Computational and behavioral investigations of the SOB-CS removal mechanism in working memory

Violette Hoareau[1] **(violette.hoareau@univ-grenoble-alpes.fr), Sophie Portrat**[1,2] **(sophie.portrat@univ-grenoble-alpes.fr), Klaus Oberauer**[3] **(k.oberauer@psychologie.uzh.ch), Benoît Lemaire**[1,2] **(benoit.lemaire@univ-grenoble-alpes.fr), Gaën Plancher**[4] **(Gaen.Plancher@univ-lyon2.fr)** and **Stephan Lewandowsky**[5] **(Stephan.Lewandowsky@bristol.ac.uk)**

[1] LPNC, University Grenoble Alpes, F-38040 Grenoble, France
[2] CNRS, LPNC UMR 5105, F-38040 Grenoble, France
[3] University of Zurich, Zurich, Switzerland
[4] Université Lumière Lyon 2, Lyon, France
[5] University of Bristol and University of Western Australia, Bristol, UK

Abstract

SOB-CS is an interference-based computational model of working memory that explains findings from simple and complex span experiments. According to the model's mechanism of interference by superposition, high similarity between memory items and subsequently processed distractors is beneficial because the more a distractor is similar to an item, the more they share similar units, leading to less distortion of the memory item. When time allows, SOB-CS removes interfering distractors from memory by unbinding them from their context. The combination of these two mechanisms leads to the prediction that when free time is long enough to remove the distractors entirely, similarity between items and distractors should no longer be beneficial to memory performance. The aim of the present study was to test this prediction. Adult participants performed a complex-span task in which the free time following each distractor and the similarity between items and distractors were varied. As predicted by the model, we observed a positive effect of the similarity between items and distractors, and a negative effect of pace on the mean working memory performance. However, we did not observe the predicted interaction. An analysis of the errors produced during recall showed that longer free time reduced the tendency of distractors to intrude in recall much less than the model predicted. The SOB-CS model accounted well for the data after a substantial reduction of the removal-rate parameter.

Keywords: Working Memory, SOB-CS model; interference by superposition; removal mechanism

Introduction

Working memory (WM) is the system responsible for holding information available for ongoing cognition (Baddeley & Hitch, 1974; Miyake & Shah, 1999). It is often tested with complex-span tasks (Barrouillet, Bernardin, & Camos, 2004), which combine an immediate memory test with a concurrent processing demand: some items (e.g., letters or words) are provided one at a time for subsequent recall in order and several distractors are also presented in-between items. The concurrent processing of distractors impairs memory, compared to a simple-span task that consists only of the immediate memory test. There has been ongoing debate about the reasons why distractors affect WM performance. The present study contributes to this question by testing a prediction of the interference-based connectionist model SOB-CS (Oberauer, Lewandowsky, Farrell, Jarrold, & Greaves, 2012).

According to SOB-CS, forgetting is due to interference between items and distractors. The model is based on a two-layer connectionist network that associates a distributed item representations with distributed position markers, for instance associating the first item of the sequence with position 1, through Hebbian learning (Anderson, 1995). Each association is registered in a two-dimensional weight matrix coding for the position and the item representations. During each processing step, SOB-CS assumes that distractors are encoded in the same way as items and associated to the position of the preceding item. In other words, SOB-CS suggests that items and distractors are superimposed in the same weight matrix, leading to a distortion of items by distractors which in turn causes forgetting. In this way, the model is able to reproduce interference between items and distractors according to their similarity: the more a distractor is similar to an item, the more feature values they share, leading to less distortion of the memory item. Therefore, this model predicts that high similarity between an item and the following distractor is beneficial to WM performance.

Oberauer, Farrell, Jarrold, Pasiecznik, and Greaves (2012) reviewed studies that have investigated item-distractor (I-D) similarity effects. They showed that phonological similarity between items and distractors is beneficial if the material was pronounceable non-words (non-words were used in order to ensure that participants do not encode stimuli by their meanings). Oberauer et al. did four experiments in which participants had to remember a list of four non-words items. The two distractors intervening after each item were also non-words and had to be read aloud. The phonological similarity between the items and the distractors was manipulated. In the first three experiments, distractors were similar to the preceding item whereas in the fourth experiment distractors were similar to the following item. The findings of experiments 1, 2 and 3 showed a positive effect of phonological similarity between items and distractors which meshes well with the mechanism of interference by superposition implemented in SOB-CS. Moreover, experiment 4 confirmed the hypothesis of SOB-CS suggesting that distractors are associated to the preceding item and not to the following item: no beneficial effect of I-D similarity was observed when similar distractors preceded, rather than followed, the items to which they were similar.

The SOB-CS model also proposes an explanation for the cognitive load effect (Barrouillet, Portrat, & Camos, 2011). This effect has been observed in several studies showing that WM performance depends on the proportion of time during which distractors capture attention (Barrouillet, Bernardin, Portrat, Vergauwe, & Camos, 2007; Barrouillet et al., 2004, 2011). According to decay-based theories (Baddeley, 1986; Towse & Hitch, 1995; Barrouillet et al., 2011), the cognitive-load effect can be explained as follows: forgetting is mostly due to the time-based decay of the memory traces when distractors are processed. In order to avoid forgetting, memory traces can be reactivated when free time is available between distractors. A sole interference mechanism cannot account for such a positive impact of free time on WM performance. Hence, in SOB-CS, the cognitive load effect is explained as follows: forgetting is counteracted by a removal mechanism in such a way that each distractor that has just been encoded is ”removed” during free time. The removal process consists of an unbinding, by Hebbian anti-learning, of the association between each distractor and the study context, thereby rendering the context signal more effective as a retrieval cue for the memoranda. SOB-CS suggests that the strength of removal exponentially depends on the time devoted to it. This mechanism leads to the prediction that the more free time elapses after each distractor, the more time is available for removing the interfering distractor that just has been encoded and hence the better the WM performance.

To sum up, two mechanisms are important in SOB-CS to specifiy the effect of distractors on WM performance. First, according to the mechanism of interference by superposition, distractors which are similar to the preceding item should distort that item less than dissimilar distractors, leading to better performance at recall. Second, the mechanism of ”removal” leads to the prediction that distractors are unbound from WM during free time in order to clear memory from irrelevant information. The combination of these two mechanisms gives rise to an interesting hypothesis which is at the heart of the present paper: if free time is long enough to entirely unbind an irrelevant distractor from WM, there is no reason to observe an effect of I-D similarity as distractors would not be present in WM anymore.

Overview of the experiment

The aim of our experiment was to test this prediction of SOB-CS concerning both the removal and the interference by superposition mechanisms. To do that, our experiment replicates and extends the second experiment presented in Oberauer, Farrell, et al. (2012). It consisted of a verbal complex span task in which items and distractors were pronounceable non-words (i.e. words without semantic meanings). The length of the memory list was constant and set to four items. In the high similarity condition, the similar distractor always immediately followed the items to which they were similar and all the items were dissimilar to each other. Then, as memoranda were non-words, serial recall was done by reconstruction among a candidate set containing the four list items, four of the distractors and four not presented lures (NPLs). The NPLs were non-words which had never been seen by participants in the current experiment.

In their experiment, Oberauer, Farrell, et al. (2012) only manipulated the similarity between items and distractors. We extended that experiment by adding the manipulation of the pace of the distractor presentation to vary the free time available to remove distractors. We tested participants and the SOB-CS model with three paces (fast, medium, slow). To allow comparisons of our findings with Oberauer, Farrell, et al. (2012), the faster pace of our experiment was the pace used by Oberauer, Farrell, et al. (2012). This extension allowed to test the special prediction that the positive effect of I-D similarity decreases as the free time increases.

Simulation 1 with SOB-CS

To test the prediction that the positive effect of I-D similarity decreases as the free time increases, we reused and adapted the simulation presented in Oberauer, Farrell, et al. (2012).

Method

The creation of the stimuli was done similarly as in Oberauer, Farrell, et al. (2012): stimuli were generated and organized in 8 dissimilar sets for each trial, each set containing 10 similar stimuli. From these sets, items, distractors and non-presented lures (NPLs) were selected according to the condition of similarity (i.e. high vs low). The recall candidate sets were composed of the four items of the trial, four distractors and four NPLs. The NPLs were added in order to balance the global attractiveness of the candidate sets between similarity conditions. In the high similarity condition, a distractor is attractive for two reasons: it has been processed and it was similar to the items. In the low similarity condition, distractors are therefore less attractive. In contrast to the distractors, NPLs were dissimilar to the items in the high similarity condition, whereas they were similar to the items in the low similarity condition.

In all the simulations presented in Oberauer, Farrell, et al. (2012), which reproduced well the behavioral data, the encoding duration of the distractor was set to 1000 ms. As the pace of the processing task of all their experiments is 1000 ms, no free time was available to remove the distractor. This means that they did not use the removal mechanism in their simulations. In order to replicate the results in this baseline condition (which is the condition with the faster pace in our experiment), we also set the encoding duration of the distractor to 1000 ms.[1] For the moderate (1800 ms) or slow (2600 ms) paces, the removal mechanism was used because there were 800 ms or 1600 ms available free time.

[1]The encoding duration of the distractor is an arbitrary value, as we did not know the exact duration of the attentional capture of the reading task of non-words, but we were interested on the relative effect of an additional free time and not on the absolute effect of the free time in this study.

We ran 1000 simulated subjects, each one completing five trials in each condition as in the experiment. Oberauer, Farrell, et al. (2012) used the SOB-CS default parameter values except for the distinctiveness parameter c, which they lowered from 1.3 to 0.45 to approximately move the overall accuracy into the range of data. This new value of parameter c was justified because non-words are less distinctive than well-known words. In our simulation, we did as Oberauer, Farrell, et al. (2012) except that we lowered the c parameter even more from 0.45 to 0.3. The reason is that, in our experiment, we ensured that each non-word, as an item, a distractor or a NPL, was seen only once by a participant. In contrast, in Oberauer, Farrell, et al. (2012), 100 trials were performed using a set of 36 non-words only. One trial required 16 items, which is almost half the set of non-words. This means that each participant saw each item more than 40 times during the test, which would make them familiar with the non-words as they go along the test. This difference could make their task easier. This is why, in the simulation, it was justified to set the distinctiveness parameter c to 0.3 instead of 0.45.

Results: Simulated data

Correct responses Recall responses were scored as correct when a correct item was chosen in its exact serial position. Figure 1 (panel B[2]) presented the percentage of responses correctly recalled by the model as a function of pace and similarity. As expected, the simulation shows an effect of pace (0.38, 0.75, and 0.77 at fast, moderate and slow pace respectively) and an interaction effect according to which the beneficial effect of similarity disappears as the pace slows down (i.e. as free time increases). In fact, we can see that at a fast pace the percentage of correct recall is higher when distractors are similar (compared to dissimilar), to the preceding item (0.43 vs. 0.33) whereas at moderate and slow paces, the difference between similarity conditions is null (0.75 vs. 0.75 and 0.76 vs. 0.78 for moderate and slow paces respectively).

We also analyzed three different kinds of errors. An error could be an intrusion of distractor, an intrusion of NPL or a transposition error (an item from the list in a wrong position).

Distractor intrusions Figure 2 (panel B) presents the proportion of distractor intrusions. First, the simulation showed a strong effect of pace: around 20% of the responses at fast pace contained distractor intrusions whereas distractor intrusions are negligible (less than 2%) at moderate and slow pace. It appears that distractors are sufficiently removed after 800 ms, for not being recalled. No effect of similarity and no interaction were observed.

NPL intrusions Figure 3 (panel B) presents the proportion of NPLs intrusions. Even if NPLs are not encoded into WM, the NPLs can be recalled as they can be confused with the memoranda. The more the WM is distorted by distractors, the more we should observe confusion errors at recall. We observed that NPLs intrusion decreased when the free time increased as WM is less distorted. We also observed an effect of similarity: there are more NPLs intrusion in the low-similarity condition as the NPLs are similar to the items in this condition. This effect is much stronger at fast pace (when distractors are not removed) than at moderate and slow pace. In fact, we observed that the differences of intrusion rates between low-similarity and high-similarity are 0.09, 0.02 and 0.02 for the fast, moderate and slow pace respectively.

Transposition errors Finally, Figure 4 shows the proportion of transposition errors (order errors) for which a small pace effect was observed. At the fast pace, the proportion of transposition errors was increased by 8% as compared to the slow and moderate pace. No effect of similarity and no interaction were observed.

Summary of the simulation results In summary, the SOB-CS model with its standard parameters (except the c parameter) predicts a beneficial effect of I-D similarity, which is present only when there is no removal of the distractors (i.e. in the fast pace condition). As soon as there is free time (800 ms or 1600 ms), the similarity effect disappears. The analysis of the different kind of errors show that as soon as there is free time, distractor intrusions is negligible. This finding can explain why we do not observe the similarity effect at a moderate and slow pace: distractors are totally removed according to the SOB-CS model. These predictions will now be compared with human data.

Experiment

Method

Participants Participants were 34 students from the University of Bristol. They participated voluntarily in 1-hr session in exchange for course credit. Each participant performed the 6 conditions: three different paces (slow, moderate, fast) × two similarity conditions (low and high).

Material Participants were presented with four non-words (e.g "zaff") for memorization, each followed by a pair of non-word distractors. The memoranda were presented in red and the distractors in black. Participants were asked to read aloud all the non-words as soon as they appeared but to only memorize the red ones in serial order.

Items and distractors were sampled from a set of non-words selected from the ARC Nonword Database (Rastle, Harrington, & Coltheart, 2002). A database of 720 non-words was used to ensure that participants never saw a non-word more than once. Each non-word was pronounceable, composed of one syllable and four letters. The 720 non-words were organized in 240 rhyming groups, each containing three non-words (e.g., "baff, daff, haff" was a rhyming group).

The candidate set for recall was constructed such that its similarity structure was the same for both conditions (low and high similarity). Whatever the similarity condition, partici-

[2] All the results discussed below are represented by the solid lines in all panels B, which correspond to the simulation of the model with the default value (r=1.5) of the removal strength parameter. The dashed lines will be discussed latter.

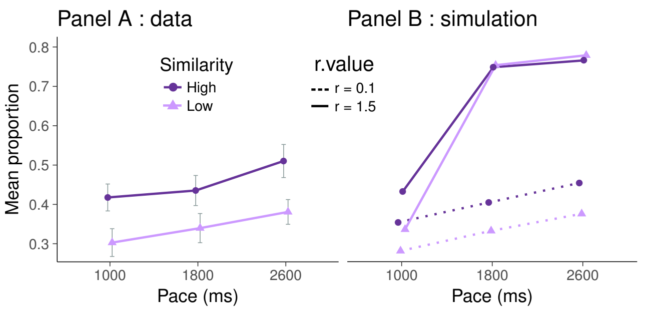

Figure 1: Proportion of correct responses. Error bars are 95% confident intervals for within-subject comparisons.

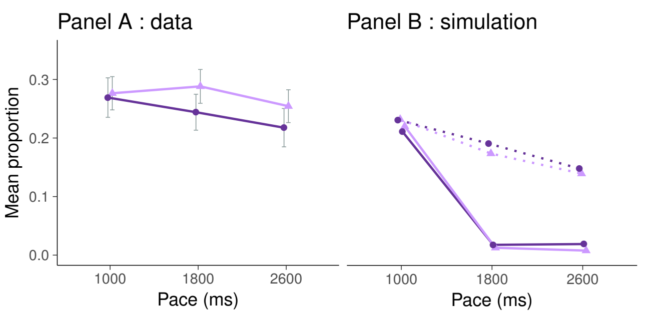

Figure 2: Proportion of distractor intrusions. Error bars are 95% confident intervals for within-subject comparisons.

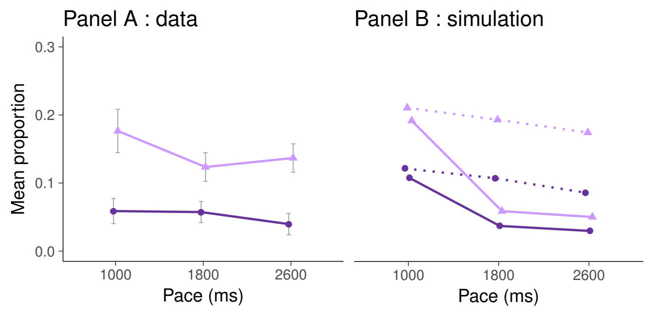

Figure 3: Proportion of NPLs intrusions. Error bars are 95% confident intervals for within-subject comparisons.

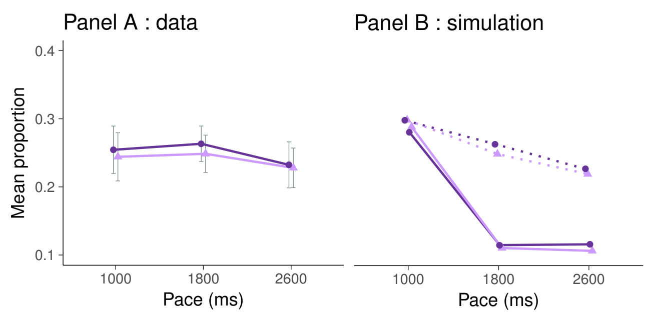

Figure 4: Proportion of order errors. Error bars are 95% confident intervals for within-subject comparisons.

pants saw four items, four stimuli similar to each item and four stimuli dissimilar to the items. In the high-similarity condition, the four stimuli similar to each item were the distractors whereas in the low conditions they were not-presented lures (NPLs).

In the high similarity condition, one stimulus from four different rhyming groups was chosen at random to be an item, and the other two stimuli of each rhyming group were used as the pair of distractors that immediately followed that item, such that each pair of distractor was similar to their preceding item. The NPLs, for the recall set candidates, were chosen at random from 4 other rhyming groups, such that NPLs did not rhyme with any item or distractors.

In the low similarity condition, four groups were used to create the list of items and NPLs, such that each NPL was similar to an item. Two stimuli from each of four other rhyming groups were chosen at random to serve as distractors. In this way, no pair of distractors rhymed with any item on the low-similarity condition.

For all conditions, we ensured that the four to-be-maintained items were dissimilar to each other.

Procedure A MATLAB program using Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) coded by Oberauer and collaborators (2011) was reused with some modifications to display stimuli and record responses. Each trial started with a black centered fixation cross presented during 1,500 ms, followed by a computer-paced presentation of items and distractors. Items always appeared during 800 ms followed by a 400 ms blank. Distractors appeared at the rate of one stimulus per 1,000 ms (800 ms on, 200 ms off) in the fast condition, 1,800 ms (800 ms on, 1000 ms off) in the moderate condition and 2,600 ms (800 ms on, 1,800 ms off) in the slow condition. After the last distractor, 12 recall candidates simultaneously appeared on the screen in blue, each in a blue frame. They were displayed at random in a 3×4 matrix. Participants selected recall choices by clicking inside the items' boxes in the order in which they were presented. A sound indicated that a response has been recorded. They were asked to guess if they could not remember an item. Each participant completed 30 trials, 5 in each condition, in a random order. They were also prompted to take self-paced breaks every six trials. In addition, there were four practice trials at the start with four different conditions: similar/fast, dissimilar/moderate, similar/slow and dissimilar/fast.

Results: human data and comparisons with simulated data

We ran a two-way ANOVA on the mean proportion of correct responses and different types of errors over trials with similarity (high and low I-D similarity) and pace (slow, moderate and fast) as within-subjects factors.

Correct responses Figure 1 (panel A) shows that, as predicted by the model, there was an effect of similarity $[F(1,33) = 31.2, p < .001, \eta_p^2 = .48]$ and an effect of pace $[F(2,33) = 12.6, p < .001, \eta_p^2 = .27]$. However, contrary to SOB-CS predictions, no interaction was observed

$[F(2,33) < 1]$. In fact, even at slow pace, we observed a positive effect of high similarity versus low similarity condition on recall performance.

Distractor intrusions Figure 2, panel A, shows a small effect of pace on distractor intrusions $[F(2,33) = 3.18, p = .047, \eta_p^2 = .08]$ with 27%, 26% and 24% of distractor intrusions among responses at fast, moderate and slow pace respectively. In contrast, the model predicted a strong effect of the pace with almost no intrusion of distractors at medium and slow pace compare to 20% at fast pace. This discrepancy suggests that participants did not remove distractors as much as the model did. No similarity effect $[F(1,33) = 2.69, p = .11, \eta_p^2 = .07]$ and no interaction $[F(2,33) < 1]$ was observed on the distractor intrusion, as predicted by the model.

NPL intrusions We observed a strong effect of similarity on NPL intrusions $[F(1,33) = 77.3, p < .001, \eta_p^2 = .70]$ and a small pace effect $[F(2,33) = 4.5, p = .014, \eta_p^2 = .11]$ (Fig. 3, panel A). Here again, the model predicted a much stronger pace effect as compared to the experimental data. No significant interaction was found $[F(2,33) = 2.24, p = .11, \eta_p^2 = .06]$ suggesting that the effect of similarity on NPLs is constant over the pace whereas the model predicts a stronger effect of similarity at fast pace.

Transposition errors No similarity and no pace effect on the transposition errors were found [respectively; $F(1,33) < 1$ and $F(2,33) = 1.27, p = .28, \eta_p^2 = .04$] (Fig. 4, panel A). No significant interaction was found $[F(2,66) = 1.27, p = .28, \eta_p^2 = .03]$. In line with these data, the model predicted no effect of the similarity on the transposition errors. However, the model predicted a small effect of pace between the fast and the two other paces.

Discussion

The present results replicated the observations found in Experiment 2 of Oberauer, Farrell, et al. (2012) suggesting that forgetting in WM is partly due to interference by superposition. First, whatever the experimental condition, the mean proportion of distractor intrusions was higher than the proportion of NPLs (0.25 vs. 0.1 on average). This result demonstrates that distractors, unlike NPLs, are encoded into WM which is a necessary prerequisite for studying distractor interference. Moreover, evidence in favor of the interference by superposition mechanism was provided by replicating the strong benefit of high over low I-D similarity.

However, we observed a discrepancy between some of the model predictions and the data. SOB-CS only fits well the data in the fast condition that is similar to Oberauer, Farrell, et al. (2012)'s experiment, where no removal was used in the simulation. As soon as there is free time and hence removal, the SOB-CS simulation erroneously predicted an interaction between pace and I-D similarity. The error analyses revealed that this difference between model and human seems to be due to an overestimation of the removal strength by the model compared to the experimental findings.

In the following section, we present the results of a grid search on the removal parameter r in order to identify a better r value to reproduce the human data.

Estimation of the removal parameter

Several experiments (Oberauer, 2001, 2002) estimated that removing part of the contents of working memory takes between 1 and 2 s. In addition to the time devoted to the removal, the strength of removal depends also on a rate of removal controlled by the free parameter r. The greater the value of r, the faster associations between the distractor and its position are removed. Therefore, in SOB-CS, the removal parameter r was set to 1.5, which implies that the rate of anti-learning for removal has reached 95% of its asymptote after 2 s. According to the previous experimental analysis, it seems that distractors are not removed as quickly as in the model. To search for a value for the r parameter that would better fit the data, we conducted a grid search on a range between 0 and 1.5 with a step size of 0.1. The Root-Mean-Square Error (RMSE) was calculated for each parameter value. This measure represents the discrepancy between the model prediction and human data. The lowest RMSE corresponds to the best model. We found that the best model is the one with r equals to 0.1 instead of the standard value 1.5. If r is set to zero, meaning no removal at all, an important loss of fit is observed as the model does not predict the pace effect anymore. The dashed lines of the panel B of all Figures shows the simulation results with r set to 0.1. First, the pace and the similarity variables do not interact anymore. Second, the main effect of pace on accuracy and error rates is about as large as in the data. Globally, we observed that the proportion of the different error types fits well the human data. Our result is in contradiction with the conclusion from previous studies (Oberauer, 2001, 2002) that removal takes only 1 to 2 s, as with this new r parameter, removing completely irrelevant information would take about 30 s instead of 2 s.

General Discussion

In this paper, we aimed to contribute to the debate regarding the reasons why distractors affect working memory performance by testing predictions of SOB-CS. More specifically, we investigated the I-D similarity effect after various amounts of free time. Human results confirm several predictions of SOB-CS. First of all, our results show that distractors are actually encoded in working memory since they were more often recalled than not-presented lures. Then, experimental data reproduced the positive effect of a high similarity between items and distractors originally found by Oberauer, Farrell, et al. (2012). This finding is predicted by the mechanism of interference by superposition of SOB-CS. Finally, we also observed that memory performance increases at a slower pace than predicted by the removal mechanism.

However, results disconfirm one prediction from the model with its standard parameter values: the data show that the I-D similarity effect does not diminish with longer free time.

When simulating this experiment with the SOB-CS computational model, the similarity effect disappears when there is 0.8 s or more of free time available, because the model strongly removes distractors. In fact, we observed that at moderate and slow paces, distractors are totally removed according to SOB-CS. The total removing of the distractors cancels the recall difference between similar and dissimilar conditions. Contrary to this expectation, human data still showed distractor intrusions at moderate and slow pace.

Searching for a removal rate able to reproduce the experimental data resulted in a much lower estimate (r=0.1 instead of r=1.5), which could reproduce the observed similarity effect at all three levels of pace. The removal mechanism was supported, because r=0.1 fit better than r=0. What are the implications of our removal rate estimate, which is much lower than that in the orignal model? Either, we can consider that r=0.1 is the parameter value that holds generally, implying that removal is much slower than thought so far. A way to verify this option would be to simulate other complex span task experiments to test whether their results can be reproduced by SOB-CS with r=0.1. Or, there is something particular to delete the material of our experiment that would require a low removal strength. In future research, a comparison of the size of the pace effect across experiments could shed some light on that. In fact, the comparaison of the pace effect of our experiment with all the other experiments can help to determine if our experiment had an exceptional low pace effect or if the removal strength needs to be lowered.

According to decay-based models of working memory, such as TBRS (Barrouillet et al., 2007) or TBRS* (Oberauer & Lewandowsky, 2011), removal does not exist and free time is used to retrieve and maintain the to-be-remembered items. The maintenance of memory items can be viewed as the strengthening of the item-position bindings of the memory items and also as the strengthening of the representations of individual non-words themselves (i.e., item memory). Decay-based models predict the pace effect which has been observed many times. In fact, the more free time the more opportunity to maintain memory items. In such a model, the positive effect of high similarity between items and distractors, that is not accounted for by decay-based models, can be explained by the assumption that retrieving an item in order to refresh it is easier if it is less distorted by distractors. This process of retrieving would be required whatever the duration of the free time. The effect of similarity on retrieval therefore would lead to a beneficial effect of similar distractors whatever the pace. However, for the moment, decay-based computational models, such as TBRS* do not implement interference by superposition. In the future, it would be interesting to replace the removal mechanism by a mechanism of maintenance in SOB-CS.

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