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Ignoring distractors takes its (memory) toll

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ABSTRACT

Effective attentional selection requires filtering task-irrelevant stimuli. We examined the cognitive cost of such filtering using an object-based attention paradigm across four experiments ($N = 320$). Participants discriminated the orientation of a Gabor patch presented either alone or overlapped with an irrelevant object or scrambled stimulus. The filtering cost was measured as an increase in response times on distractor-absent trials embedded in 'mixed' blocks (with interleaved distractor-present trials) compared to 'pure' distractor-absent blocks. The filtering cost was robust and scaled with distractor probability and with the presence of one, two or four possible distractors occurring within the session. The cost disappeared when eight distractors were interleaved randomly, but re-emerged when the same eight distractors were presented orderly, one in each sequential mini-block, indicating a strategy shift once working-memory capacity is exceeded. The cost correlated negatively with interference on distractor-present trials and was unaffected by distractor semantic content, consistent with the active maintenance in working memory of distractor templates.

1. Introduction

In complex visual environments, the ability to focus on task-relevant information while ignoring irrelevant stimuli is critical for efficient behavior. From reading a book in a busy café to searching for a specific item on a cluttered desk, distractors must be ignored to prioritize the processing of relevant information. Consequently, over the past two decades, research has increasingly focused on distractor filtering mechanisms, showing that humans can learn and exploit the statistical regularities of distractors to protect target processing from interference (Chelazzi et al., 2019; Geng et al., 2019; Luck et al., 2021; Turatto, 2023; Won, 2021). In line with the idea that rare and unexpected stimuli obtain attentional priority (Itti & Baldi, 2009; Sokolov et al., 2002), the more a salient distractor appears in general (Müller et al., 2009), at a given location (Ferrante et al., 2018; Wang & Theeuwes, 2018) or in a given color (Stilwell et al., 2019), the less it captures attention. In addition, the general consensus is that capture attenuation is achieved by means of suppression being applied to the distractor features and/or locations on the basis of the corresponding statistics (Gaspelin et al., 2015; Liesefeld & Müller, 2019; Luck et al., 2021; Wang & Theeuwes, 2018).

However, as there is no free lunch in nature, it has been shown that the implementation of distractor rejection mechanisms comes at a cognitive cost (Marini et al., 2013). This *filtering cost* arises when observers expect to encounter a distractor within a block of trials, leading them to proactively (albeit implicitly) engage filtering mechanisms to limit the distractor's attentional capture and, consequently, its interference with task performance. The cognitive cost of filtering is revealed by a slowing down in target processing (i.e. longer response times, RTs) on distractor-absent trials in 'mixed' blocks, in which distractor-absent trials are randomly interleaved with distractor-present trials, compared to 'pure' blocks, in which distractor-present trials are absent altogether. Indeed, in the latter case, distractors are never presented and therefore never expected, which makes unnecessary any involvement of filtering mechanisms. In contrast, in mixed blocks, distractors appear on some trials, prompting participants to engage rejection mechanisms to protect target processing from interference (Marini et al., 2013; Marini et al., 2015; Marini et al., 2016; Petilli et al., 2020).

Although the filtering cost is observed on distractor-absent trials, its magnitude increases with higher distractor rates. This suggests that the cost reflects the engagement of filtering processes, which are more strongly activated when the probability of encountering a distractor is high. In turn, this heightened filtering draws on cognitive resources that would otherwise be allocated to target processing (Marini et al., 2013). Crucially, such cost cannot be explained by local, trial-wise adjustments (e.g., post-error slowing; Botvinick et al., 2001) or a general shift in

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response criterion (Marini et al., 2013).

Regarding how distractor filtering is implemented, Sokolov (1960, 1963) originally proposed that, through experience, the brain builds a neural model (or template) of the irrelevant sensory input when this is repetitively encountered. This model generates predictions of future inputs, which are then compared to the actual incoming stimuli; the closer the match, the more strongly the irrelevant input is rejected and ignored. Sokolov's original idea, that distractor filtering is based on the formation of a 'template' for irrelevant information, has regained popularity in recent years under the general notion of a 'template for rejection' (e.g., Carlisle, 2023; De Tommaso & Turatto, 2019; Woodman & Luck, 2007). Templates for rejection have been studied using cued-ignoring paradigms, in which participants search for a target among non-target elements. Critically, before the search display appears, participants are shown a stimulus that they must memorize for a later match-to-sample task. This stimulus can also indicate the color of a distractor in the search display, thereby serving as a cue for one of the non-target elements. The typical finding is that distractors interfere less in the search task when the cue is valid (i.e., when it matches one of the distractors) compared to a neutral condition (i.e., when it does not match). This result has been interpreted as evidence that participants can use the template active in WM to proactively direct attention away from distractors (Arita et al., 2012; Carlisle & Nitka, 2019; Conci et al., 2019; Woodman & Luck, 2007; Zhang et al., 2020). It has been proposed that the use of templates for rejection reflects a top-down strategy to anticipate distractor suppression (Carlisle & Woodman, 2011; Zhang et al., 2020; Zhang & Carlisle, 2023), although this process seems to rely more on implicit learning than on a voluntary effort (see Cunningham & Egeth, 2016), which also strategically depends on task difficulty (Conci et al., 2019). Therefore, maintaining distractor templates active in WM is likely a resource-demanding operation, which may impose additional costs to the attentional system.

So far, evidence of filtering cost has emerged from spatial attention paradigms (Marini et al., 2013; Marini et al., 2015; Marini et al., 2016). However, the fact that this cost is observed in distractor-absent trials clearly indicates that it does not directly reflect a spatial shift of attention. Instead, it likely reflects the engagement of mechanisms aimed at preventing performance decrements due to potential misallocations of attention. Importantly, distractors can compete with targets for attention not only in spatial terms (spatial-based attention), but also as discrete objects whose representations draw attentional resources away from the target, even when both appear at the same spatial location (object-based attention; Duncan, 1984; Eriksen & Schultz, 1979; Kahneman et al., 1983; Scholl, 2001; Treisman et al., 1983). In fact, the non-spatial nature of the filtering cost conceptually aligns more closely with object-based attentional competition. This consideration led us to maintain that an object-based attention paradigm might be better suited to further investigate and characterize the cognitive mechanisms underlying the filtering cost.

In this regard, it has been recently shown that the distractor rate can modulate object-based distractor interference, namely that infrequent distractors compete more for attention with the target than frequent ones, even when target and distractors share the same location (Dissegna, Caramazza, et al., 2025; Dissegna, Chiandetti, et al., 2025). In a task where participants judged the tilt of a centrally presented Gabor target overlaid with task-irrelevant real-world object distractors (e.g., animals or fruits) or their scrambled versions, the distractors' presence impaired target discrimination. Critically, real objects produced greater interference than scrambled images, pointing to two distinct sources of interference: a generic visual masking effect, present for both stimulus types and arising from the superimposition of irrelevant information on the target (Enns et al., 2000), and an additional object-specific interference consistent with object-based attentional capture (Duncan, 1984). The results also revealed a distractor frequency effect, with interference from object distractors diminishing as their occurrence increased (Dissegna, Caramazza, et al., 2025; Dissegna, Chiandetti, et al., 2025). This modulation parallels findings from spatial attentional capture paradigms, where distractor rate and spatial probability are implicitly learned and exploited to reduce distractor interference (e.g., Ferrante et al., 2018; Müller et al., 2009; Sauter et al., 2018; Turatto & Valsecchi, 2023; Valsecchi & Turatto, 2023; Wang & Theeuwes, 2018). The interference attenuation would thus be due to the formation of a neural model (Sokolov, 1960) or a template for rejection (e.g., Carlisle, 2023; De Tommaso & Turatto, 2019; Woodman & Luck, 2007), which is used to anticipate the distractor occurrence. In the present study, we adopted an object-based paradigm like that used by Dissegna, Caramazza, et al., 2025; Dissegna, Chiandetti, et al., 2025 to specifically examine the cognitive cost associated with maintaining such distractor templates, as already documented in the spatial domain (Marini et al., 2013).

In sum, before presenting the experiments, it should be made clear that we distinguish, and operationalize differently, two separate but related distractor effects: (1) distractor interference, measured as the slowing of RTs on distractor-present trials compared to distractor-absent trials; and (2) distractor filtering cost, measured only on distractor-absent trials, as the RT difference between the initial pure block and the subsequent mixed block. Thus, although in the attentional capture literature distractor interference is sometimes referred to as a distractor 'cost,' here we reserve the term 'cost' specifically to the increase in RTs in the mixed block compared to the pure block on distractor-absent trials, an increase attributable to the cognitive demands of implementing a distractor filtering mechanism.

2. Experiment 1

Participants classified a centrally presented target either in isolation or in the presence of a superimposed semitransparent object or its scrambled version (also see Dissegna, Caramazza, et al., 2025). Because relevant and irrelevant stimuli occupied the same location, any filtering mechanism based on spatial coordinates can be excluded. Participants completed two blocks of trials: a pure block with only distractor-absent trials, and a mixed block containing both distractor-present and distractor-absent trials. We used a between-participants design, where (in the mixed block) the distractor rate was 80 % for one group, and 20 % for the other group. We predicted the frequent distractor-object to interfere less than the infrequent one (Dissegna, Caramazza, et al., 2025; Dissegna, Chiandetti, et al., 2025). Crucially, in distractor-absent trials we also expected to observe slower RTs in the mixed compared to the pure block, particularly or only in the 80 % condition, consistent with a sustained activation of the filtering routine when there are more occasions for distractor interference, namely when the distractor is more likely to occur (Marini et al., 2013).

2.1. Method

2.1.1. Participants

Participants ($N = 80$[1]) were recruited online via Prolific. Eligibility criteria included native English speakers aged 18–45 with normal or corrected vision. Participation was restricted to individuals using desktop computers, as specified in the Prolific screener. They provided informed consent and were compensated £8.00/h. The sample had a

[1] For each of the four experiments, we estimated the required sample size for ANOVAs on filtering cost using (GPower 3.1.7, Faul et al., 2007). Based on prior literature (Marini et al., 2013; Petilli et al., 2020) and our pilot data, we targeted a medium effect size for Experiment 1 and 2 ($f = 0.35$). This analysis indicated that 68 participants (34 per condition) would be needed to achieve $\alpha = 0.05$ with 80 % power. To allow for equal sample sizes across all experiments and to maintain sufficient power in Experiment 3, where we expected a slightly smaller effect ($f = 0.27$), we recruited 40 participants per condition in each experiment.

mean age of 35 years ($SD = 5$), with 40 females (50 %).

2.1.2. Stimuli and procedure

The experiment was programmed using PsychoPy3 (v2020.1.3; Peirce et al., 2019) and run online via Pavlovia (Open Science Tools, UK). To estimate participants' screen resolution, the experiment began with a calibration task in which participants used the keyboard arrow keys to adjust the size of an on-screen image of a standard credit card to match the dimensions of a real one (Li et al., 2020). Each trial began with a white fixation cross (0.3 cm × 0.3 cm) displayed for 1000 ms against a mid-gray background (RGB = 128, 128, 128). The subsequent stimulus was a 3 cm × 3 cm Gabor patch (sinusoidal carrier with a Gaussian envelope, phase = 0, spatial frequency = 7 cycles/°, opacity = 0.5) that was randomly tilted 2° clockwise or counter-clockwise from the vertical axis. In the distractor-absent condition this Gabor patch appeared in isolation and served as the baseline. The distractor-present condition included two types of trials. In the object-distractor trials, a semitransparent grayscale image (3.5 cm × 3.5 cm, opacity = 0.5) depicting either an animal or a fruit was superimposed on the Gabor. At the start of the session, one exemplar from each category was chosen at random from a pool of ten possible items (see Fig. 1) and remained fixed for the entire experiment. In scrambled-distractor trials, the same object image was divided into non-overlapping 10 × 10-pixel tiles that were randomly repositioned within a 3 cm × 3 cm circular window, preserving local pixel statistics while disrupting global object form. The resulting scrambled image was then overlaid on the Gabor, providing a control for low-level visual masking that was matched in luminance and contrast but devoid of coherent object structure.

Each stimulus remained on screen for 1500 ms, during which participants indicated as fast and accurately as possible the orientation (relative to the vertical axis) of the Gabor patch (with reference to its upper part) by pressing the left arrow key for a counter-clockwise tilt or the right arrow key for a clockwise tilt. Incorrect responses or failures to respond within the 1500-ms window triggered an 800-ms feedback message ("Wrong!" or "Too slow!"). The trial ended with an 800-ms blank gray interval before the next onset of the fixation cross. The full temporal sequence of events is illustrated in Fig. 2.

After a practice block of 10 distractor-absent trials, participants completed 2 blocks of 100 trials each. The first block included distractor-absent trials alone (pure block) whereas the second block included distractor-present trials in addition to distractor-absent ones (mixed block). We did not counterbalance the order of the 'pure' and 'mixed' blocks; instead, the mixed block was always administered after the pure one. Since the filtering cost is calculated as the RT difference between the mixed and pure blocks (mixed minus pure), our design may actually favor a practice effect in the mixed block, potentially reducing the RT difference relative to the pure block. Therefore, any residual slowing of RTs on distractor-absent trials in the mixed block, compared to the pure block, would represent a conservative estimate of the filtering cost. For one group of participants the distractor rate was 20 % of the total trials (10 % were object-distractors and 10 % were scrambled distractors), whereas for the other group it was 80 % (40 % were object-distractors and 40 % were scrambled distractors).

2.1.3. Data analysis

Incorrect responses were removed from the dataset before the RTs analyses. An outlier-latency analysis on the correct responses was used to identify and exclude RTs exceeding 2.5 *SD* above or below the mean, which resulted in the removal of 2.7 % of the data.

Data were analyzed by considering two measures: 1) the distractor interference, namely the RT difference between distractor-present trials (both for object-distractors and scrambled-distractors) and distractor-absent trials in mixed blocks; 2) the filtering cost, namely the RT difference in distractor-absent trials between the mixed and pure blocks.

The two measures distributions were analyzed using mixed ANOVA models. For the distractor interference, the ANOVA model included the Distractor rate (20 % and 80 %) as between-participants factor, the Distractor type (scrambled-distractor and object-distractor) as within-participant factor, and their interaction. For the filtering cost, the ANOVA model included the Distractor rate (20 % and 80 %) as between-participants factor.

ANOVAs including Trial type (distractor-absent, scrambled-distractor, and object-distractor), Distractor rate (20 % and 80 %), and their interaction were used to analyze error rates distributions in the pure and the mixed block.

We also conjectured that during the course of the mixed blocks, distractor interference might undergo a progressive reduction, likely reflecting the dynamic implementation of the filtering mechanism. In order to test this possibility, we assessed whether, at the individual level, the reduction in distractor interference during the course of the mixed block was parallelled by an increase in filtering cost. To do so, we computed both measures separately for each participant within the two halves of the block (i.e., trials 1–50 and 51–100). Specifically, we calculated the variation in distractor interference as the difference between the second and first semiblock (negative difference indicates an interference reduction), and the variation in filtering cost using the same approach. We then examined the relationship between these two individual-level differences using linear regression models, after excluding outliers defined as observations deviating more than 2.5 SD from the predicted values. A negative slope in these models would indicate that participants who exhibited greater reductions in distractor interference also showed corresponding increases in filtering cost.

We reported Greenhouse-Geisser corrected results whenever *Mauchly*'s test returned a violation of the sphericity assumption. *Post-hoc*

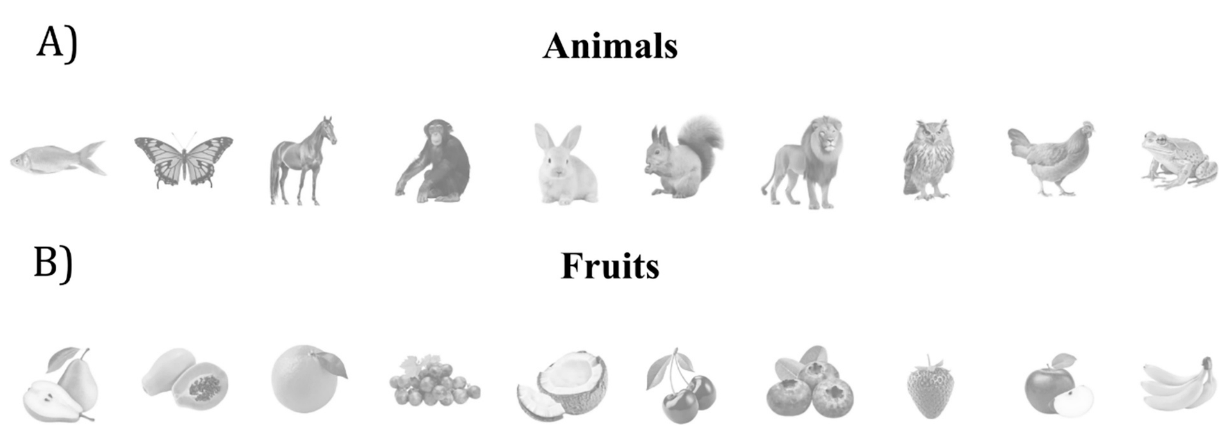

Fig. 1. Distractor images in Experiment 1. *Note.* For each participant, distractors were exemplars of the 'animal' category (panel A) and of the 'fruit' category (panel B).

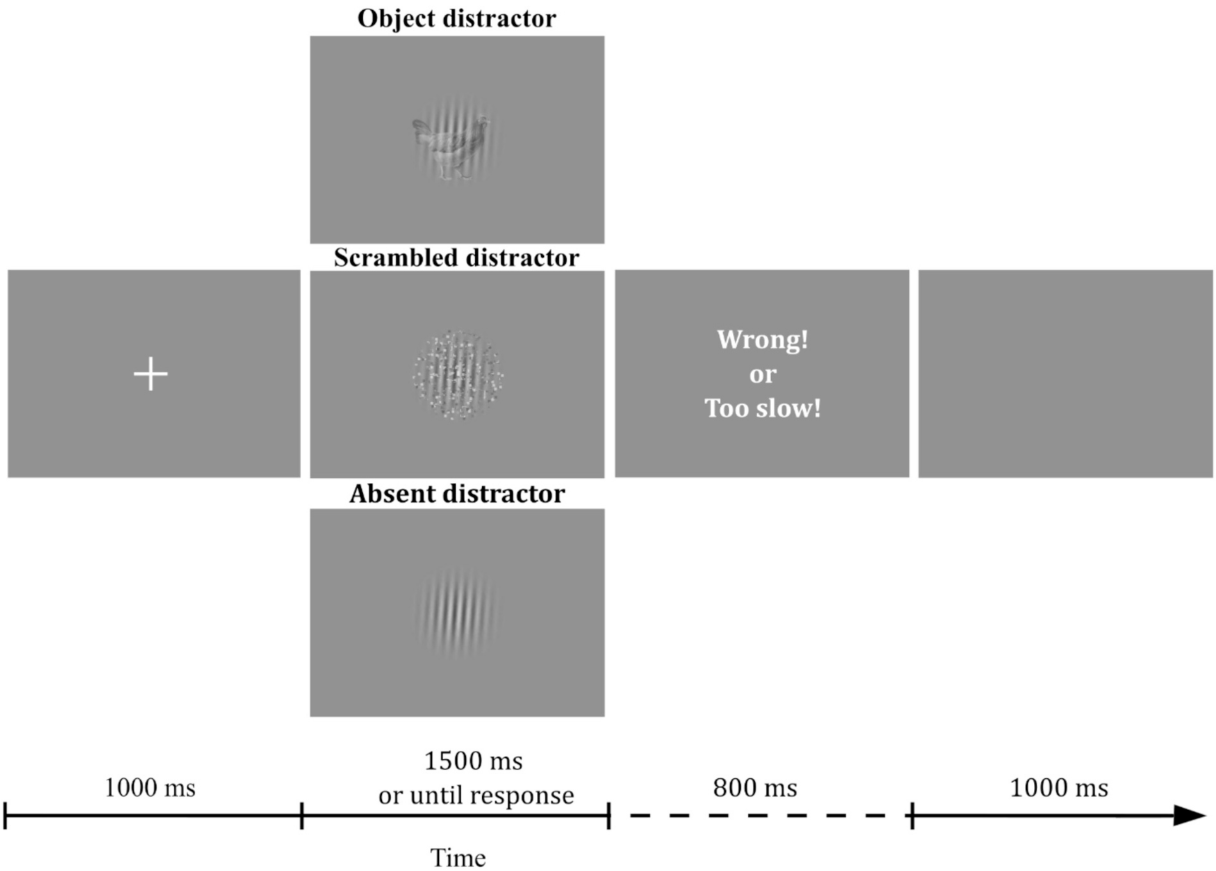

Fig. 2. Events of Experiment 1. *Note.* Participants reported the gabor orientation (right vs left with respect to the vertical axis) under different viewing conditions. In object-distractor trials (upper panel), the gabor appeared overlapping in transparency with the image of either an animal or a fruit object; in scrambled-distractor trials (middle panel), a scrambled image was obtained from an object distractor and presented in overlap with the gabor. In distractor-absent trials (lower panel), the gabor was the only object on the screen.

comparisons were conducted using *Tukey*'s *t*-tests. As estimates of the effect size, we provided: 1) partial eta squared (η^2_p) for the interactions and main effects of the ANOVA *F*-tests, and 2) Cohen's *d* for the *t*-tests. Data were analyzed using R, version 4.2.1 (R Core Team, 2023) and the package dplyr (Wickham et al., 2022), tidyr (Wickham & Maximilian, 2022), ggplot2 (Wickham, 2016), afex (Singmann et al., 2022), and emmeans (Lenth, 2022).

2.2. Results

The outlier-latency criterion resulted in the removal of 2.7 % of the correct responses. RTs are reported in Table 1. The ANOVA conducted on the distractor interference (Fig. 3A) revealed a significant main effect of the Distractor rate, $F(1, 78) = 90.15$, $p < .001$, $\eta^2_p = 0.54$, and a significant main effect of the Distractor type, $F(1, 78) = 77.04$, $p < .001$, $\eta^2_p = 0.50$. The Distractor rate × Distractor type interaction was not significant, $F(1, 78) = 1.22$, $p = .273$, $\eta^2_p = 0.01$. Specifically, the interference was larger for the 20 % distractor condition ($M = 204$ ms, $SD = 105$ ms) than for the 80 % distractor condition ($M = 69$ ms, $SD = 60$ ms), $t(78) = 9.49$, $p < .001$, $d = 2.15$, and it was larger for the object distractor ($M = 177$ ms, $SD = 116$ ms) than for the scrambled distractor ($M = 96$ ms, $SD = 84$ ms), $t(78) = 8.77$, $p < .001$, $d = 0.99$.

Table 1
Mean RTs by Distractor rate, Block type, and Trial type for Experiment 1.

Distractor rate	Block type	Trial type	RT (SD)
20 %	Pure	Distractor-absent	542 (79)
20 %	Mixed	Distractor-absent	555 (76)
20 %	Mixed	Object-distractor	805 (162)
20 %	Mixed	Scrambled-distractor	714 (98)
80 %	Pure	Distractor-absent	546 (76)
80 %	Mixed	Distractor-absent	602 (88)
80 %	Mixed	Object-distractor	707 (103)
80 %	Mixed	Scrambled-distractor	636 (88)

Note. Mean RTs and their SDs are reported in milliseconds.

The ANOVA conducted on the filtering costs (Fig. 3B) revealed a significant main effect of the Distractor rate, $F(1, 78) = 19.98$, $p < .001$, $\eta^2_p = 0.21$, with the filtering cost being greater for the 80 % distractor condition ($M = 56$ ms, $SD = 44$ ms) than for the 20 % distractor condition ($M = 13$ ms, $SD = 41$ ms). The modest filtering cost observed in the 20 % distractor condition was however significant ($p = .045$).

A linear model examining the relationship between changes in distractor interference and filtering cost across the two semiblocks (Fig. 3C) revealed a significant negative association in the 80 % condition ($b = -0.66$, s.e. $= 0.14$, $p < .001$, $R^2 = 0.35$), indicating that individuals who showed greater reductions in distractor interference also exhibited larger increases in filtering cost. No significant relationship was observed in the 20 % condition ($b = -0.33$, s.e. $= 0.30$, $p < .281$, $R^2 = 0.04$).

The analysis of the error rates basically confirmed the RTs findings. In the pure block, the mean error rates were 5.4 % ($SD = 5.0$ %) in the 20 % distractor condition and 5.1 % ($SD = 4.7$ %) in the 80 % distractor condition. In the mixed block, the mean error rate distribution in the 20 % distractor condition was 6.1 % ($SD = 5.5$ %) for the distractor-absent trials, 10.2 % ($SD = 11.9$ %) for the scrambled-distractor trials, and 17.2 % ($SD = 17.1$ %) for the object-distractor trials. In the 80 % distractor condition, the error rates were 6.0 % ($SD = 8.3$ %) for the distractor-absent trials, 10.6 % ($SD = 9.1$ %) for the scrambled-distractor trials,

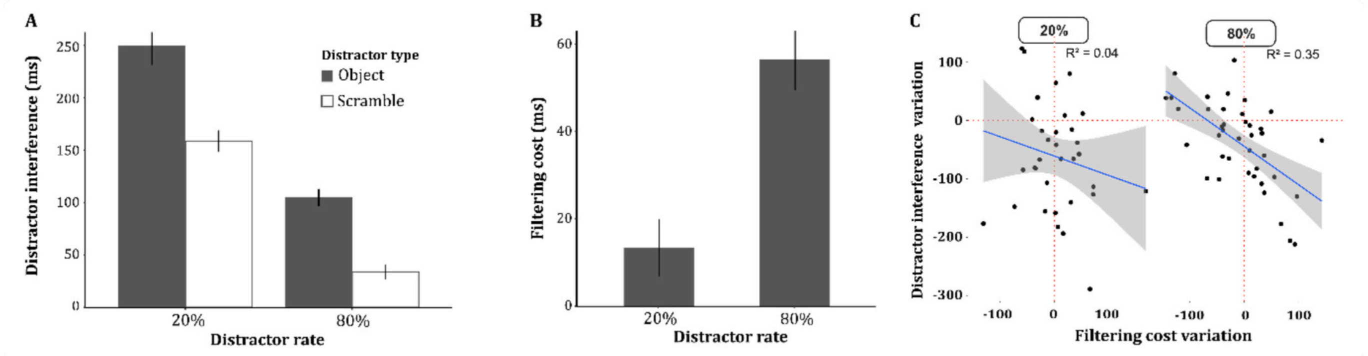

Fig. 3. Effects of the Distractor rate and Distractor type on the gabor discrimination. *Note.* Panel A depicts mean distractor interference (RTs distractor-present – RTs distractor-absent in mixed block). Panel B depicts mean filtering cost (RTs distractor-absent in mixed blocks – RTs distractor-absent in pure blocks). Bars represent ±1 standard errors of the mean. Panel C shows the relationship between changes in distractor interference and filtering cost across the two semi-blocks of the mixed block (each point of the scatterplot represents an individual).

and 15.2 % (SD = 11.8 %) for the object-distractor trials.

The analysis of error rates of the mixed block revealed a main effect of the Trial type, $F(1.67,129.93) = 22.08$, $p < .001$, $\eta^2_p = 0.22$, while neither the Distractor rate effect nor the Trial type × Distractor rate interaction were significant (all $ps > 0.05$). The error rate for the object distractor was significantly larger than for the scrambled distractor, $t(78) = 3.37$, $p < .001$, $d = 0.38$, and the error rate in the scramble distractor was larger than in the distractor-absent condition, $t(78) = 3.79$, $p < .001$, $d = 0.43$. There was no significant difference between error rates in distractor-absent trials in the pure and the mixed block (all $ps > 0.05$).

Although we attributed the slower RTs on distractor-absent trials in the mixed block, compared to the pure block, to a filtering cost, an alternative explanation could involve the post-error slowing phenomenon, i.e., the tendency for people to respond more slowly on a task immediately after making an error (Botvinick et al., 2001). Given that error rates were generally higher in the mixed block due to errors on distractor-present trials, we tested whether the slower responses observed in distractor-absent trials could be attributed to this effect. To this aim, we identified and removed from the dataset used for the filtering cost analysis all trials that followed an incorrect response. We then performed the same ANOVA. Results were unchanged, confirming a significant main effect of the Distractor rate, $F(1, 78) = 18.91$, $p < .001$, $\eta^2_p = 0.19$, with the filtering cost being greater for the 80 % distractor condition ($M = 57$ ms, $SD = 46$ ms) than for the 20 % distractor condition ($M = 14$ ms, $SD = 40$ ms), and the filtering cost observed in the 20 % distractor condition that was modest but still significant ($p = .030$).

Alternatively, the increased filtering cost in the 80 % distractor rate condition relative to the 20 % condition may be due to increased post-distractor slowing. Indeed, one might argue that after having encountered a distractor on a given trial, participants might have become more cautious in responding on a subsequent trial in general, and therefore also on distractor-absent trials. Because the probability of encountering a distractor was larger in the 80 % condition compared to the 20 % condition, RTs on distractor-absent trials were on average slower in the former than in the latter condition, which would explain the putative "filtering cost".

To exclude this possibility, we analyzed RTs in the mixed blocks using a 3-way ANOVA with two within-participant factors, Trial N (distractor-absent vs. distractor-present) and Trial N–1 (distractor-absent vs. distractor-present), and one between-participant factor, Distractor rate (20 % vs. 80 %). Results revealed a main effect of Trial N, $F(1,76) = 173.26$, $p < .001$, $\eta^2_p = 0.69$, with slower RTs on distractor-present compared to distractor-absent trials. There was also a significant Trial N × Distractor rate interaction, $F(1,76) = 34.98$, $p < .001$, $\eta^2_p = 0.31$, reflecting slower RTs for distractor-present trials in the 20 % condition than in the 80 % condition, and slower RTs for distractor-absent trials in the 80 % condition than in the 20 % condition. In addition, a significant Trial N × Trial N–1 interaction emerged, $F(1,76) = 5.34$, $p = .024$, $\eta^2_p = 0.07$. Post-hoc Tukey's tests showed that RTs on distractor-present trials were not influenced by the preceding trial type, $t(76) = 1.71$, $p = .246$, whereas RTs on distractor-absent trials were slower following a distractor-present trial than a distractor-absent trial, $t(76) = 2.82$, $p = .025$. By contrast, the three-way interaction (Distractor rate × Trial N × Trial N–1) was not significant, $F(1,76) = 0.90$, $p = .347$, $\eta^2_p = 0.01$, $BF_{01} = 4.2$, indicating that post-distractor slowing affected RTs on distractor-absent trials to the same extent in both Distractor rate conditions and, therefore, cannot explain the observed difference in filtering cost.

2.3. Discussion

Irrelevant overlapping distractors slowed down RTs, with greater interference resulting from objects than scrambled images, indicating an object-based attentional interference (Dissegna, Caramazza, et al., 2025; Kahneman et al., 1983; Treisman et al., 1983). Also, like in the case of spatial attentional capture (e.g., Sauter et al., 2018; Wang & Theeuwes, 2018), the distractor rate influenced the object-based capture.

Crucially, RTs on distractor-absent trials were slower in mixed than pure blocks, with the largest filtering cost at 80 % distractor probability, when a sustained activation of filtering was justified given the high chances to encounter a salient irrelevant element in the display (Marini et al., 2013). This cost cannot be attributed to post-error slowing (Botvinick et al., 2001) of RTs, as removing post-error trials did not change the result, nor it can be attributed to a lack of practice with distractor-absent trials, as we ran the pure block first, so in the mixed block participants were already fully practiced in this condition. Hence, if anything, by running the pure block second, we may have underestimated the filtering cost. Finally, post-distractor slowing affected RTs on distractor-absent trials to a similar extent in both distractor rate conditions; therefore, it cannot account for the observed differences in filtering cost. By contrast, the fact that in the 80 % rate condition individuals who showed greater reductions in distractor interference also experienced larger increases in filtering cost, is consistent with the idea that such cost increases as a rejection mechanism is gradually implemented.

While the filtering cost has been previously reported in spatial attention studies, the results showed that the same cost can be reliably observed also in an object-based attention paradigm, which attests its independence from any spatial orienting components. As we have seen, the filtering cost was greatest at the highest distractor rate, where we also observed the weakest capture, suggesting that the strongest attenuation of capture resulted from a robust implementation of filtering. However, another factor that may influence the filtering cost is the degree of attentional capture itself. In other words, it seems reasonable to expect that, for the same distractor rate, stronger filtering would be deployed as distractor interference increases, since such situation poses a greater threat to target processing.

Although in the present experiment objects produced more interference than the corresponding scrambled images (Dissegna et al., 2025), the two types of distractors were intermixed within the same block, which precluded us from evaluating the impact of different levels of attentional capture on the filtering cost. The next experiment was therefore designed to address this question.

3. Experiment 2

Participants completed four alternating blocks, in the following order: pure-mixed-pure-mixed. Each mixed block contained only one type of distractor, either an object or its scrambled version. The order of the two types of mixed blocks was counterbalanced across two groups of participants. Distractors rate was always 80 % to elicit a robust filtering cost (see Experiment 1). If the amount of filtering cost is proportional to the amount of distractor interference, then it should be larger for object distractors than for their scrambled counterparts.

3.1. Method

3.1.1. Participants

Forty participants took part in the experiment, and were recruited online with the same modalities as in Experient 1.

3.1.2. Stimuli and procedure

Stimuli and procedure were as in Experiment 1, with the following exception. Participants completed four blocks of trials, alternating between pure and mixed blocks in a fixed order. In the mixed blocks, the distractor appeared on 80 % of the trials. For one group of participants, the first mixed block included the object distractor and the second the scrambled distractor, whereas this order was reversed for the other group.

3.1.3. Data analysis

Data were analyzed as in Experiment 1 with the following exception: filtering costs were computed separately for the mixed block containing the scrambled distractor and the object distractor.

3.2. Results

The outlier-latency criterion resulted in the removal of 3.4 % of the correct responses. RTs are reported in Table 2. The ANOVA conducted on the distractor interference (Fig. 4A) revealed a significant main effect of the Distractor type, $F(1, 36) = 22.45$, $p < .001$, $\eta^2_p = 0.48$. Specifically, the interference was larger for the object distractor ($M = 104$ ms, $SD = 51$ ms) than for the scrambled distractor ($M = 58$ ms, $SD = 35$ ms).

The ANOVA conducted on the filtering costs (Fig. 4B) revealed that scrambled distractors and object distractors led to similar costs (scramble: $M = 36$ ms, $SD = 39$ ms; object: $M = 32$ ms, $SD = 32$ ms), $F(1, 36) = 0.29$, $p = .592$, $\eta^2_p = 0.01$, $BF_{01} = 4.93$. For all conditions, the cost was significantly greater than 0 (all $ps < 0.05$).

Table 2
Mean RTs by Block type and Trial type for Experiment 2.

Block type	Trial type	RT (SD)
Pure	Distractor-absent	545 (83)
Mixed - Object distractor	Distractor-absent	577 (85)
Mixed - Object distractor	Distractor-present	655 (110)
Mixed - Scrambled distractor	Distractor-absent	582 (90)
Mixed - Scrambled distractor	Distractor-present	609 (92)

Note. Mean RTs and their SDs are reported in milliseconds.

The linear model examining the relationship between changes in distractor interference and filtering cost across the two semi-blocks (Fig. 4C) revealed a significant negative association for both scrambled distractors ($b = -0.30$, s.e. $= 0.12$, $p = .029$, $R^2 = 0.14$) and object distractors ($b = -0.51$, s.e. $= 0.16$, $p < .001$, $R^2 = 0.23$).

As for the error rate analysis, in the pure block, the mean error rate was 5 % ($SD = 4.0$ %). In the mixed block with the scrambled distractor, the mean error rate was 5.5 % ($SD = 8.8$ %) in distractor-absent trials and 9.8 % ($SD = 8.7$ %) in scrambled-distractor trials. In the mixed block with the object distractor, the mean error rate was 6.5 % ($SD = 9$ %) in distractor-absent trials and 15.7 % ($SD = 12.4$ %) in object-distractor trials.

The ANOVA performed on error rates of the mixed block revealed a main effect of the Trial type, $F(1.86, 66.86) = 23.05$, $p < .001$, $\eta^2_p = 0.39$. Error rates in the object-distractor condition were significantly larger than in the scrambled-distractor condition, $t(36) = 3.71$, $p < .001$, $d = 0.62$, and error rates in the scrambled condition were larger than in the distractor-absent condition, $t(36) = 3.11$, $p < .001$, $d = 0.52$. The analysis of distractor-absent trials revealed no significant difference between error rates in the pure and in the mixed block ($p > .05$).

To exclude the possibility that the observed filtering costs were the by-product of post-error slowing of responses during the mixed-block, we removed post-error trials from the dataset and conducted the same ANOVA as before. Results confirmed that scrambled distractors and object distractors led to similar filtering costs (scramble: $M = 33$ ms, $SD = 42$ ms; object: $M = 29$ ms, $SD = 31$ ms), $F(1, 36) = 0.22$, $p = .644$, $\eta^2_p < 0.01$. For both conditions, the cost was significantly greater than 0 (all $ps < 0.05$).

3.3. Discussion

Object distractors caused greater interference than scrambled distractors, confirming previous findings using a similar paradigm (Dissegna et al., 2025). Since objects and their scrambled counterparts were equivalent in terms of the energy impinging on the eyes, this suggests that, beyond any masking effect the superimposed image may have exerted on Gabor discrimination (which was the same for both types of distractors), objects introduced an additional interference. This additional cost reflects genuine object-based attentional capture (Dissegna, Caramazza, et al., 2025; Dissegna, Chiandetti, et al., 2025).

However, despite the stronger interference caused by object distractors, they surprisingly produced a filtering cost similar to that of scrambled images, indicating that the filtering does not seem to be determined by the degree of object-based capture. Hence, based on the combined results of Experiments 1 and 2 it seems that the distractor rate of occurrence is the main factor influencing the filtering cost (Marini et al., 2013).

An interesting question then regards the mechanism that causes the filtering cost. Since the seminal work of Sokolov on the habituation of the orienting reflex (1960, 1963), it has been suggested that the brain learns to ignore the repetitive irrelevant stimuli by building a corresponding neural model. In agreement with this view, in more recent years the notion of ‘distractor template’ has been proposed (Arita et al., 2012; Carlisle, 2023; De Tommaso & Turatto, 2019; Won & Geng, 2018; Woodman & Luck, 2007). This template can be used to anticipate the distractors occurrence, which capture attention in proportion to how much they are unexpected or surprising (also see Itti & Baldi, 2009). However, the filtering cost clearly indicates that the active maintenance of a distractor template is resource demanding. If the cost would thus reflect the maintenance of such template in memory, subtracting resources from target processing, we expect that increasing the number of distractors templates in memory should increase the filtering cost.

4. Experiment 3

If the filtering cost reflects the maintenance in memory of such

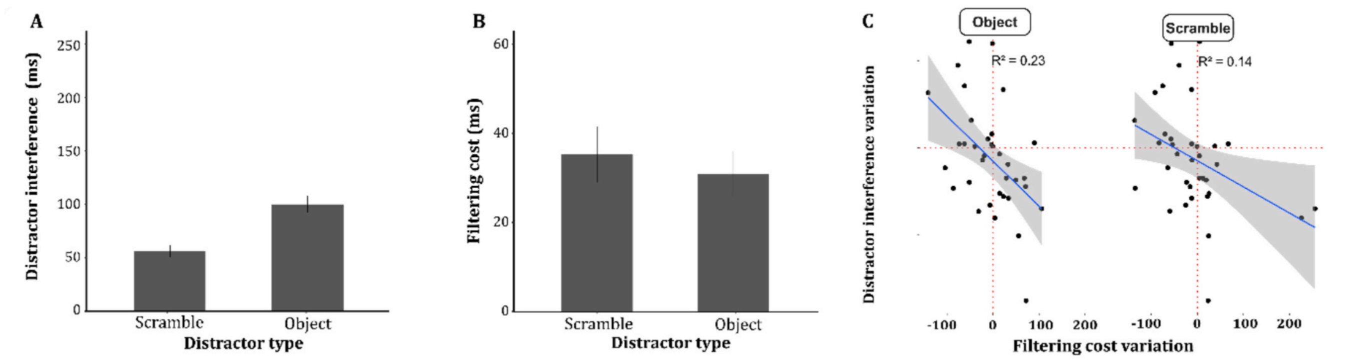

Fig. 4. Effects of the Distractor type on the Gabor discrimination. *Note.* Panel A depicts mean distractor interference (RTs distractor-present – RTs distractor-absent in mixed block). Panel B depicts mean filtering cost (RTs distractor-absent in mixed blocks – RTs distractor-absent in pure blocks). Bars represent ±1 standard errors of the mean. Panel C shows the relationship between changes in distractor interference and filtering cost across the two semi-blocks of the mixed block (each point of the scatterplot represents an individual).

templates, another factor that could play a role in modulating the filtering cost is the number of distractor templates being currently active. To address this question, in a between-participants design, we manipulated the number of possible distractors being presented (one at the time) in the mixed blocks, while keeping the overall distraction rate constant (80 %). In the mixed block they were exposed either to a single frequent distractor (80 % rate), or to two (40 % each), four (20 % each) and eight (10 % each) different distractors. In terms of distractor interference, although the overall distractor rate was the same (80 %) in all conditions, we expect capture to increase as the number of distractors increases, as each one is presented at a progressively lower rate (see also De Tommaso & Turatto, 2023; Valsecchi & Turatto, 2023). As for the filtering cost, the prediction is that the larger the number of distractor templates active in memory the larger the filtering cost.

4.1. Method

4.1.1. Participants

One-hundred and sixty participants took part in the experiment, and were recruited online with the same modalities as for Experiment 1.

4.1.2. Stimuli and procedure

The stimuli and procedure were identical to those used in Experiment 1, with the following exceptions. Only object distractors were presented in the mixed blocks. The objects were selected from the category sets shown in Fig. 5. In the mixed block the overall distractor rate was 80 % in each of the four groups of participants. In the 1-distractor condition, participants (N = 40) were exposed to a single distractor (distractor-specific rate = 80 %); in the 2-distractor condition, participants (N = 40) were exposed to two different distractors (distractor-specific rate = 40 %); in the 4-distractor condition, participants (N = 40) were exposed to four different distractors (distractor-specific rate = 20 %); finally, in the 8-distractor condition, participants (N = 40) were exposed to eight distractors (distractor-specific rate = 10 %). Objects were counterbalanced across participants in each group. In the 8-distractor condition, two objects were selected at random from each category.

4.1.3. Data analysis

Data were analyzed as in Experiment 1 with the following exception. For the distractor interference, the ANOVA model included the Distractor number (One, Two, Four, and Eight) as between-participants factor. For the filtering cost, the ANOVA model included the Block type (Pure and Mixed) as additional within-participants factor.

4.2. Results

The outlier-latency criterion resulted in the removal of 2.8 % of the correct responses. RTs are reported in Table 3. To begin with, the ANOVA conducted on the distractor interference (Fig. 6A) revealed a significant main effect of the Distractor number, $F(3, 156) = 14.62$, $p < .001$, $\eta^2_p = 0.21$. Specifically, while distractor interference did not differ between the 1- and 2-distractor conditions (M = 65 ms, SD = 46 ms, and M = 71 ms, SD = 44 ms respectively), interference in both conditions was significantly smaller than in the 4-distractor condition (M = 107 ms, SD = 41 ms), 1 vs 4 $t(156) = 4.57$, $p < .001$, $d = 0.73$; 2 vs 4 $t(156) = 3.84$, $p < .001$, $d = 0.62$. The 1- and 2-distractor conditions also significantly differed from the 8-distractor condition (M = 115 ms, SD =

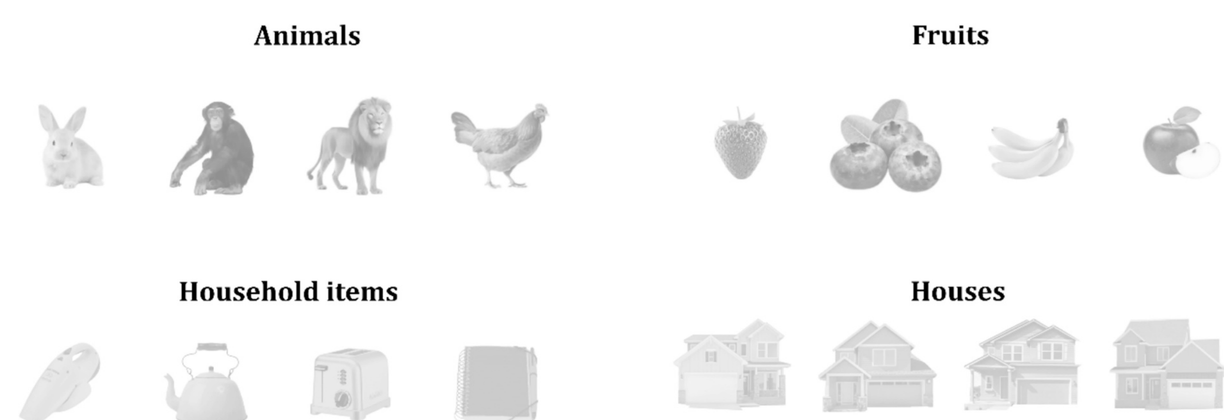

Fig. 5. Distractor images in Experiment 3. *Note.* For each participant, distractors were selected from the four sets above.

Table 3
Mean RTs by Distractor number, Block type, and Trial type for Experiment 3.

Distractor number	Block type	Trial type	RT (SD)
1	Pure	Distractor-absent	553 (94)
1	Mixed	Distractor-absent	571 (108)
1	Mixed	Object-distractor	635 (103)
2	Pure	Distractor-absent	566 (86)
2	Mixed	Distractor-absent	616 (112)
2	Mixed	Object-distractor	687 (96)
4	Pure	Distractor-absent	554 (73)
4	Mixed	Distractor-absent	603 (78)
4	Mixed	Object-distractor	710 (78)
8	Pure	Distractor-absent	567 (88)
8	Mixed	Distractor-absent	580 (77)
8	Mixed	Object-distractor	696 (87)

Note. Mean RTs and their SDs are reported in milliseconds.

33 ms), 1 vs 8 $t(156) = 5.39$, $p < .001$, $d = 0.86$; 2 vs 8 $t(156) = 4.66$, $p < .001$, $d = 0.75$). Distractor interference was not statistically different between the 4- and 8-distractor conditions. Overall, this pattern confirmed previous observations showing that capture increases as the item-specific distractor rate decreases (e.g., De Tommaso & Turatto, 2023; Valsecchi & Turatto, 2023).

The ANOVA conducted on the filtering costs (Fig. 6B) revealed a significant main effect of the factor Distractor number, $F(3, 156) = 6.57$, $p < .001$, $\eta^2_p = 0.11$. The filtering cost in the 1-distractor condition (M = 17 ms, SD = 50 ms) was significantly smaller than in the 2-distractor condition (M = 50 ms, SD = 66 ms) $t(156) = 2.98$, $p = .017$, $d = 0.48$, and the 4-distractor condition (M = 49 ms, SD = 36 ms) $t(156) = 2.89$, $p = .022$, $d = 0.46$. Quite surprisingly, however, the filtering cost in the 1-distractor condition was comparable to that in the 8-distractor condition (M = 13 ms, SD = 42 ms), $t(156) = 0.37$, $p = .981$, $d = 0.01$. The cost in the 8-distractor condition was also significantly smaller than in the 2-distractor condition $t(156) = 3.36$, $p = .005$, $d = 0.54$), and the 4-distractor condition $t(156) = 3.26$, $p = .007$, $d = 0.52$). In all conditions the cost was significantly greater than 0 (all one-sample t-test $ps < 0.05$).

The linear model examining the relationship between changes in distractor interference and filtering cost across the two semi-blocks (Fig. 6C) revealed a significant negative association for all conditions (one distractor: $b = -0.71$, s.e. = 0.11, $p < .001$, $R^2 = 0.51$; two distractors: $b = -0.52$, s.e. = 0.09, $p < .001$, $R^2 = 0.44$; four distractors: $b = -0.47$, s.e. = 0.10, $p < .001$, $R^2 = 0.34$; eight distractors: $b = -0.46$, s.e. = 0.12, $p < .001$, $R^2 = 0.26$).

The analysis of errors revealed that in the pure block, the mean error rates were similar in all conditions (M = 5.61 %, SD = 5.30 %, all $ps > 0.05$). The analysis of error rates in the mixed block revealed a main effect of the Trial type, $F(1,156) = 108.71$, $p < .001$, $\eta^2_p = 0.41$, with larger error rates for distractor present trials (M = 12.4 %, SD = 9.03 %) than distractor absent trials (M = 6.47 %, SD = 7.92 %). Neither the main effect of Distractor number, nor the Trial type × Distractor number interaction was significant ($ps > 0.05$).

As in the previous experiments, we excluded the possibility that the observed filtering costs were the by-product of post-error slowing of responses during the mixed-block by removing post-error trials from the dataset and repeating the ANOVA on the data. Results confirmed the original pattern, with the filtering cost in the 1-distractor condition (M = 19 ms, SD = 44 ms) significantly smaller than in the 2-distractor condition (M = 48 ms, SD = 64 ms) $t(156) = 2.72$, $p = .035$, $d = 0.44$, and the 4-distractor condition (M = 50 ms, SD = 34 ms) $t(156) = 2.87$, $p = .023$, $d = 0.46$, but comparable to that of the 8-distractor condition (M = 10 ms, SD = 43 ms), $t(156) = 0.85$, $p = .830$, $d = 0.14$. The cost in the 8-distractor condition was also significantly smaller than in the 2-distractor condition $t(156) = 3.58$, $p = .002$, $d = 0.57$), and the 4-distractor condition $t(156) = 3.72$, $p = .001$, $d = 0.60$).

4.3. Discussion

The results confirmed that object-based capture is directly proportional to how rare or unexpected a distractor is (Dissegna et al., 2025). The analysis of the filtering cost, on the other hand, revealed an unexpected pattern of results. The filtering cost increased from one to four distractors, consistent with the idea that more cognitive resources are engaged the more templates are used. However, with eight distractors the cost surprisingly dropped below the level observed with one distractor. This finding is puzzling on the assumption that the filtering cost reflects the cognitive resources required to maintain a certain number of distractor templates in memory. If distractors templates are stored in working memory (WM), which has a capacity limit of approximately four elements (Luck & Vogel, 1997), then the 8-distractor condition may have exceeded this limit. However, the cost should have been at least comparable to that in the 4-distractor condition, not significantly smaller and similar to the 1-distractor condition.

To explain the marked drop in filtering cost, we hypothesized that once the limit was reached, participants perhaps switched to a filtering mechanism not based on the maintenance of distinct distractor templates in WM. If our hypothesis is correct, we could predict that the filtering cost should be restored by serializing distractor-present trials,

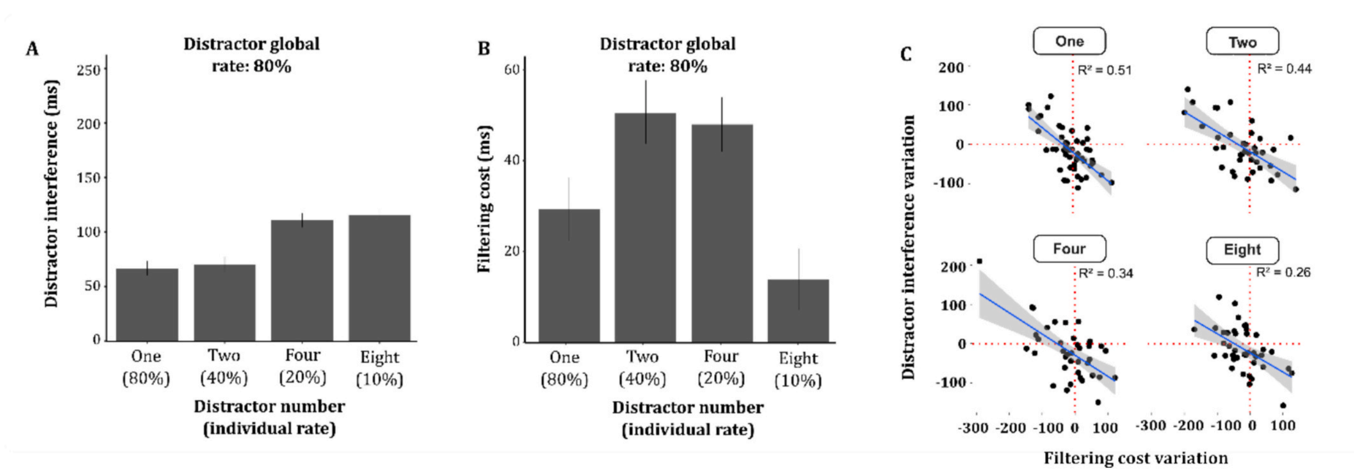

Fig. 6. Effects of the Distractor number on the gabor discrimination. *Note.* Panel A depicts mean distractor interference (RTs distractor-present – RTs distractor-absent in mixed block). Panel B depicts mean filtering cost (RTs distractor-absent in mixed blocks – RTs distractor-absent in pure blocks). Bars represent ±1 standard errors of the mean. Panel C shows the relationship between changes in distractor interference and filtering cost across the two semi-blocks of the mixed block (each point of the scatterplot represents an individual).

namely by presenting the same eight distractors into blocked sequences instead of being randomly interleaved with each other. This method should promote the active maintenance of distractor templates in memory, as only one template is needed at a time, a possibility that was explored in the next experiment.

5. Experiment 4

The unexpected drop in cost observed with eight distractors might have emerged because this number exceeded the WM capacity. This happened because participants were exposed to all the different distractors in a relatively limited number of trials, and thus the corresponding templates were all competing to have access in WM. However, we reasoned that perhaps this WM bottleneck could be avoided if the same number of different distractors were presented not randomly, but in a series of fixed sequences of the same distractors, which would prevent WM from being overloaded. Indeed, with such a presentation, only a single template needs to be maintained active in memory during each specific distractor sequence. When a new distractor sequence begins, the previous template would be progressively abandoned. Thus, in the worst-case scenario, no more than two templates were active in WM at a time, with the one corresponding to the current distractor sequence being particularly rehearsed or highly active. If this is the case, then as compared to Experiment 3 we expected the filtering cost to increase substantially, potentially becoming more like the cost observed with two distractors.

To test this hypothesis, we implemented an experimental design similar to the 8-distractor condition of Experiment 3. Participants completed two blocks of trials: a pure block followed by a mixed block. The mixed block featured eight distractors, each one presented into a mini sequence of trials, consisting of ten distractor-present trials and two to four distractor-absent trials randomly interspersed in the mini sequence. Note that with respect to the block of trials, the overall distractors rate was 80 %, whereas the specific distractor rate was 10 %, as in Experiment 3.

5.1. Method

5.1.1. Participants

Forty participants took part in the experiment and were recruited online with the same modalities of Experiment 1.

5.1.2. Stimuli and procedure

They were as in the eight-distractor condition of Experiment 3, except that in the mixed block the distractors were not presented in random order, but into mini-sequences of trials consisting of ten distractor-present trials of the same distractor and two to four distractor-absent trials randomly interspersed. Thus, each single distractor appeared with a rate of 10 %. Objects were those used in Experiment 3.

5.1.3. Data analysis

Data were analyzed as in Experiment 3. We compared the data from the 8-distractor condition of Experiment 3 (random condition) with those from the new experiment (serial condition). For the distractor interference, the ANOVA model included the Condition (random vs serial) as between-participants factor. For the filtering cost, the ANOVA model included the Block type (pure and mixed) as additional, within-participants factor.

5.2. Results

The outlier-latency criterion resulted in the removal of 2.5 % of the correct responses. RTs are reported in Table 4. The ANOVA conducted on the distractor interference (Fig. 7A) revealed no significant main effect of Condition, $F(1, 79) = 0.67$, $p = .416$, $\eta^2_p < 0.01$: the average interference was 115 ms ($SD = 33$ ms) in the random condition and 110 ms ($SD = 34$ ms) in the serial condition.

Table 4
Mean RTs by Condition, Block type and Trial type for Experiment 4.

Condition	Block type	Trial type	RT (SD)
Serial	Pure	Distractor-absent	541 (64)
Serial	Mixed	Distractor-absent	576 (79)
Serial	Mixed	Object-distractor	685 (86)
Random	Pure	Distractor-absent	567 (88)
Random	Mixed	Distractor-absent	580 (77)
Random	Mixed	Object-distractor	696 (87)

Note. Mean RTs and their SDs are reported in milliseconds.

The ANOVA conducted on the filtering costs (Fig. 7B) revealed a significant main effect of Condition, $F(1,79) = 5.35$, $p = .023$, $\eta^2_p = 0.06$. The filtering cost in the serial condition ($M = 36$ ms, $SD = 42$ ms) was significantly larger than in the random condition ($M = 13$ ms, $SD = 42$ ms), $t(79) = 2.27$, $p = .025$, $d = 0.51$.

The linear model examining the relationship between changes in distractor interference and filtering cost across the two semi-blocks (Fig. 7C) revealed a significant negative association ($b = -0.53$, s.e. $= 0.09$, $p < .001$, $R^2 = 0.44$).

The mean error rate for distractor-absent trials in the pure block of the serial condition was 6.44 % ($SD = 5.85$ %) which was not significantly different from the mixed block 5.49 % ($SD = 8.12$), nor from the random condition (all $ps > 0.05$). The error rate in the object-present trials of the mixed block was 15.3 % ($SD = 9.52$ %). The ANOVA revealed a significant main effect of the Trial type, $F(1,79) = 126.66$, $p < .001$, $\eta^2_p = 0.62$, and a Trial type × Condition type interaction, $F(1,79) = 14.20$, $p < .001$, $\eta^2_p = 0.15$. Specifically, participants in the serial condition made significantly more errors than in the random condition, $t(79) = -2.89$, $p = .005$, $d = 0.61$, while the error rate for distractor-absent trials was similar ($p > .05$).

The ANOVA conducted after the removal of post-error trials from the dataset confirmed a larger cost for the serial condition ($M = 35$ ms, $SD = 45$ ms) compared to the random condition ($M = 10$ ms, $SD = 43$ ms), $t(79) = 2.50$, $p = .014$, $d = 0.56$.

5.3. Discussion

The results confirmed that by serializing the presentation of the eight distractors, we reproduced a robust filtering cost, likely because participants stored a single distractor template in WM at a time. While the procedure used in the current experiment successfully restored a significant filtering cost, even with eight distractors, it remains unclear why the cost almost disappeared when the same number of distractors were presented in random order, as in Experiment 3. Although the reason is not immediately evident, in the next section we will offer a tentative hypothesis to account for this unexpected finding.

6. General discussion

Across four experiments, we consistently found a reliable filtering cost on distractor-absent trials when these were intermixed with distractor-present trials, compared to identical trials in distractor-free blocks. This replicated, with an object-based attention paradigm, the results originally reported by Marini and colleagues with a spatial-attention task (Marini et al., 2013, 2016). The dominant interpretation of this phenomenon is that when facing a context with probable distractors observers proactively and tonically engage distractor-filtering mechanisms. Although this facilitates distractor rejection, it imposes a cognitive cost that becomes evident in distractor-absent trials. Conversely, when the distractor is a rare event, this distractor-filtering strategy is probably abandoned in favor of a more reactive one (Morishima et al., 2010; Müller et al., 2009). Obviously, in no-distractor contexts the filtering mechanism is not implemented, as there is no expectation to encounter distracting stimuli.

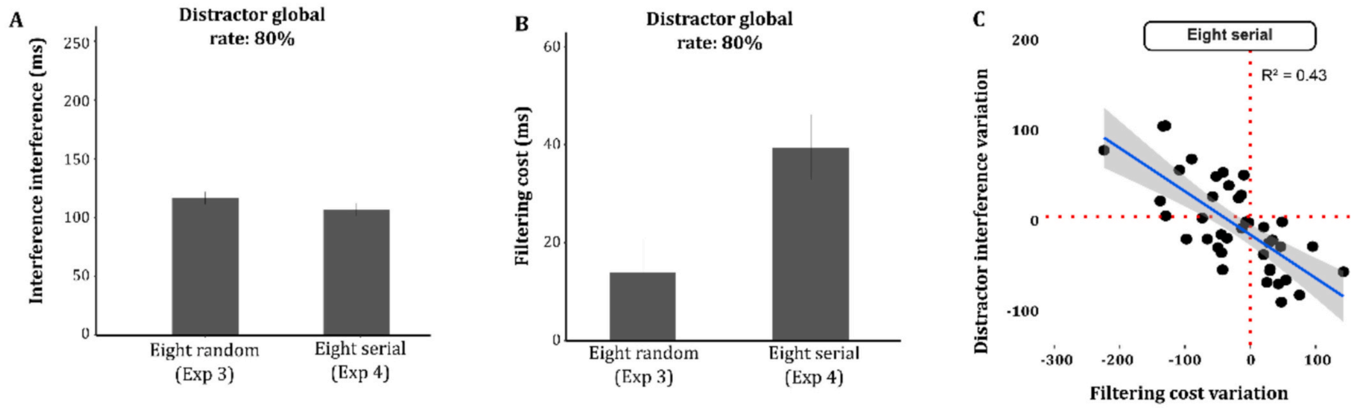

Fig. 7. Effects of the Distractor number on the gabor discrimination. *Note.* Panel A depicts mean distractor interference (RTs distractor-present – RTs distractor-absent in mixed block). Panel B depicts mean filtering cost (RTs distractor-absent in mixed blocks – RTs distractor-absent in pure blocks). Bars represent ±1 standard errors of the mean. Panel C shows the relationship between changes in distractor interference and filtering cost across the two semi-blocks of the mixed block (each point of the scatterplot represents an individual).

The results of Experiment 1, where the filtering cost was significantly greater at an 80 % rate compared to a 20 % rate, support this general view, indicating that filtering cost scaled with the expected distractor prevalence. If the cost reflects the implementation of a filter to limit distractor interference, then one could expect that the greater is the interference, the higher the filtering cost. For example, the amount of suppression applied at the high-probability location of a color singleton is proportional to its visual saliency, with stronger suppression exerted where a highly salient distractor, compared to a less salient one, is presented (Failing & Theeuwes, 2020). However, Experiment 2 showed that the filtering cost was not modulated by distractor interference per se, as scrambled and object distractors produced equivalent costs despite eliciting different amounts of interference.

Building on Sokolov's original idea that habituation to irrelevant stimuli relies on the formation of a corresponding neural model (Sokolov, 1963; Sokolov et al., 2002), and drawing on similar, more recent concepts such as the 'template for rejection' (Arita et al., 2012; Chetverikov et al., 2020; De Tommaso & and Turatto, 2019; Woodman & Luck, 2007), 'negative template' (Carlisle, 2023), and 'distractor template' (Won & Geng, 2018), we hypothesized that the observed filtering cost reflected the cognitive resources required to maintain these templates in memory. In support of this scenario, Experiment 3 showed that the filtering cost was modulated by the number of distractors templates. However, while the cost increased from one to four distractors, probably due to an increased load on WM, quite surprisingly the cost was drastically reduced with eight distractors. As we have already argued, a possible explanation for this unexpected finding is that eight distractor templates largely exceeded WM capacity of about four elements (Luck & Vogel, 1997), therefore promoting a different filtering strategy. A possibility is that instead of using a specific template for each potential distractor, participants may have set a single filter based on some kind of 'aggregate template', reflecting for example the average distractors' spatial frequencies, clearly different from those of the Gabor, which could explain the drop in the filtering cost. If this is the case, it remains unclear, however, why participants did not implement this less resource-demanding filtering strategy in the first place. Another possibility is that as the number of distractors increased, participants maintained distractor templates in WM until its capacity was reached, after which the distractors were offloaded to long-term memory through implicit learning mechanisms (e.g., Woodman et al., 2013). The idea is that long-term memory retrieval is fast and automatic, and operates with broader capacity limits (Logan, 1988), possibly resulting in the reduced filtering cost compared to WM processes.

While at present we can only speculate about the reasons behind the unexpected drop in filtering cost observed with eight distractors, Experiment 4 provided further evidence supporting the WM involvement. Indeed, we showed that when the distractor presentation was serialized, therefore requiring the maintenance of ideally only one template in WM at a time, the filtering cost increased substantially compared to the 8-distractor condition of Experiment 3. Note that the cost was larger (36 ms) than that observed in the single-distractor condition (17 ms) of Experiment 3, likely because when a new distractor series was encountered the previous distractor template was progressively dismissed, but during a transition phase two templates could have been temporarily active in WM.

Finally, we found that participants who exhibited greater reductions in distractor interference across the two halves of the mixed block also showed greater increases in the filtering cost relative to the pure block. This covariation suggests that the evolution of the cost tracks the progressive implementation of a distractor-filtering mechanism, with increased filtering coinciding with more effective interference reduction. Intriguingly, these results show that individuals differ in how strategically and efficiently they deploy filtering, indicating that distractibility is not merely a passive failure to ignore irrelevant stimuli, but rather reflects the effectiveness of a resource-demanding filtering process (Marini et al., 2013; Marini et al., 2015; Marini et al., 2016; Petilli et al., 2020).

In sum, our study shows that implementing filtering mechanisms to protect ongoing cognitive tasks from distractor interference imposes a cognitive effort, reflected in the filtering cost (Marini et al., 2013). The data strongly suggest that this cost represents the cognitive resources required to maintain distractor templates in memory. Importantly, the cost is neither determined by the degree of interference exerted by a given distractor in a graded fashion, nor by its objecthood or semantic content. Rather, the key factor is the engagement and maintenance of templates over time, as the filtering mechanisms develop progressively as the block unfolds. In this sense, the filtering cost depends primarily on the number of templates kept active and on their sustained use, and it is further modulated by distractor rate - that is, by the frequency with which distraction is experienced.

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Artificial intelligence

No artificial-intelligence-assisted technologies were used in this research or the creation of this article.

Ethics

This research received approval from a local ethics board (Comitato Etico per la Sperimentazione con l'Essere Umano, Università degli Studi di Trento, Italy, Approval nr. 2022–065).

CRediT authorship contribution statement

Andrea Dissegna: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Leonardo Chelazzi:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Massimo Turatto:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

All authors declare no conflicts of interest.

Data availability

I have shared my data/code through an OSF link

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