink & Hommel, 2013). This idea is in line with Chao, Hsiao, and Huang (2022), where task demands are thought to modulate the binding processes. Particularly, they showed that depending on the task context (i.e., a target detection task, a target location task, or a target discrimination task) the binding between the different features of the target could be modulated. In fact, only when discrimination was required, there was clear evidence for the binding of the form and other features of the target. In our case, the different event-file features (i.e., location or color) tested in this experiment could be used to select the associated WM representations. However, it should be mentioned that in the color task, even though participants had to ignore the location, the placeholders were lateralized and therefore, location was never fully irrelevant, which can be critical when interpreting these results. This is also in agreement with Hu and collaborators (2010; 2011), who highlight location as a key characteristic when considering exogenous effects. In addition to task demands, CTOA manipulations can also modulate exogenous effects, as it has been proven in exogenous attention classical studies in perception (see Chica et al., 2014), where a specific CTOA depending on the type of task (i.e., detection, discrimination, etc.) can reduce or increment the exogenous cueing effect. Coherently, in our task (a choice-reaction/discrimination *retro*-cue task), even though the cue matched something previously encoded into working memory, the decrement in CTOA potentiated the exogenous effect, increasing the differences in RTs and accuracy scores in cued compared to uncued object trials. Another critical factor in our outcomes could be the level of execution of the S-R associations, since there is evidence that visual WM representations directly coupled to an action plan render this stimulus more salient (Trentin, Slagter & Olivers, 2023). In fact, these authors propose that visual WM is a fundamentally action-oriented cognitive operation, and their results support the notion that

attention is better conceived as an emergent property of the coupling of motor to sensory representation. In this regard, for example, van Ede and collaborators' (2020) asked participants to move the mouse and reproduce a certain orientation. Hence, future studies should address whether the level of implication of the motor response could be a modulator of pure exogenous effects on WM. Lastly, one potential limitation is that our results could be explained just by stimulus activation rather than S-R associations or due to long-term memories. Nevertheless, there are several reasons that lead us to believe that the response component must be activated as well (i.e., the S-R association) and held active in WM, which align well with the BRAC (Frings et al., 2020) and the TEC (Hommel, 2019) theories: responses were orthogonalized to the location in all three experiments, the association between space and color was completely random in Experiment 2, the colors appeared in any of the two locations from trial-to-trial, and including catch trials force the active maintenance of both representations in WM with its corresponding location, color, and response trial-to-trial. In any case, all these aspects should be considered in future studies.

Furthermore, Experiment 2 also revealed certain differences between the color and location tasks in RT and accuracy scores. Here, we used HDDM to provide deeper insight into the possible mechanisms underlying these differences. This analysis hinted at the possibility of a difference in the mechanisms through which exogenous non-predictive cues interact with the rest of the elements of the *event file*. Considering the drift rate, in the color task, evidence accumulated faster for the cued as compared to uncued object trials, whereas no differences were found in the location task. The fact that drift rate was affected by the exogenous non-predictive *retro*-cue is in line with the matched filter hypothesis (Hayden & Gallant, 2013; Myers et al., 2015, Muhle-Karbe, Myers & Stokes, 2021), which predicts that differences between cued and uncued trials are primarily driven by a greater efficiency in extracting relevant information for later decisions in cued trials. This hypothesis holds that such benefit is afforded by selective attention shifts the tuning properties of sensory and association neurons so that they more closely approximate the relevant stimulus. Regarding non-decision time, there was a benefit associated with cued object trials, primarily in the location task. This alteration in non-decision time in the location task could be explained by a retrieval head start hypothesis (Souza & Oberauer, 2016). Essentially, according to this hypothesis, cues could act primarily to reduce the time taken to access the relevant representation in memory upon probe presentation, and in addition protect cued representations from visual interference (Shepherdson, 2018).

Thus, although *retro*-cues affected both drift rate and non-decision time (but differently as a function of the task set), our results raise the possibility that the mechanisms through which exogenous attention selects and prioritizes complex WM contents depend, at least in part, on the hierarchical relevance of the dimensions that have been encoded. This is also coherent with task-set modulations over the exogenous cueing effect when using classical paradigms in perception (Martín-Arévalo et al., 2021). Altogether, this idea that attentional modulations in WM are complex and possibly mediated by several processes and/or mechanisms follows van Ede and Nobre's (2023) proposal in which they argue that internal selective attention can be driven by multiple sources, can act on various representational targets, and can be mediated by multiple stages and mechanisms to yield various consequences, highlighting the complexity and richness of this interaction. Furthermore, these results also fall in line with recent studies evaluating S-R bindings under different task sets (i.e., detection, localization, or discrimination tasks), which provide evidence that binding effects are task-dependent (Schöpper et al., 2020; Schöpper & Frings, 2022; 2023). Hence, future studies should consider task demands as well as more fine-grained approaches such as HDDM in combination with neural signals or ocular patterns. Both ocular patterns and brain oscillations have proven to be informative in uncovering processes like covert spatial attention (see Liu, Nobre & van Ede, 2022). In essence, by evaluating ocular movements and/or neural oscillations, we could possibly disentangle the mechanisms underlying exogenous attentional orientation (Balestrieri, Michel, & Busch, 2022) and the selection and prioritization of WM contents (Beste, Münchau & Frings, 2023).

Conclusion

The present study provides initial evidence that pure exogenous attention can select and prioritize complex WM contents including S-R associations. Moreover, it also shows that, besides space, exogenous attention can interact with other dimensions of the S-R held in WM. Importantly, our results suggest that exogenous attention might operate on different dimensions of WM content through different mechanisms. In sum, the obtained evidence challenges the classical conceptualizations of exogenous attention by opening the door to a more fine-grained approach which posits that regardless of its automaticity, exogenous attention might interact with complex WM contents in a more sophisticated manner as it was initially thought. Essentially, the base of this interaction might rely on the necessity of a flexible behavioral adaptation to the changing demands of the environment.

CRediT authorship contribution statement

Á. Fuentes-Guerra: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **F. Botta:** Writing – review & editing, Validation, Supervision, Conceptualization. **J. Lupiáñez:** Writing – review & editing, Validation, Supervision, Conceptualization. **P. Talavera:** Investigation. **E. Martín-Arévalo:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **C. González-García:** Writing – review & editing, Validation, Supervision, Software, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All the preregistrations, task design script, raw data and the scripts for the statistical analyses are uploaded into an open repository which is linked in the main text.

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