VISUAL COGNITION
https://doi.org/10.1080/13506285.2024.2435652

Competing working memory contents: perceptual over semantic prioritization and voluntary retrieval following retro-cueing

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ABSTRACT

This study investigated how voluntary and involuntary retrospective attention prioritize working memory (WM) representations of low-level visual features (perceptual dimension) and high-level categories (semantic dimension) using real-world objects. Reaction time and accuracy from two retro-cueing experiments were analyzed with a hierarchical drift-diffusion model to assess impacts on representation quality (drift rate) and retrieval time (non-decision time). Voluntariness of attention did not differentially affect perceptual and semantic WM contents. Drift rates showed stronger retro-cueing effects on perceptual compared to semantic contents, while non-decision times revealed retro-cueing effects only for voluntary attention. These findings suggest: (1) voluntariness does not differentiate between perceptual and semantic contents competing in WM; (2) attention prioritizes perceptual over semantic contents; and (3) voluntariness is critical for retrieving WM contents in advance of decision-making. This work highlights how WM content type and attentional voluntariness independently shape the effects of retrospective attention.

ARTICLE HISTORY
Received 28 February 2024
Accepted 21 November 2024

KEYWORDS
Top-down attention; bottom-up attention; visual working memory; drift-diffusion model

The orientation of attention can manifest in two primary modes: external, termed perceptual attention, and internal, known as internal attention (Chun et al., 2011; van Ede & Nobre, 2023). The first type operates by selecting and modulating sensory information, while the second acts on internally generated information, such as working memory (WM) contents. WM refers to the process by which information is stored and manipulated in an online fashion and independently from sensory stimulation (Nobre & Stokes, 2020; Souza & Oberauer, 2016). One task that allows us to assess the effects of internal attention on WM contents (i.e., retrospective attention) is the retro-cueing paradigm (Griffin & Nobre, 2003; Landman et al., 2003; Souza & Oberauer, 2016), where first, participants are asked to memorize a memory array. Then, at the end of a given trial, different test arrays may be presented depending on the type of retro-cueing task. In local recognition tasks (e.g., Berryhill et al., 2012; Fu et al., 2022), participants are asked whether a probe stimulus matches -or not- a stimulus presented at the same location. In spatial retro-cueing paradigms, the key manipulation is that during the interval between the memory array offset and the probe onset, a retro-cue is shown (e.g., arrow), which may point to the location of the stimulus that will be probed (valid condition), divert attention to another item (invalid condition), or rather point to all directions or no direction at all (i.e., neutral condition) (Souza & Oberauer, 2016). In general, valid conditions induce performance benefits at the attended location, while invalid conditions produce costs, the sum of both sub-effects being the retro-cue effect (RCE).

Attention can further be classified as involuntary (exogenous or bottom-up) or voluntary (endogenous or top-down) at external (Carrasco, 2011; Chica et al., 2013, 2014) and internal levels (e.g., Berryhill et al., 2012; van Ede et al., 2020). Voluntary attention is sustained over time, guided by the current goals, and under strategic control, while involuntary attention has been characterized as fast, short-lasting, and driven by the salience of stimulus properties (e.g., an arrow among straight lines). Voluntary attention

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/13506285.2024.2435652.

is measured with high-reliable cues regarding probe location, which are instructed to be attended to, while involuntary attention is measured with low-or-non-predictive cues, which are instructed to be ignored. Previous studies have explored how involuntary and voluntary external attention affect the storage of memory arrays within fragile and robust WM (e.g., Botta et al., 2010, 2019; Botta & Lupiáñez, 2014; Schmidt et al., 2002). However, until now, a characterization of involuntary and voluntary retrospective attention operating within the contents of WM remains largely unexplored, and most researchers have relied on voluntary retro-cues uniquely (Camos et al., 2018). Nevertheless, some studies have investigated the effects of involuntary and voluntary attention on WM contents employing retro-cueing paradigms (Berryhill et al., 2012; Fu et al., 2022; Han et al., 2023; Han & Ku, 2022; Shimi et al., 2014; van Ede et al., 2020). Generally, through recognition and delay estimation tasks, these studies have shown that voluntary attention elicits both benefits and costs on accuracy and/or reaction times (RTs), when measured. In contrast, involuntary attention induces smaller RCEs, and a less consistent pattern of benefits and costs. While these investigations have predominantly focused on the effect of the reliability and type of retro-cues, an examination of how involuntary and voluntary attention impact on different types of WM representations remains uncharted.

Notably, previous studies comparing voluntary and involuntary attentional mechanisms have employed low-level representations such as coloured squares (e.g., Fu et al., 2022), oriented bars (e.g., van Ede et al., 2020), and gratings (e.g., Han & Ku, 2022). However, high-level representations, such as real-world stimuli, have remained unexplored. It is crucial to understand how involuntary and voluntary attention impact these representations regardless of whether—as products of sensory processing—they serve as the primary units of representation in WM (e.g., Cowan, 2010; Luck & Vogel, 1997; van Ede & Nobre, 2023), or whether their features are parallelly, hierarchically, and noisily represented in WM (Brady et al., 2024), In addition, real-world stimuli are recognizable, meaningful, and WM capacity for them is larger than for simpler stimuli (e.g., Brady & Störmer, 2022; Chung et al., 2023). This underscores the semantic dimensionality of real-world stimuli, which not only vary on low-level features as in previous studies, but also vary on higher levels of visual processing. This variation in both low (perceptual) and high (semantic) representation levels can be experimentally manipulated (e.g., Kerrén et al., preprint; Lifanov et al., 2021; Linde-Domingo et al., 2019). The present study seeks to leverage this distinction in order to understand whether involuntary and voluntary attention prioritize perceptual and semantic WM representations differently.

Three lines of research support the plausibility of this distinction. First, the brain processes visual features and categorical information differently. The visual system initially analyzes the fundamental physical features of a stimulus in a progressive manner, from early areas like V1, V2, and V3, before processing more complex information, such as words or faces, in more anterior regions like the inferior temporal lobe (e.g., Cichy et al., 2014; Clarke et al., 2013; Clarke & Tyler, 2015). Second, evidence from external attention indicates that involuntary and voluntary attention also operate at different time scales (e.g., Chica et al., 2013; Liu et al., 2007; Müller & Rabbitt, 1989), while involuntary attention is fast and short-lasting, voluntary attention requires more time to be deployed and it can be sustained in time. Thus, at the internal level, the temporal dynamics of information processing in the visual system may also interact with those of involuntary and voluntary attention, possibly prioritizing low-level WM features under involuntary attention and high-level WM representations under voluntary attention. Third, indeed, evidence from external attention studies (e.g., Esterman et al., 2008; Fernández & Carrasco, 2020, 2023; Landau et al., 2007; Prinzmetal et al., 2009) suggests that voluntary attention induces larger performance effects at deep levels of visual processing (e.g., conjunctions of features), whereas involuntary attention exhibits a reduced impact at these levels. For instance, Prinzmetal et al. (2009), compared voluntary and involuntary external attention on target processing of low (features) and high (conjunction of features) levels of visual processing. On reaction times, larger validity effects (invalid - valid) of involuntary attention were found on features, while on conjunction targets, the effects of voluntary attention were larger. Additionally, other studies found larger validity effects for voluntary than for involuntary attention on a (high-level) discrimination task of faces (Esterman et al., 2008; Landau et al., 2007); while other studies evidenced that transcranial magnetic stimulation on (low-level) visual areas V1-V2 of the occipital cortex impairs the effects of involuntary attention, but not those of voluntary attention (Fernández & Carrasco, 2020, 2023). Whether retrospective internal attention operates similarly to external attention remains to be explored. This study aims to address this question, specifically examining how attention impacts on low (i.e., colour or perceptual) and high-level (i.e., category or semantic) WM representations from real-world stimuli. The key questions are whether the effects of voluntary retrospective attention are larger on semantic WM contents and whether the effects of involuntary attention are larger on perceptual WM representations.

To investigate this hypothesis, the present study conducted two experiments using a retro-cueing paradigm (Exp. 1 with a WM load of three, and Exp. 2 with a load of four). The study independently examined the effects of involuntary and voluntary retrospective attention on competing perceptual (colour: grey vs. sepia) and semantic (category: natural vs. artificial) WM contents of real-world stimuli. For each type of attention, participants performed one task with central retro-cues. While both central and peripheral retro-cues could be used in this study, central retro-cues were chosen to avoid confounding the effects of eccentricity and voluntariness. In the case of involuntary attention, a low-reliable arrow-shaped retro-cue was employed to automatically orient spatial attention. Conversely, for voluntary attention, high-reliable arrow-shaped retro-cues consistently pointed to all item directions, with the validity determined by the colour of the arrows, indicating the specific item to attend to (participants being instructed to attend to the item indicated by the high-reliable colour, as illustrated by Lasaponara et al., 2011). For voluntary attention, this design ensured a consistent automatic orienting of attention for all contents stored in WM, eliminating the influence of involuntary attention and allowing an independent assessment of both orienting mechanisms. Symbolic voluntary retro-cues (e.g., Berryhill et al., 2012), such as numbers, were intentionally avoided to maintain equivalence between voluntary and involuntary tasks. Finally, accuracy and RT data were collected and analyzed. Afterwards, behavioural data from both experiments were modelled with a drift-diffusion model (DDM) (Shepherdson, 2020; Shepherdson et al., 2018). This model facilitated a deeper examination of the underlying psychological processes affected by the experimental manipulation, with the drift rate parameter (v) serving as an indicator of the quality of WM representations, and the non-decision time parameter (t0) representing the time required for WM retrieval.

Experiment 1

This experiment assessed the effects of voluntary and involuntary internal attention on competing perceptual and semantic WM representations of real-world stimuli. For this, we measured the RCE, and two variables were manipulated: first, the voluntariness of retrospective attention (involuntary vs. voluntary), and second, the type of WM content (perceptual vs. semantic). Based on the above rationale, an interaction between voluntariness and type of WM content was predicted: for involuntary attention, larger RCEs –on accuracy and/or RT– were expected on perceptual than on semantic WM contents; on the contrary, for voluntary attention, larger RCEs were expected on semantic than on perceptual WM contents.

Method

Sample

Twenty-three university students volunteered for this experiment and the final sample size was twenty-one participants (15 ciswomen and 6 cismen) aged 18–32 ($M = 22.7$ years old). Participants were paid fourteen euros for their participation. The study was approved by the Ethics Committee (code: 1928/CEIH/2020) of the Universidad de Granada and met the criteria established in the Helsinki (World Medical Association, 2001). The sample size was determined following a sequential Bayes Factor (BF) with maximal n approach (Schönbrodt et al., 2017; Schönbrodt & Wagenmakers, 2018). Bayesian ANOVAs were conducted on error rates and median RTs introducing the three factors manipulated in the experiment (Suppl. Table 1). Data collection continued until each BF for each main effect or interaction reached substantial evidence for H1 ($BF_{10} > 3$) or H0 ($BF_{10} < 1/3$).

Procedure

In the same session, participants performed two local recognition retro-cueing tasks (e.g., Berryhill et al., 2012; Fu et al., 2022; Shimi et al., 2014) adapted to the use of real stimuli which varied in their colour (grey or sepia) and category (semantic or artificial). One task assessed involuntary attention and the other one voluntary attention (Figure 1). The tasks were performed in a counterbalanced order across participants. Participants sat approximately 60 cm from the monitor in an illuminated room. Between tasks, participants had a 5–10 min break. Seven breaks with a self-administrated duration were included in each task between intervals of approx. 4 min of task. Before the beginning of each task, participants performed a minimum of 15 practice trials with feedback and with no maximum limit. They finished when 4 consecutive trials were accurate.

Retro-cueing tasks

Participants were required to memorize the colour and category of each item in a memory array. In the voluntary task, participants were explained that a high-reliability retro-cue would appear, and they were asked to direct their attention to the colour/category of the item that was pointed by the relevant coloured arrow. On the contrary, in the involuntary task, volunteers were told to ignore the retro-cue given it had a very low reliability, and to remember all colours and categories. Each trial began with the presentation of a central fixation dot (0.5°) for 500–1000 ms. Subsequently, a memory array consisting of three images equidistant to each other and the fixation dot was presented for 500 ms. The triangular-shaped memory array was randomly rotated on each trial –i.e., keeping distances and orientations constant–, and images were presented at 5.8° (their

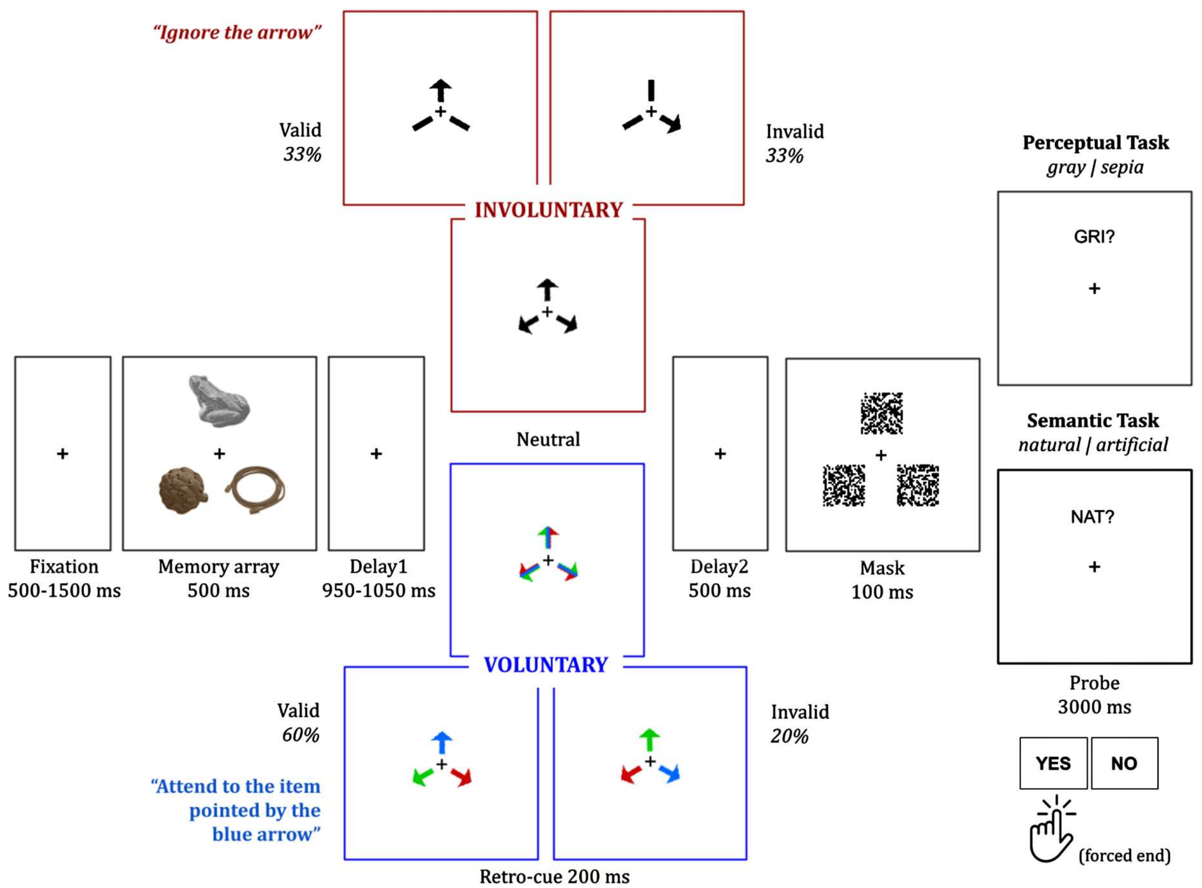

Figure 1. Involuntary and voluntary retro-cueing tasks in Experiments 1 and 2. The memory array contained three items in Experiment 1 and four in Experiment 2. In the example trial (Exp1) of the voluntary task, participants had to memorize the colours and categories of an array of three real-world stimuli, and then to pay attention to the colour and category of the item –previously– presented at the location pointed by the blue arrow. In the involuntary version, participants were told to ignore the arrows given they had a very low predictive value. At the end of the trial, participants were asked about one of the colours (grey = "GRI?" or sepia = "SEP?") or categories (natural = "NAT?" or artificial = "ART?") of one of the items presented in the memory array. The three images were taken and modified from the BOSS database (Brodeur et al., 2014). Sizes are not proportional.

maximum wide or length value occupied 5.3°). Then, the fixation dot remained for 950–1050 ms (Delay1). Next, a central retro-cue was presented for 200 ms with no spatial overlap with the memory array, and it was valid, neutral, or invalid. In the involuntary task, the valid retro-cue consisted of a black arrow (0.6° x 1.1°) pointing to the probe and two black lines (0.2° x 1.1°) pointing to the remaining items, the invalid retro-cue pointed to one of the items not probed, and the neutral retro-cue consisted of three black lines pointing to the three items. The retro-cue in the voluntary task consisted of three coloured arrows (red, green, and blue) pointing to the three items, with validity being determined by the task-relevant coloured arrow. This arrangement was chosen in the voluntary task to rule out any involuntary effect of the orienting of internal spatial attention. The task-relevant coloured arrow was predefined for each participant –and counterbalanced between participants–. In the valid condition, the relevant arrow pointed to the probe, while in the invalid one, it pointed to a non-probed item. The neutral retro-cue for each participant consisted of three equally coloured arrows with a random colour combination –constant for each participant– of the three possible colours. After the presentation of the retro-cue, the fixation dot remained for an interval of 500 ms (Delay2) until three masks were presented for 100 ms at the previous item locations. These masks, composed of randomly mixed black and white squares (24×24 matrix, 5.3°x5.3°), were presented to reduce any potential contamination by visual sensory memory representations of the memory array onto the test array (Lepsien et al., 2005; Sligte et al., 2008, 2009), with no anticipated modulation of attentional effects at this temporal latency (Chiarella et al., 2023). Finally, a question was presented in one of the three item locations depending on the experimental condition. This question was one out of four: GRI? (grey?), SEP? (sepia?), NAT? (natural?), or ART? (artificial?), and referred to the colour or category of the item encoded in that location. Participants were informed about it and instructed to answer yes or no, with the corresponding keys –S and L on the keyboard– which were counterbalanced between participants. The question remained on the screen until participants pressed a key or for a maximum of 3000 ms. The two non-probed images were selected from one of the three remaining combinations –colour(2) x category(2)– which were never the same as the target. All combinations of questions (correct answer: 50% yes and 50% no), colours, and categories were counterbalanced for each participant within each experimental condition (cue type x task x validity). Participants completed 320 and 288 trials in the voluntary and involuntary tasks, respectively, with the following condition proportions (and instructions): 60% valid, 20% neutral, and 20% invalid trials in the voluntary task (high-reliability, 75%, and instructions to attend to item cued by the relevant coloured cue); all conditions were presented on 33.3% of trials in the involuntary task (low-reliability, 50%, and instructions to ignore the cues). The tasks were programmed with PsychoPy (v2021.2.3; Peirce, 2007, 2009).

Selection and processing of images

Most images for the experimental tasks were downloaded from the browser of Google Images under fair use, and some were chosen from the C.A.R.E. (Russo et al., 2018) and BOSS databases (Brodeur et al., 2014). 466 Artificial images consisted of human-made objects including musical instruments, home and public space objects, kitchen utensils, appliances, clothes, accessories, tools, and weapons, among other categories. Half of all 466 natural images consisted of –non-repeated– species from the animal kingdom including insects, amphibians, fish, whales, birds, spiders, primates, jellyfish, reptiles, nematodes, dogs, and cats –in this case from different breeds–, and others –excluding humans–. The other half of natural images consisted of –not repeated– species from the plant kingdom, which were represented as flowers, fruits, vegetables, plants, trees, and leaves. After the natural and artificial datasets were obtained, a series of steps were applied to each image: first, the image was cropped until the item limits; second, the image was proportionally downsized to 200 pixels (maximum wide or length); third, it was converted to a black and white scale (saturation = 0); and fourth, two datasets were created, in the first, a layer with 50% opacity was added with a #404040 HEX colour (grey), and in parallel, for the second, a #6c4013 HEX colour (sepia) was added. Finally, for each participant, natural and artificial images were randomly divided into two datasets, one for the involuntary task (432 images) and the other one for the voluntary task (480 images). Within each task, images were presented twice, once in each half of the task, regardless of their colour version or whether they were presented first as probes or not.

Data analysis

Misses and responses faster than 200 ms were computed as errors (0.6%). Two participants were excluded for having an accuracy below 60% and three SD below the average. Then, accuracy and correct RTs were modelled with generalized linear mixed models (GLMMs). This approach does not require variance homogeneity and normal distribution of residuals and is recommended to analyze RT and accuracy data (e.g., Dixon, 2008; Lo & Andrews, 2015) while avoiding data normalization and transformation, which may lead to misinterpretation of results (e.g., Whelan, 2008). GLMMs also have the advantage of including all the data at the trial level. To establish the best structure for the random and fixed components we followed a well-known procedure (see Zuur et al., 2009). First, several random structures were proposed for each GLMM, from those we selected the one that yielded the lowest Akaike information criteria (AIC). We compared random structures including all possible combinations of the random slopes of the fixed effects and their interactions at the participant level. Subsequently, the fixed structure was selected by comparing pairs of models with likelihood ratio tests, the first one was the full model which included cue type (voluntary and involuntary), task (semantic and perceptual), and validity (valid, neutral, and invalid) factors, and then we systematically dropped –one by one– non-explicative interactions or effects based on the one that yielded the lowest deviance. For the accuracy GLMM, the best random structure included cue type and task as random slopes within participants, while for the RT GLMM slopes were included for the interactions cue type x validity and task x validity. For the RT GLMM, an inverse Gaussian with an identity link function was chosen, while for the accuracy GLMM a binomial distribution with a logit link function was selected. Then, for each GLMM, an analysis of deviance (ANODE) –similar to ANOVA– was performed. For significant main and interaction effects, post-hoc z-tests adjusted by the Holm–Bonferroni method were performed on least-square means.

Transparency and openness

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study. All data and scripts of analysis are available at https://osf.io/ga682/?view_only=fa7310dc7faa4d2596c70dcefff3e585. Modified images, and experimental tasks are available upon request. Data were statistically analyzed using R (version 4.1.2; R Core Team, 2020) and the following packages: *lme4* for GLMMs (version 1.1–29, 2022; Bates et al., 2009), *emmeans* for estimated marginal means (version 1.7.3, 2022; Lenth et al., 2019), and *BayesFactor* for bayesian ANOVAs (version 0.9.12–4.3, 2021; Morey et al., 2015). This study was not preregistered.

Results

Accuracy

The average accuracy of the involuntary task was 85.6% while for the voluntary task, it was 82.7%. Least-square means for each condition are shown in Table 1 (Figure 2, A,and B). The best GLMM model (Suppl. Table 2) included task and validity as fixed effects and their interaction, while it also included the main effect of cue type. Participants were better in the involuntary than in the voluntary task [Wald $\chi2(2) = 7.5$, $p = .006$]. The validity effect was significant [Wald $\chi2(2) = 58$, $p < .001$], while the task effect was not [Wald $\chi2(1) = 0.2$, $p = .659$]. Importantly, the interaction task x validity was significant too [Wald $\chi2(2) = 28.5$, $p < .001$]. Corrected post-hoc z-tests revealed that the RCE (valid - invalid) [$z = 7$, $p < .001$] and cost (neutral - invalid) [$z = 6$, $p < .001$] were significant in the perceptual task, while the benefit (valid - neutral) was not [$p > .05$]. No significant attentional modulations were found in the semantic task [all $p > .05$].

Reaction time

The average RT of the involuntary task was 1062 ms while for the voluntary task it was 1079 ms. Least-square means for each condition are shown in Table 1 (Figure 2, C, and D). The best GLMM model (Suppl. Table 2) included cue type and validity as fixed effects and their interaction, but task was not included. The cue type [Wald $\chi2(1) = 15.2$, $p < .001$] and validity [Wald $\chi2(2) = 24.9$, $p < .001$] main effects and their interaction [Wald $\chi2(2) = 19$, $p < .001$] were all significant. Corrected post-hoc z-tests for this interaction revealed that the RCE (invalid - valid) [$z = 4.7$, $p < .001$] and the benefit (neutral - valid) [$z = 3.7$, $p = .015$] were both significant in the voluntary task, while the cost (neutral - invalid) was not [$p > .05$]. No

Table 1. Means of ERs and RTs for each condition in Experiments 1 and 2. Error rate (ER) and reaction time (RT) average values are reported as estimated marginal means from full GLMMs for both experiments. ERs values were calculated from estimated probabilities in the accuracy GLMMs. () = standard error.

			Exp. 1 (3 items)		Exp. 2 (4 items)	
CUE TYPE	TASK	VALIDITY	ER	RT	ER	RT
voluntary	perceptual	invalid	20.1 (2.5)	1154 (28)	21.7 (2.2)	1291 (23)
voluntary	perceptual	neutral	13.2 (1.9)	1089 (22)	16.2 (2.2)	1161 (18)
voluntary	perceptual	valid	12.3 (1.5)	1054 (18)	16 (1.6)	1122 (15)
voluntary	semantic	invalid	19.5 (2.2)	1149 (29)	22.2 (2)	1280 (23)
voluntary	semantic	neutral	18.7 (2.1)	1087 (20)	19.4 (2)	1157 (18)
voluntary	semantic	valid	18.4 (1.7)	1029 (16)	18.8 (1.7)	1110 (14)
involuntary	perceptual	invalid	15.7 (2.2)	1041 (17)	19.4 (1.9)	1085 (16)
involuntary	perceptual	neutral	8.5 (1.4)	1060 (21)	13.3 (1.8)	1136 (16)
involuntary	perceptual	valid	9 (1.4)	1078 (20)	13.4 (1.5)	1127 (17)
involuntary	semantic	invalid	15 (1.9)	1061 (19)	16.3 (1.8)	1111 (17)
involuntary	semantic	neutral	16.3 (2)	1054 (20)	19.4 (2.1)	1103 (17)
involuntary	semantic	valid	14.3 (1.8)	1039 (18)	16.2 (1.9)	1071 (16)

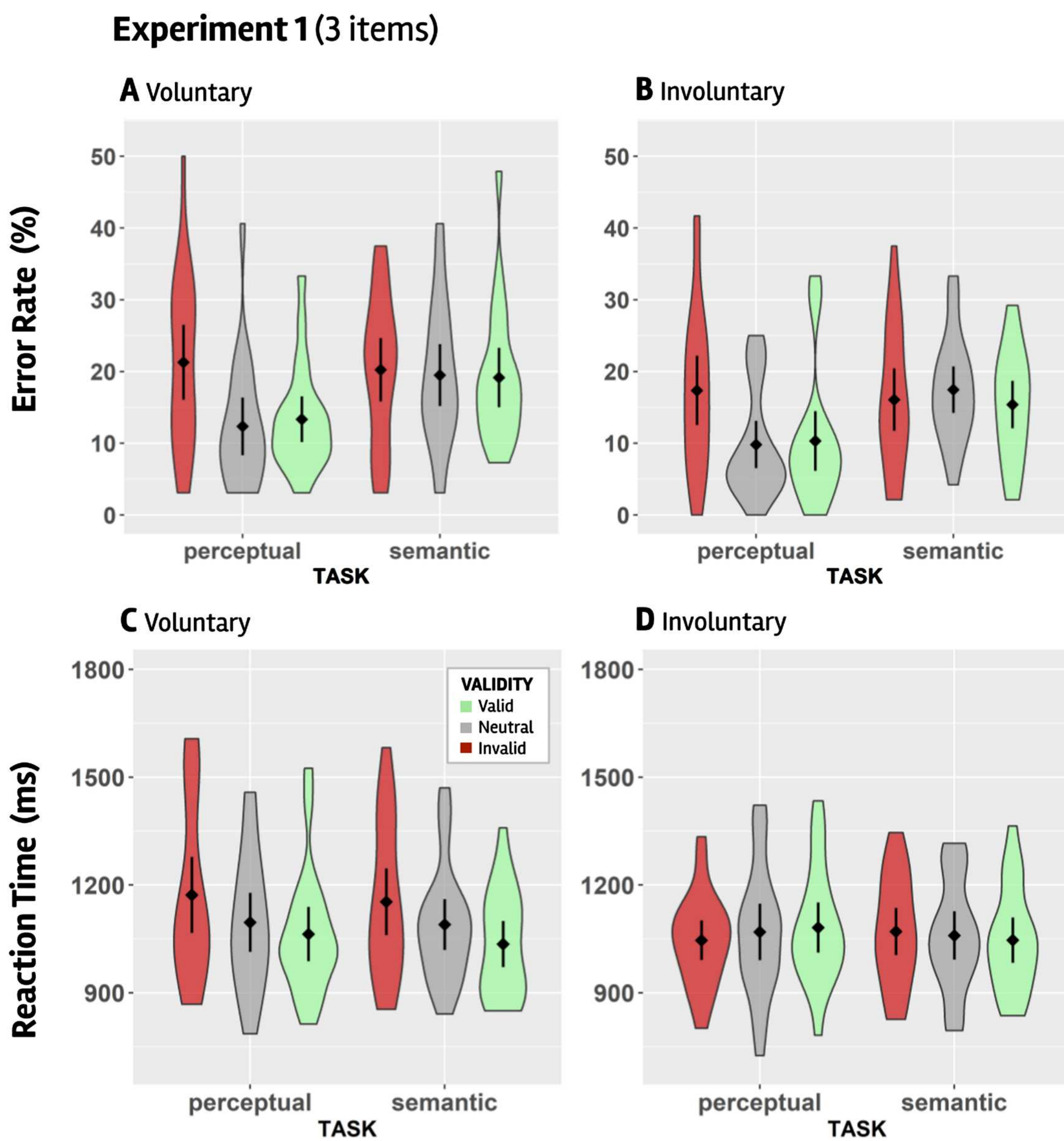

Figure 2. ERs and RTs in Experiment 1. Error rates –in percentages– (A: voluntary, B: involuntary) and mean reaction time –in ms– (C: voluntary, D: involuntary) averages for Experiment 1 are shown. Error bars represent +/— 2 standard errors.

significant effects were found in the involuntary task [all $p > .05$].

Discussion

Accuracy and RT results did not support the prediction of an interaction between voluntariness and the type of WM content. Instead, a different pattern emerged. On accuracy, an interaction between task and validity indicated that regardless of voluntariness, attention impacted on perceptual WM contents by means of a cost of invalid retro-cues. In turn, on RTs, an interaction between voluntariness and validity was found. Regardless of the type of WM content, voluntary attention elicited a RCE composed of benefits, and no evidence of a RCE was found for involuntary attention. In the following experiment, we aimed to replicate this pattern of findings while assessing whether an increment in the WM load would enable retro-cueing benefits in accuracy.

Experiment 2

The absence of retro-cueing benefits on accuracy in Experiment 1 might be due to a low WM load. Existing research has delved into the relationship between WM load and retro-cueing effects on both accuracy and response times (RTs). Previous findings point to larger retro-cueing benefits as the WM load (i.e., set size) increases (Exp.3 Astle et al., 2012; Nobre et al., 2008; Shepherdson et al., 2018; van Moorselaar et al., 2015; but see Gressmann & Janczyk, 2016; Makovski et al., 2008; Exp. 1 and 2; Ohl & Rolfs, 2020). Therefore, to boost retro-cueing benefits on accuracy by means of increasing the WM load, Experiment 2 replicated the design of Experiment 1, but the memory array contained four items instead of three. In addition, Experiment 2 aimed to replicate the main findings from Experiment 1: perceptual retro-cueing costs on accuracy, and voluntary retro-cueing benefits on RTs.

Method

Sample

The sample size was determined following the same sequential Bayes Factor approach as in Experiment 1 (Suppl. Table 1). Forty-one university students volunteered in this study and the final sample size was forty (25 ciswomen, 14 cismen, and 1 gender non-conforming person) aged 18–32 (M = 23.8 years old).

Procedure

Same as in Experiment 1.

Retro-cueing tasks

Same as in Experiment 1. One equidistant item was added to the memory array –square shaped–, hence, a yellow retro-cue was included.

Selection and processing of images

The same dataset of Experiment 1 was employed, though in this case 384 images were randomly selected for each participant in the involuntary task, and 424 were selected for the voluntary task. Images were presented three times in total, each time within a third of the task.

Data analysis

Same as in Experiment 1. Misses and responses faster than 200 ms were computed as errors (0.2%). One participant was excluded for having an accuracy under 60% and three SD below the average. For the accuracy and RT GLMMs, the best random structure contained random slopes for the interactions cue type x task and task x validity, while for the RT GLMM, the interaction cue type x validity was also included.

Transparency and openness

Same as in Experiment 1. In addition, the design, sample collection, and statistical analyses of Experiment 2 were executed as stated in the pre-registration: https://aspredicted.org/blind.php?x=KZT_FHS.

Results

Accuracy

The average accuracy of the involuntary task was 83.7% while for the voluntary task, it was 81.1%. Least-square means for each condition are shown in Table 1 (Figure 2, A, and B). The best GLMM model (Suppl. Table 3) included cue type, task, validity, and their interactions. The cue type [Wald $\chi2(1) = 2$, $p = .162$] and task [Wald $\chi2(1) = .1$, $p = .787$] effects were not significant, neither the interactions cue type x validity [Wald $\chi2(2) = .5$, $p = .788$], Task x Validity [Wald $\chi2(2) = 1.4$, $p = .492$], cue type x Task

[Wald $\chi2(1) = 3.1$, $p = .078$]. Importantly, the triple interaction cue type x task x validity was significant [Wald $\chi2(2) = 6.5$, $p = .039$]. To assess this interaction, we analyzed two additional GLMMs, one for the voluntary task and one for the involuntary task. For the voluntary task, the validity [Wald $\chi2(2) = 11$, $p = .004$] effect was significant. The RCE (valid - invalid) [$z = 3.5$, $p = .004$] was significant, while the benefit and the cost were not [all $p > .05$]. For the involuntary task, the task x validity interaction [Wald $\chi2(2) = 16$, $p < .001$] was significant. Post-hoc contrasts revealed a RCE in the perceptual task [$z = 3.6$, $p = .026$], while no other contrast was significant [all $p > .05$].

Reaction time

The average RT of the involuntary task was 1092 ms while for the voluntary task, it was 1172 ms. Least-square means for each condition are shown in Table 1 (Figure 3, C, and D). The best GLMM model (Suppl. Table 2) included cue type, task, validity, and their interactions. The main effect of task [Wald $\chi2(1) = .3$, $p = .573$] and the interactions task x validity [Wald $\chi2(2) = .2$, $p = .9$] and cue type x task [Wald $\chi2(1) = 2.4$, $p = .118$] were not significant, respectively. The cue type [Wald $\chi2(1) = 72.5$, $p < .001$] effect and the interaction cue type x validity were significant [Wald $\chi2(2) = 70.6$, $p < .001$]. More importantly, the cue type x task x validity interaction

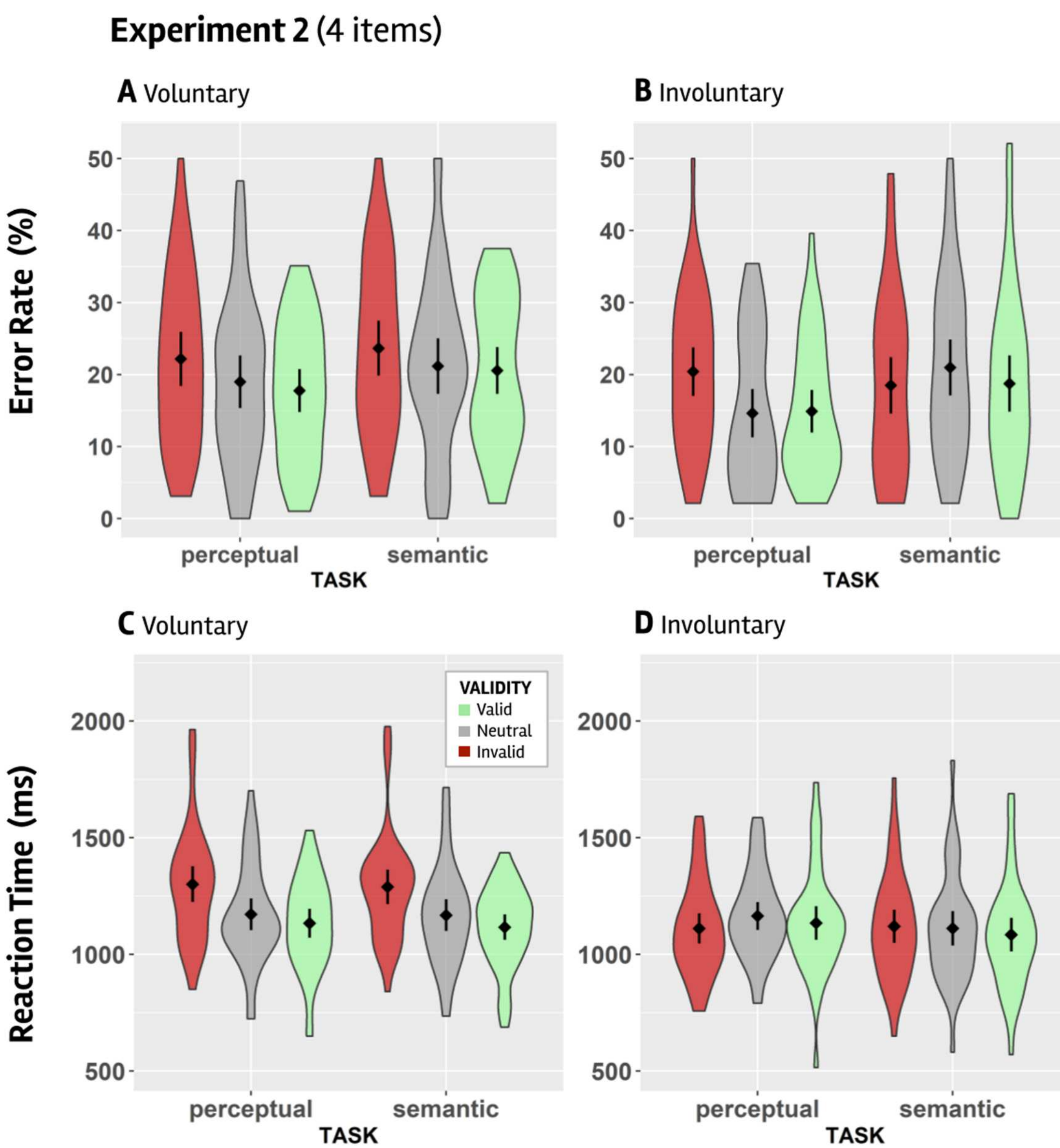

Figure 3. ERs and RTs in Experiment 2. Error rates –in percentages– (A: voluntary, B: involuntary) and mean reaction time –in ms– (C: voluntary, D: involuntary) averages for Experiment 2 are shown. Error bars represent +/— 2 standard errors.

was also significant [Wald $\chi2(2) = 10.4$, $p = .005$]. To assess the triple interaction, we analyzed two additional GLMMs, one for the voluntary task and one for the involuntary task. For the voluntary task the validity effect was significant [Wald $\chi2(2) = 80.3$, $p < .001$]. The RCE (invalid - valid) [$z = 6.9$, $p < .001$], the benefit (neutral - valid) [$z = 4$, $p < .001$], and the cost (invalid -neutral) [$z = 4.6$, $p < .001$] were all significant. For the involuntary task, the task x validity interaction was significant [Wald $\chi2(2) = 10.6$, $p = .005$], but all post-hoc contrasts were not [all $p > .05$].

Discussion

In Experiment 2, we sought to expand upon the findings of Experiment 1 by increasing the size of the memory array from three to four items. This aimed to replicate the pattern of findings observed in Experiment 1. In addition, Experiment 2 aimed to assess whether an increase in the WM load –from three to four items– would enable retro-cueing benefits on accuracy. Essentially, in Experiment 2, the general pattern observed in Experiment 1 was replicated: first, a RCE on accuracy for perceptual WM contents was found for both, voluntary and involuntary attention, though costs did not attain statistical significance; and second, a significant RCE was found on RTs for voluntary attention, but not for involuntary attention, and it was characterized by both reliable benefits and costs, the latter marginally significant in Experiment 1.

In addition to findings from Experiment 1, on accuracy, a triple interaction indicated that voluntary attention induced a net RCE on semantic WM contents. This latter effect may indicate that by increasing the memory load voluntary attention was able to impact on semantic WM contents, while involuntary attention was not. Though such an interpretation should not be discarded, Bayesian analyses on accuracy and –in the following section on– drift rates pointed against this possibility. For both experiments, the Bayesian ANOVAs for accuracy (Suppl. Table 1) and drift rates provided evidence in favour of the Task x Validity interaction, while evidence against the Cue type x Task x Validity interaction was found.

Finally, regarding the increment in the memory load, Experiment 2 did not induce substantial accuracy benefits which is in line with several previous studies (Gressmann & Janczyk, 2016; Makovski et al., 2008; Exp. 1 and 2; Ohl & Rolfs, 2020), but which differs from some others (Exp.3 Astle et al., 2012; Nobre et al., 2008; Shepherdson et al., 2018; van Moorselaar et al., 2015). Based on the studies that did find such an effect when the WM load was increased, one likely reason for not finding it –in Experiment 2– might be that a larger difference between set sizes should be compared (e.g., three vs. five items).

Drift-diffusion model analysis

To specifically analyze how retrospective attention impacted on the representation quality and retrieval of WM contents, and to draw stronger conclusions for the predictions of experiments 1 and 2, a Drift-Diffusion Model (DDM) analysis was conducted by means of modelling data from both experiments altogether. Experimental effects on reaction times and accuracy measures could be derived from several underlying cognitive processes (e.g., Voss et al., 2013). In addition, analyzing those measures separately can lose statistical power when an effect is distributed among both variables or what is worse, it could lead to speed-accuracy trade-offs. One solution implemented by Ratcliff (1978) is the DDM, which allows us to model the response time distribution of a binary decision task including all information at the trial level. Parameters are estimated from the empirical distribution and allow us to understand whether differences between conditions are explained by (1) an accelerated information uptake, (2) a liberal response criterion, and –or– by (3) shorter non-decisional processes. The basic DDM includes four parameters from the response time distribution of hits and errors: the drift rate (v), which refers to the slope of the diffusion process and represents the speed of information uptake; the threshold separation (a), which represents the amount of information considered to reach a decision; the starting point (z), which indicates whether there exists a priori bias to reach decision A or B; and the non-decision time (t0) that is the sum of processes non-related to the decision-making such as perceptual, mnemonic or motor execution processes.

In the context of WM, previous studies have interpreted drift rates as the quality of information that enters the decisional process while non-decision time indicates the retrieval time of those contents (Shepherdson, 2020; Shepherdson et al., 2018). In these studies, which explored voluntary attention, larger drift rates and shorter non-decision times were associated with the benefits of valid retro-cues. Researchers interpreted that the larger drift rates manifested a protective effect from the visual interference produced by the following probe presentation, while shorter non-decision times were associated with focusing attention on the cued item which would lead to an ahead retrieval of its information. Based on these studies and the results of experiments 1 and 2, drift rates were expected to reflect the task x validity interaction on the accuracy, and non-decision times the cue type x validity interaction of reaction times. In addition, considering that both experiments mainly yielded the same results, the factor load –between experiments– was not expected to modulate the pattern of findings.

Hierarchical drift diffusion model

We modelled our experimental data using the hierarchical drift-diffusion model (HDDM) toolbox (Wiecki et al., 2013), which has the advantage of considering all available data to retrieve parameters that model reaction time distributions for both, correct and incorrect trials. HDDM is hierarchical as it first estimates group-level parameters, and then it uses such group-level priors to restrict parameters estimation at the subject level. This yields more stable results in comparison to other traditional algorithms (Lerche et al., 2017). We first established a cut-off so that RTs below 200 were discarded, and when estimating the models, we used the HDDM command "p_outlier" to specify a 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) (as Formica et al., 2024). To estimate model parameters, we employed a Markov-chain Monte Carlo sampling procedure (Gamerman & Lopes, 2006). A chain with 5000 samples was used; and the first 500 samples were discarded as burn-in, to allow for 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.

To assess the RCE in the present study, we fitted six models and compared their fitness to select the one that better explained the data (see Suppl. Table 4). Results from retro-cueing tasks revealed that validity and load factors modulated both, v and t0 parameters (Shepherdson, 2020; Shepherdson et al., 2018; Souza & Frischkorn, 2023). In addition, due to results from experiments 1 and 2, we considered that cue type and task factors could also modulate those parameters. Finally, following Shepherdson et al. (2018) recommendation, and considering cue type and load were counterbalanced between blocks and experiments, respectively – i.e., not randomized factors–, we hypothesized that the threshold parameter may potentially capture systematic differences in how participants approach those different tasks, while given participants do not know in advance of the probe whether the trial would be valid/invalid or perceptual/semantic, validity and task factors were not included in this parameter. Based on this reasoning, we proposed three models that allowed the four factors –load, cue type, task, and validity– to vary both, on v and t0. Threshold (a) was allowed to vary once with load, once with cue type, and once with both factors. Given that results from experiments 1 and 2 were almost identical, we proposed three additional models which excluded load from varying on v and t0.

Next, the best-fitting model was chosen based on two criteria. First, based on the Deviance Information Criterion (DIC), where lower values indicate a better fit of the model to the empirical data. DIC also penalizes adding extra parameters to the model. Secondly, we assessed model fit in more detail. First, we ran a posterior predictive check: 500 datasets were generated from random parameter values drawn from the posterior distributions. From these 500 datasets, we calculated the mean accuracy, mean RT and mean of the .1, .3, .5, .7, and .9 quantiles for correct and error distribution. We then inspected the mean squared error (MSE) which quantifies the misfit between the mean of the predicted values compared to the observed values. Finally, to get a more condition-specific and visual assessment of the model fit, we simulated data for all conditions (5000 trials per condition, based on the mean of the posterior parameter estimates) and qualitatively compared the predicted and observed RT distributions. Based on these assessments, two models were selected for the analysis of experimental effects (Suppl. Table 4), models 4 and 6, which yielded better DIC and MSE, respectively. Given that both models yielded identical results we will report results from model 4.

Finally, to analyze and compare the experimental effects observed in experiments 1 and 2 with the HDDM parameters, we submitted the estimated data at the individual level for each parameter –a, v, and t0– to a Bayesian ANOVA using the *anovaBF* function in R (BayesFactor package). By means of the specification *whichModels = top* and 500000 iterations, the resulting JZS Bayes Factor (BF) reveals the level of evidence for removing effects/interactions from the full model. We employed the default values for the width of the prior distribution of all possible effect sizes, though wider and narrower priors yielded similar results. To ease understanding, a BF higher than 3 will represent substantial evidence in favour of the alternative hypothesis (H1) –i.e., main effect or interaction– over the null hypothesis (H0) –i.e., no effect–, while BFs lower than 1⁄3 reveal substantial evidence in favour of H0. A posteriori, for significant main effects and interactions, Bayesian t-test paired contrasts were performed using the *ttestBF* function.

Results

Drift rate (v)

Mean v values are shown in Table 2 (Figure 4, B, and C). The Bayesian ANOVA on v values revealed the main effects of cue type (involuntary > voluntary: BF > 100), task (BF > 100), and validity (BF > 100). The evidence for a cue type x validity interaction was ambiguous (BF = 0.909), while the evidence against the double interaction cue type x task (BF = 8.5) and the triple interaction was substantial (BF = .263). Importantly, the evidence for the task x validity interaction was substantial (BF > 100) (Figure 4A). In the perceptual task, post-hoc Bayesian t-tests revealed a RCE with larger drift rates on the valid than on the invalid condition (BF > 100), which was due to a cost of invalid retro-cues (BF > 100). There was substantial evidence against the benefit of valid retro-cues (BF = 0.14). On the semantic task, there was substantial evidence for a RCE (BF = 6), though it was substantially smaller than in the perceptual task (perceptual RCE > semantic RCE: BF = 6.6). However, in the semantic task, the RCE was due to a benefit (BF = 14) and not to a cost (BF = 0.16).

Table 2. Mean values for drift rate and non-decision time DDM parameters. Drift rate (v) and non-decision time (t0) mean values for each condition of the combined data from experiments 1 and 2 are shown. () = standard error.

			Experiments 1 and 2	
CUE TYPE	TASK	VALIDITY	v	t0
voluntary	perceptual	invalid	0.86 (0.05)	670 (19)
voluntary	perceptual	neutral	1.13 (0.05)	616 (17)
voluntary	perceptual	valid	1.14 (0.06)	559 (17)
voluntary	semantic	invalid	0.89 (0.04)	671 (18)
voluntary	semantic	neutral	1.01 (0.05)	604 (16)
voluntary	semantic	valid	1.01 (0.05)	542 (14)
involuntary	perceptual	invalid	1.09 (0.05)	577 (13)
involuntary	perceptual	neutral	1.3 (0.05)	612 (15)
involuntary	perceptual	valid	1.28 (0.05)	601 (16)
involuntary	semantic	invalid	1.16 (0.06)	585 (16)
involuntary	semantic	neutral	1.07 (0.06)	581 (14)
involuntary	semantic	valid	1.2 (0.06)	576 (14)

Non-decisional time (t0)

Mean t0 values are also shown in Table 2 (Figure 4, E, and F). The Bayesian ANOVA revealed substantial evidence for cue type (BF = 17.2) and validity (BF > 100) effects, while ambiguous evidence was found for the task effect (BF = 2). Substantial evidence against the double interactions of cue type x task (BF = 0.133) and task x validity (BF = 0.154) was found, and against the triple interaction (BF = 0.072). Importantly, substantial evidence in favour of the cue type x validity (BF > 100) interaction was found (Figure 4D). For voluntary retro-cues, substantial RCEs (BF > 100) composed of benefits (BF > 100) and costs (BF > 100) were found. On the contrary, for involuntary retro-cues, the evidence pointed against a RCE (BF = 0.19) or a benefit (BF = 0.30), while the evidence against a cost (BF = 0.83) was ambiguous.

Threshold (a)

Finally, on a values, the Bayesian ANOVA revealed substantial evidence against the effect of cue type (BF = 0.303), while ambiguous evidence for the effects of Load (BF = 0.4), and for their interaction (BF = 0.476) was found.

Discussion

Data from experiments 1 and 2 was modelled with a HDDM. Drift rates were expected to capture the task x validity interaction found on accuracy, while non-decision times were expected to parallel the cue type x validity interaction on reaction times. The HDDM analysis confirmed this pattern and, as for accuracy and reaction times, the voluntariness of attention did not interact with the WM content type. Specifically, regardless of voluntariness, drift rates evidenced perceptual retro-cueing costs –but no benefits–, while semantic retro-cueing benefits

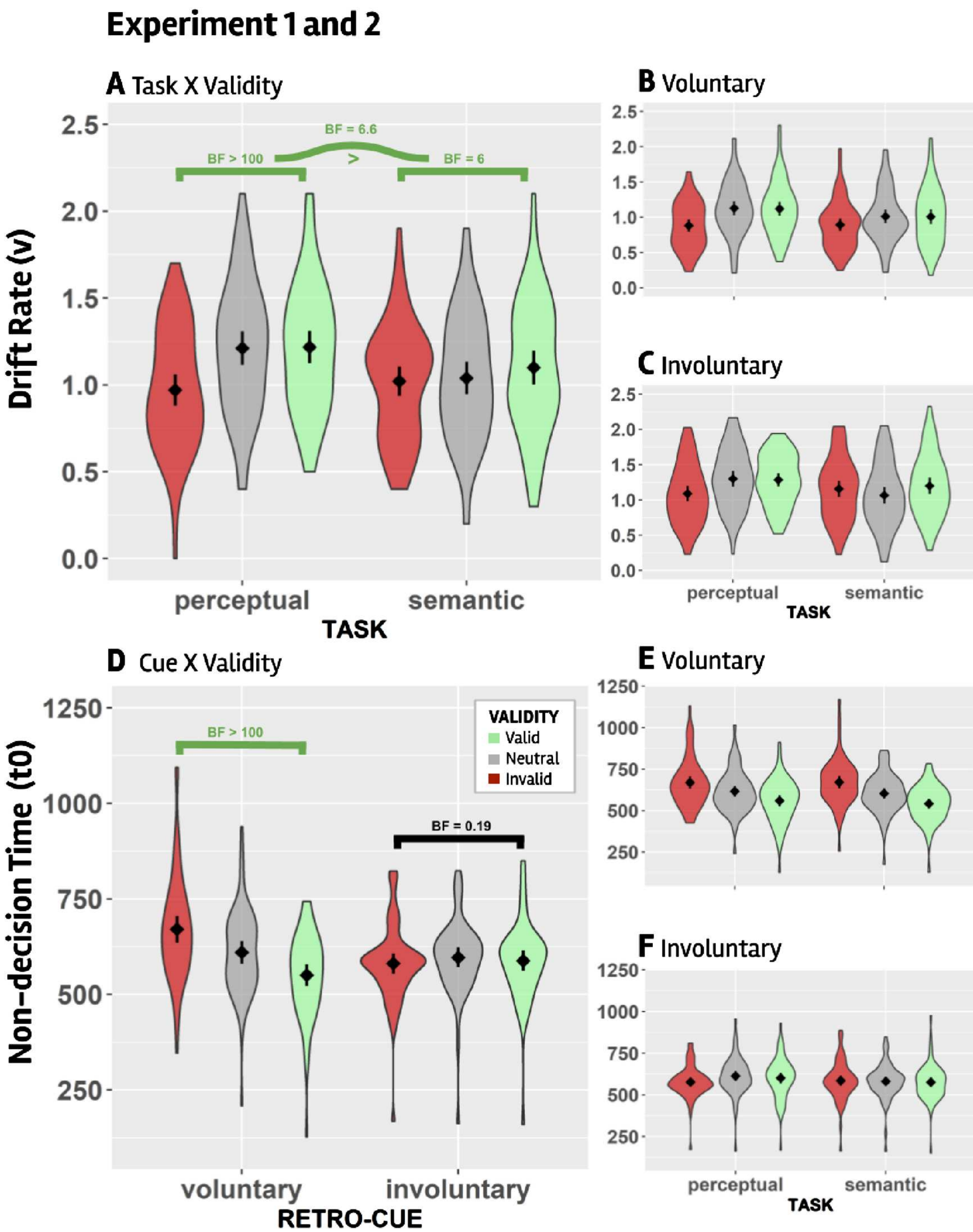

Figure 4. Drift rate and non-decision time effects. Combined data from experiments 1 and 2 was used to generate a hierarchical drift-diffusion model. Drift rate (B: voluntary, C: involuntary) and non-decision time (B: voluntary, C: involuntary) parameter estimate averages are shown. The two interactions with substantial evidence for H1 are represented: task x validity (A) for drift rates; and cue type x validity (D) for non-decision times. BFs that support a difference between conditions (BF > 3) are shown in green, and those BFs which have substantial evidence against a contrast (BF < 1/3) are shown in black. Black bars represent +/– 2 standard errors.

were found –but no costs–. This semantic benefit was driven by a small drop in the drift rate in the neutral condition for involuntary attention (see Table 2). Hence, from now on, this semantic benefit was interpreted as inconclusive. Moreover, the net RCE was larger for perceptual than for semantic WM contents. In turn, regardless of the WM content type, non-decision times confirmed a RCE for voluntary attention composed of benefits and costs, while the evidence pointed against a RCE for involuntary attention.

General discussion

The present study assessed whether voluntary and involuntary internal attention exert a different impact on perceptual (low-level) and semantic (high-level) WM contents. We conducted two experiments (Exp. 1: 3 items, Figure 2; Exp. 2; 4 items, Figure 3), analyzing reaction time and accuracy results. Subsequently, we employed a hierarchical drift-diffusion model to comprehensively model these results, allowing us to evaluate drift rates (indicative of information quality) and non-decision time parameters (reflecting retrieval time) (Figure 4). The initial prediction, which was rooted in direct (Prinzmetal et al., 2009) and indirect evidence (Esterman et al., 2008; Fernández & Carrasco, 2020, 2023; Landau et al., 2007) from external attention studies, posited that the effects of voluntary retrospective attention would be more pronounced on semantic WM contents, while the effects of involuntary attention would be more prominent on perceptual WM representations. In contrast with this prediction, Bayesian analyses of accuracy, reaction times and HDDM parameter estimates provided evidence against a triple interaction between validity, task, and cue type and revealed a different pattern of results. First, irrespective of voluntariness, the WM content type interacted with retro-cue validity on drift rates, mirroring accuracy results, demonstrating larger RCEs on perceptual (attributed to costs) than on semantic WM contents (Figure 4A). Secondly, irrespective of the WM content type, voluntariness of attention interacted with retro-cue validity on non-decision time, similar to reaction time, where only voluntary attention led to both benefits and costs, with no RCEs observed for involuntary attention (Figure 4D). Next, the implications of these findings are discussed.

First of all, these results suggest that, when participants are required to remember both perceptual and semantic contents at the same time, so that they compete for WM storage, voluntariness of internal attention does not differently alter their representation. Since the original prediction was based on external attention studies, the present results might indicate that internal and external attention mechanisms may be, at least partially, different. This aligns with the proposal that internal attention involves an additional step, the reformatting of the WM representation into a prospectively oriented state (Myers et al., 2017), and with studies revealing partially distinct neural activity patterns associated with both types of attention (Panichello & Buschman, 2021; Tamber-Rosenau et al., 2011; but see, Zhou et al., 2022). Alternatively, several methodological differences might account for the contrast with prior studies, such as employing different memoranda, retro-cues, presentation durations, or stimulus-onset asynchronies. One difference between Prinzmetal et al.'s (2009) study and the present one is worth mentioning. In the present study, participants were randomly asked about the colour (low-level) or the category (high-level) of one item on each trial, while in Prinzmetal's study, feature (low level) and conjunction (high level) trials were presented in blocks. While the present mixed design aimed to assess attentional effects on competing perceptual and semantic WM contents and circumvent selection history effects of blocked presentations (Awh et al., 2012), it may have attenuated differences between both types of representations by biasing participants to attend to WM contents in an object-based fashion. Conversely, in a blocked design, where there is no need to store the other dimension in WM, participants may orient internal attention to perceptual and semantic contents independently, akin to feature-based attention (e.g., Niklaus et al., 2017; Wheeler & Treisman, 2002). This possibility should be directly tested in future studies. Despite this consideration, the instructions for participants to memorize both colours and categories, coupled with the observed larger RCEs on perceptual rather than semantic contents, reinforce the notion that participants likely attended to both content types separately, and not in an object-based fashion. In essence, the current results indicate that the voluntariness of retrospective attention does not interact with the type of WM content when perceptual and semantic representations are in competition. Further testing is required to elucidate whether this is evidence for separate mechanisms of internal and external attention and/or whether it is specific to a scenario where contents contend for WM storage.

Results on accuracy and drift rates evidenced a novel pattern of RCEs on the interaction between retro-cue validity and the WM content type. Regardless of the voluntariness of attention, a RCE was found on perceptual WM contents, whereas mostly no RCE was observed on semantic WM representations, and when present, it was smaller than the perceptual RCE. This perceptual RCE was generated by costs of invalid retro-cues. First, these results suggest that retrospective attention was more effective in impacting the quality of perceptual WM contents rather than semantic representations, when both competed for WM storage. One possible explanation for this perceptual advantage lies in the faster processing of visual features such as colour compared to high-level semantic categories in the ascending visual hierarchy (e.g., Cichy et al., 2014; Clarke et al., 2013; Clarke & Tyler, 2015), placing perceptual features in a more accessible mental state for prioritization by internal attention, leading to larger RCEs. Significantly, this bias for perceptual contents persisted regardless of the voluntary or involuntary nature of attention. Considering the likelihood of distinct triggering mechanisms for both types of attentional orienting (e.g., van Ede et al., 2020), these results reaffirm the notion that perceptual WM representations may be inherently more accessible to be modulated by internal attention than semantic WM contents, irrespective of the underlying process driving prioritization. Second, drift rates also showed that the perceptual RCE resulted from retro-cueing costs. Several mechanisms have been proposed to explain the RCE (reviewed in Souza & Oberauer, 2016), and one may be behind this perceptual cost. Costs may be accounted for by a mechanism of removal of the colour memory trace of uncued colours/categories (e.g., Oberauer, 2001; Williams et al., 2013). Participants may have discarded or temporarily silenced those traces from WM. Consequently, during the presentation of the test array in the invalid condition, when uncued colours/categories are retrieved, they might be in a suboptimal state of representation, resulting in a drop in drift rates. A potential method to test the removal hypothesis for perceptual contents and the mechanisms behind the semantic RCE would be to analyze the contralateral-delay activity component (CDA) of the event-related potentials, interpreted as an index of WM storage (Luria et al., 2016). This could be achieved by separating the CDA waveform into its ipsilateral and contralateral signals for retro-cued items, which have been respectively analyzed as evidence for the removal of uncued representations and the strengthening of cued WM contents (Gunseli et al., 2019). Finally, future studies should test other perceptual and semantic manipulations to explore whether present findings are generalizable to other perceptual and semantic dimensions, such as exploring drawings vs pictures, while also employing other categories such as animate vs inanimate (e.g., Lifanov et al., 2021; Linde-Domingo et al., 2019). In short, retrospective attention prioritizes at a larger extent the quality of perceptual rather than semantic contents when both types of representations simultaneously compete for the limited storage of WM. This advantage manifests in perceptual retro-cueing costs, likely arising from the removal of memory traces of uncued colours.

The analysis of reaction times and non-decision times revealed a different pattern of results compared to accuracy and drift rates. The voluntariness of attention interacted with retro-cue validity, which was true regardless of the WM content type. RCEs (benefits and costs) were found for voluntary attention, while no RCE was found for involuntary attention. These results have several implications. First, in agreement with prior research (Shepherdson, 2020; Shepherdson et al., 2018), we posit that RCEs on non-decision times evidence that retro-cues prompt the retrieval of the selected colour and category ahead of subsequent decision-making processes during the presentation of the test array (retrieval head start hypothesis, Souza et al., 2016). Second, the current findings establish that this prior retrieval of the attended WM contents occurs exclusively when internal attention is voluntarily directed, but not when it is involuntarily attended. This parallels prior studies that employed perceptual memoranda, which have shown larger RCEs on reaction times for voluntary compared to involuntary attention (Shimi et al., 2014; van Ede et al., 2020; but see Berryhill et al., 2012; Han & Ku, 2022). The present study extends these findings by showing that this voluntary advantage persists even when the effects of involuntary attention are ruled out, given the independent assessment of both attentional types, underscoring the substantial potential of voluntary attention in prioritizing internal contents for retrieval. Thirdly, previous studies did not assess voluntary and involuntary attention concurrently while examining costs and benefits. By addressing this gap, this study reveals that the voluntary retrieval of WM contents not only induces benefits –on cued representations–, but also it induces costs of uncued contents. This is indicative that voluntary retrieval resources are focused on the cued item on valid and invalid trials, while on neutral trials, participants may distribute their attention among all items to retrieve them as accurately as possible. Fourthly, the present RCE persisted irrespective of the type of WM contents, which indicates voluntary mechanisms of retrieval operate regardless of the quality and nature of the WM representation. Lastly, regarding involuntary attention, it is important to note that two studies (Han & Ku, 2022; Shimi et al., 2014) evidenced RCEs on reaction times by employing peripheral spatial retro-cues. In contrast, in the present investigation, no such effects of involuntary attention were observed by using central retro-cues. Hence, peripherality might turn out to be a requisite to detect involuntary RCEs of spatial attention in non-decision times. An evaluation is needed to ascertain whether such effects may also be attributed to an advanced retrieval of WM contents or to a distinct attentional process. In essence, retrospective attention can retrieve WM contents in advance of decision-making: first, only when it is voluntarily oriented; second, in accordance with the trial-by-trial requirement for the distribution of retrieval processes; and third, regardless of the representation quality of its contents.

Finally, some limitations and future directions should be acknowledged. Firstly, while memory arrays comprised visually presented real-world items, the potential involvement of verbal WM due to labelling should be acknowledged. The present design makes a consistent verbal strategy difficult to implement across trials given each trial presented unique combinations of locations (i.e., the triangle/square disposition of three/four items memory array randomly rotated from trial-to-trial), colours and categories (e.g., grey-natural up, grey-artificial left-down, sepia-artificial right-down) which changed from trial-to-trial. However, participants may have partially relied on verbal labels—such as "gray-natural up"—which might indicate that colours and categories were represented in visual and verbal WM. In particular, the use of a verbal test, instead of a probe item similar to those presented in the memory array (e.g., Berryhill et al., 2012; Fu et al., 2022) may have encouraged this approach. This novel design (analogous to Kerrén et al., 2022 preprint; Lifanov et al., 2021; and Linde-Domingo et al., 2019), aimed to independently retrieve either the colour or category of an item, which would have been difficult if a probe resembling the memory array items had been used. If participants did rely on verbal WM, this may explain the larger retro-cue effects (RCEs) observed for perceptual compared to semantic contents, as verbal representations might have supported the latter more than the former. This aligns with findings by Shepherdson et al. (2018), who reported larger RCEs for visual than for verbal WM. Future research should include articulatory suppression tasks to limit verbal labelling (e.g., Brady & Störmer, 2022; Souza et al., 2018) and explore the effects of different retrieval methods, though this would challenge the ability to assess perceptual and semantic dimensions independently. Secondly, another aspect worth considering is that the involuntary task yielded larger accuracy than the voluntary one. Previous studies have reported varying results for neutral trials across both tasks (e.g., Berryhill et al., 2012; Fu et al., 2022; Han et al., 2023), and in this study, we attribute the accuracy difference to how involuntary and voluntary retro-cues are processed. Involuntary retro-cues, being processed automatically, impose no cognitive load, whereas voluntary retro-cues require active encoding, potentially leading to lower baseline performance in the voluntary task. While future research could aim to equate performance on neutral trials, this may not be necessary as long as within-task contrasts remain the primary focus, as in the current study. Thirdly, while previous research has shown retro-cue effects with varying stimulus-onset asynchronies (SOAs) between the retro-cue and probe (e.g., 800 ms in the present study; 500 ms in Berryhill et al., 2012; p. 1000 ms in Han & Ku, 2023; and 2000ms in van Ede et al., 2020), future studies should explore whether different SOAs influence the interaction between cue type, task, and validity. In external attention studies (Carrasco, 2011; Chica et al., 2013, 2014), voluntary attention has been shown to be sustained over time, requiring at least 300 ms to deploy, while involuntary attention operates more rapidly but decays after around 300 ms (but see a recent meta-analysis from external attention for long lasting central arrow cueing effects, Chacón-Candia et al., 2023). If internal attention follows a similar temporal pattern, shorter or longer SOAs could potentially amplify involuntary or voluntary attention, respectively. However, given that internal attention acts on existing representations, its temporal dynamics may differ from external attention, which is prospectively aligned with target onset. Finally, although the voluntary task yielded RCEs on non-decision times and the involuntary task did not, the involuntary cues used in the current study were not entirely non-predictive of the item tested—as Exp. 2, Shimi et al. (2014)—. Thus, the reduced reliability of these cues may have contributed to the observed RCEs on drift rates, despite instructions to ignore them. It is to be explored whether this low reliability partially triggered the RCE seen in this task. In essence, future research should extend the current findings by examining the involvement of verbal WM when representing real-world stimuli in visual WM, investigating the temporal dynamics of involuntary and voluntary attention, and by assessing the role played by low-reliability in the involuntary task.

In conclusion, the outcomes of two retro-cueing experiments challenge the hypothesis of an interaction between the voluntariness of attention and WM content type when perceptual and semantic representations compete for WM storage. Instead, a novel pattern of findings indicates, firstly, irrespective of voluntariness, retrospective attention is more effective in prioritizing the quality of perceptual rather than semantic WM contents; and secondly, the selective retrieval of WM representations prior to decision-making is under voluntary control and remains independent of the quality and nature of the content stored in WM. This study underscores the separate contributions of voluntariness and the type of WM content in shaping the effects of retrospective attention.

Acknowledgements

This work is part of the doctoral thesis of G.C., under the supervision of F.B. and J.L. . G.C. was supported by Grant PRE2021-100459 funded by 10.13039/501100011033. C.G.G. was supported by Project PID2020-116342GA-I00 funded by MCIN/AEI/10.13039/501100011033, and Grant RYC2021-033536-I funded by MCIN/AEI/10.13039/501100011033 and by the European Union NextGeneration EU/PRTR. E. M-A. was supported by Project PID2020-116342GA-I00 funded by MCIN/AEI/10.13039/501100011033. F.B was supported by Project PID2020-118214GB-I00 funded by MCIN/AEI/10.13039/501100011033. This study was supported by Projects PID2020.118214GB.I00 and Project PID2020.114790GB.I00 both funded by MCIN/AEI/10.13039/501100011033. This publication is funded by ESF+, CEX2023-001312-M by MCIN/AEI/10.13039/501100011033 and UCE-PP2023-11 by University of Granada.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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