**Processes Determining Short-term Probe Recognition: Familiarity and Learning**

**Abstract**

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**Keywords:** Memory search; Old-new recognition; Automatic processing; Response times; Short-term memory

# Introduction

Short-term memory (STM) lies at the heart of cognition. It has limited capacity and therefore exerts a profound influence on people’s ability to remember, decide, plan, retrieve, and act. The operations and capacity of STM have been studied extensively with various behavioral tasks and neural measurements. Behavioral tasks include recognition, recall, cued recall, serial recall, free recall, and continuous monitoring for short-term repeats of earlier items. Reviewing the voluminous literature on STM goes well beyond the scope of this article. Rather, the present focus is on one method for assessing STM: short-term probe recognition. In this paradigm, a short list of items is presented sequentially. The lists typically vary in length from one to eight items. The items can be letters, numbers, words, pictures, colors, among other choices. Following the list a test item (the probe) is presented. Test probes selected from the just seen list are termed *old* items or *targets*; test items not from that list are termed *new* items or *foils*. Observers are instructed to indicate whether the test probe was old or new as rapidly as possible without making (very many) errors. The results demonstrate one form of limited capacity because accuracy drops and response time (RT) gets longer as the list-length increases.

The earliest studies of this sort were carried out in such a way (e.g. slow presentations) that rehearsal could have been (and likely was) used during presentation of the list (Sternberg, 1966). More recent studies have minimized rehearsal opportunities. Typical results (Monsell, 1978; McElree & Dosher, 1989; Nosofsky et al., 2011) show that performance decreases as a test probe’s *lag* on the study list increases (where *lag* is defined as the number of items intervening between the item’s presentation on the study list and its test). A simple account has item strength dropping as time after presentation increases. In addition the lag functions lie more or less lie atop one another for different list lengths, so average performance for longer lists decreases due to the inclusion of items with greater lags. We will see later that these results depend on the use of a ‘varied mapping’ procedure (VM): Across trials the same items are continually reused, sometimes as targets and sometimes as foils.

A class of models that does well to explain these data are based on the concept of ‘familiarity’: Due to having been seen recently on the study list, targets are more familiar (have more ‘strength’) than foils. Nosofsky et al. (2011, 2014a) implemented a version of such a familiarity model to explain both accuracy and RT as functions of list length and lag. It is based on a variant of the Exemplar Based Random Walk (EBRW) model proposed originally by Nosofsky and Palmeri (1997) for categorization: Evidence is accumulated as a random walk until a target or foil boundary is reached. The value of familiarity determines the probability of taking a step toward either the target or foil decision boundary.

In recent research, Nosofsky, Shiffrin and Cao (Nosofsky et al., 2014b, in press; Cao, Shiffrin, & Nosofsky, 2018) have explored in detail the contributions to performance of traces of items from prior lists and of learning that takes place as list presentations continue. The paradigms compare VM to ‘consistent mapping’ (CM), critically important manipulations first explored in detail by Schneider and Shiffrin (1977) and Shiffrin and Schneider (1977). In CM, items are consistently mapped across trials: Targets remain targets and foils remain foils. As found by Shiffrin and Schneider for joint memory and visual search, Nosofsky et al.’s (2014a,b, in press) studies show that CM memory-search performance is dramatically better than VM performance. Furthermore, any list-length effects tend to disappear for CM. In addition, the CM improvements in pure memory-search paradigms occur very rapidly, early in a single session of training.

The dominant theoretical interpretation of the enhanced CM performance is that it arises due to various forms of long-term learning. Within the context of pure memory-search tasks, Nosofsky et al. (2014b) and Cao et al. (2018) have argued that observers learn long-term *item-response* mappings between items and their assigned responses: Because one set of items always serve as targets, and a separate set always serves as foils, observers can learn to attach old and new responses to the items in each set in order to perform the task, thereby bypassing the need to engage in a capacity-limited STM search of the present study list. Indeed, the process of long-term item-response learning has been posited to be among the major routes to achieving automaticity in wide varieties of cognitive tasks (not just by Shiffrin & Schneider, but by many others; e.g., Logan, 1988). We emphasize here that the process of “item-response learning” is conceptually distinct from that of “familiarity”: the latter is influenced solely by the frequency and recency with which an individual item is experienced, whereas the former depends on the extent to which items are consistently mapped to particular responses.

Although Nosofsky et al. (2014b) and Cao et al. (2018) attributed the CM advantage to item-response learning, a careful analysis reveals that it can also be broadly explained in terms of simple familiarity-based processes and by the fact that participants can adopt different familiarity-based decision criteria across VM and CM tasks. In general there are two sources of familiarity in these paradigms: Short-term familiarity caused by an item’s appearance on the list just studied, and long-term familiarity caused by an item’s appearance on prior lists in the experiment. The short-term familiarity can be used to perform the task, since it differs for targets and foils. In VM, long-term familiarity is high and equal for targets and foils, because both have been experienced numerous times in lists presented on previous trials of the experiment. Thus to the extent that long-term familiarity adds to short-term familiarity, it acts to add noise and degrade VM performance. By contrast, in CM, long-term familiarity is high for targets, but tends to be low for foils: It is high for targets because they occur with high frequency on study lists presented throughout the experiment; it is low for foils because these items are never presented on the previous study lists. Thus in CM long-term familiarity can help performance, adding extra evidence to short-term familiarity that will aid in discriminating targets from foils. Additional evidence bearing on the role of familiarity-based processing is provided by short-term probe recognition tasks that use “all-new” (AN) items (Nosofsky et al., 2014a,b; in press): These items appear on study lists at most once throughout the experiment. As opposed to CM and VM, AN items are unfamiliar on the basis of prior trials. Short-term probe recognition performance for AN is typically intermediate between CM and VM, a result consistent with predictions from familiarity-based models: AN should perform better than VM, because there is no substantial noise contributed by long-term familiarity; but worse than CM because the extra discrimination from long-term familiarity that helps CM is missing in AN. Of course item-response learning is also impossible for AN items, another factor that could reduce AN performance relative to CM. This issue will be one of those explored in the present research.

To gain evidence bearing on whether changed familiarity-based criterion settings may underlie the dramatic performance differences observed across pure-list VM, CM, and AN conditions – at least during the early stages of learning -- Nosofsky et al. (in press) tested a ‘mixed-lists’ condition. In this condition, the individual study lists contained equal mixtures of VM, CM and AN items, so that responding would be based on a common set of processes and criteria. For purposes of comparison, they also tested pure-list VM, CM and AN conditions. The main results are shown in Figure 1. As can be seen in the left panels, the pure CM and VM conditions show the dramatic differences in performance that were expected. By contrast, the mixed conditions (right panels) showed a complicated pattern but the key result was that there was virtually no difference in performance for the old-CM versus the old-VM targets. Because the old-CM and old-VM items were roughly equally familiar and the mixed-list design forced the use of a common set of decision criteria, the broad pattern of results seems explainable in terms of a familiarity-based decision model. The mixed-condition results challenged the view that an automatic form of item-response learning took place for the old-CM items: The old-CM items received consistent item-response mappings, so automatic learning should have produced better performance for CM-targetss than VM-targets in the same list.

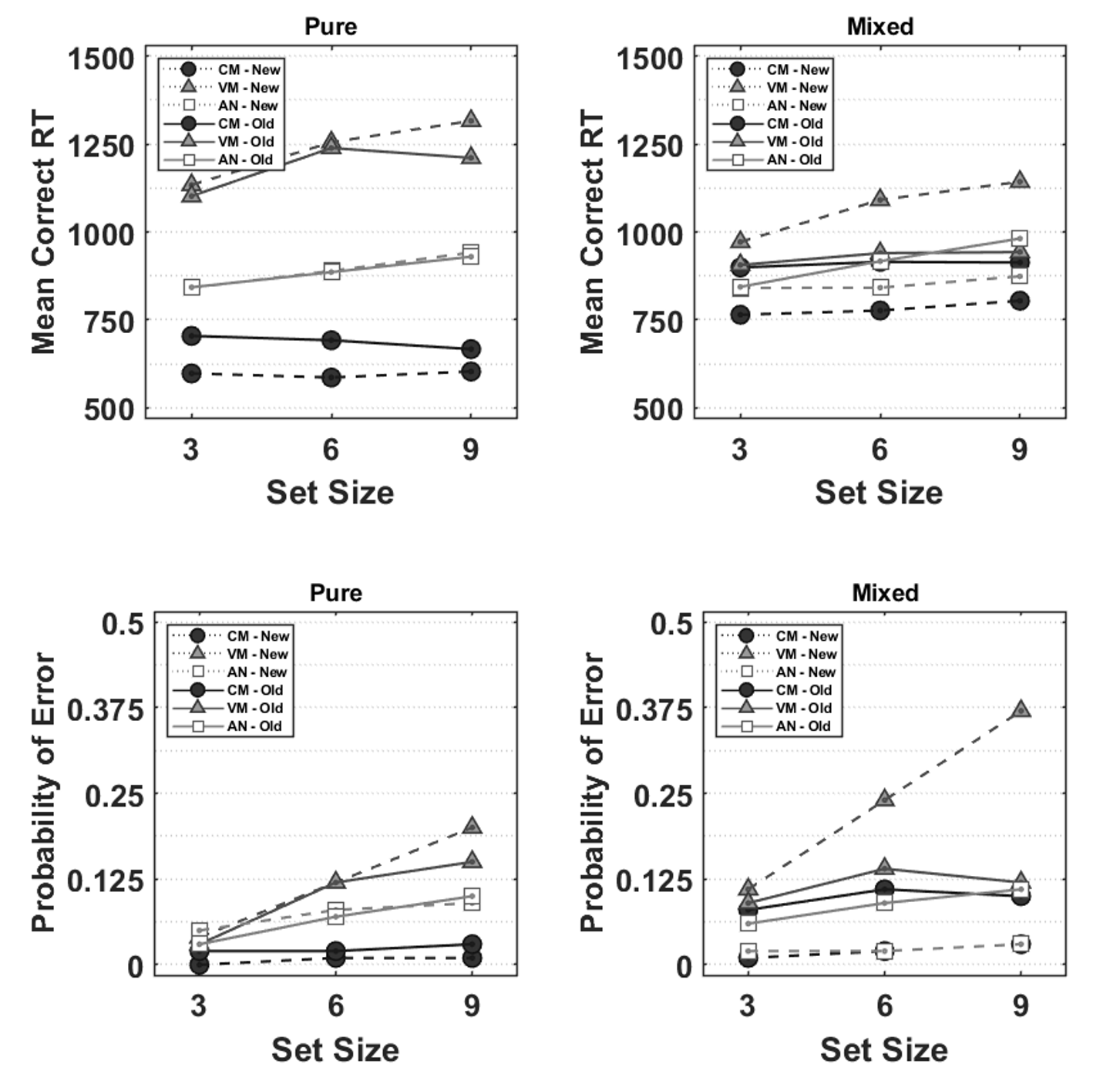


Figure 1

Thus the question arises whether or not item-response-learning does indeed take place for CM items during early stages of STM memory search—the qualitatively large features of the results can be explained by the use of familiarity without learning. The present research pursues this question using a modified version of the STM probe-recognition paradigm designed to equate overall familiarity for targets and foils, to equate these in both pure CM and pure VM conditions, and to match familiarity in CM to VM. We refer to our version of the STM probe-recognition task as the “side paradigm” – for an illustration involving CM, see Figure 2. Our method presented lists of study stimuli either to the left side or right side of fixation, followed by the test probe. The instructions required the participant to press a response key on the same side as the study list if the test probe was old, but to press a response key on the opposite side of the study list if the test probe was new. In CM one set of items was always studied on the left, whereas another set of items was always studied on the right. Foils were always chosen from the set on the other side. Thus a given CM test probe always required a consistent response with the same key, whether a target or foil. The design was symmetric so all CM items had equal familiarity. We also tested VM conditions that varied the side of presentation of every item from trial to trial; on average these VM items had the same familiarity as the CM items. In a second side-study we also tested AN conditions in which individual items did not repeat across trials, so always had low familiarity. This short-term probe recognition design allows us to assess whether item-response learning takes place for CM items, to assess the role of different sources of familiarity and to assess the joint contributions of familiarity and item-response learning.

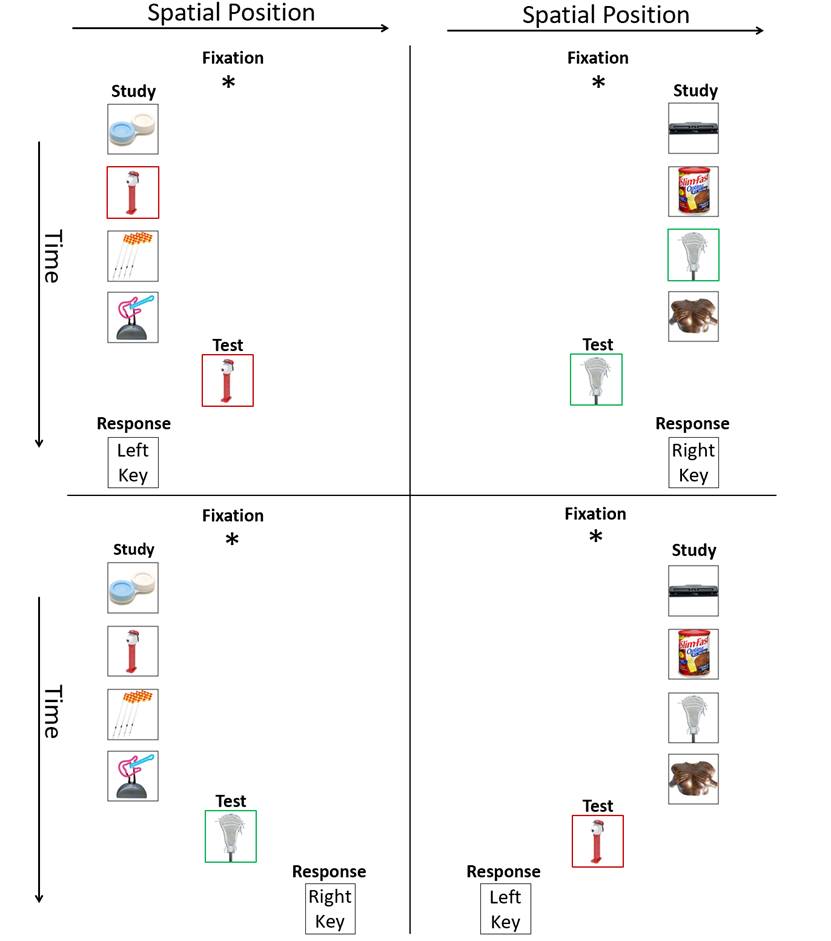


Figure 2

# Experiment 1

This experiment tested the side paradigm using pure-CM, pure-VM, and mixed CM-VM study lists.

## Method

**Participants** Undergraduates participated for class credit in single sessions lasting less than one hour. There were three groups of participants, trained respectively in a pure CM condition (28 participants), a pure VM condition (28 participants) and a Mixed VM/CM condition (30 participants). Two participants were deleted from analysis due to performance near chance, one in pure CM and one in pure VM.

**Stimuli and Apparatus** The stimuli were composed of 2,400 daily life pictures from the website of Talia Konkle (Brady, Konkle, Alvarez, and Oliva, 2008). Each image subtended a visual angle of approximately 7 degrees and was displayed on the center of a grey background. The experiment was conducted with MATLAB Psychophysics Toolbox (Brainard, 1997) on PCs. All participants were tested in private, sound-attenuated booths.

**Procedures** In all conditions, on each trial, two, four or eight pictures were presented sequentially for study, and then a single picture was tested, half the time from the list (termed a target or OLD item) and half the time not from the list (termed a foil or NEW item). The side used for presentation was chosen randomly from trial to trial. Test probes were presented centrally.The participant responded with an F key (on the left) for any target (OLD test picture) presented on the left of fixation, and responded with the J key (on the right) for any target presented on the right of fixation. The participant responded with the opposite key for any foil test.

*Timing:* Trials were self-initiated. A fixation point (\*) appeared on the center of the screen for 0.5 seconds prior to the first picture. Pictures were presented for 0.5 secs with 0.1 secs between pictures. After the last picture a new fixation point ("+") appeared on the center screen for 0.5 second, followed by a test probe that stayed on the screen until the key response was registered. Then there was a blank screen for 0.5 secs, and then feedback ("correct" or "incorrect"), which lasted for 1 second.

*Session*: There were 9 blocks of 25 trials each, taking about 45 minutes. The first block was considered as a training block that was not included in the final analysis. *Pure-CM*: Eight of a participant’s set of pictures were assigned to be targets presented for study always on the left side, and the other eight pictures were assigned to be targets presented for study always on the right side. The pictures that served as targets on one side served as foils on the other side. A target test probe was chosen randomly from those presented; a foil was randomly selected from the set used as targets on the other side of fixation. *Pure-VM*: For each participant there was a set of 16 pictures eligible for presentation. On each trial, two, four or eight pictures were selected randomly from that participant’s set and studied. A target was chosen randomly from the presented set and a foil was chosen randomly from all the pictures not presented. *Mixed CM/VM*: On each trial half the studied pictures were VM, and half CM, presented in a random order. CM: Four pictures were assigned to the left and four to the right. There were a total of 8 VM items, on each trial randomly presented for study on left or right. Note that the frequency of presentation of individual items was equated across the pure-CM, pure-VM, and mixed CM/VM conditions.

**Results**

Data from trials where responses occurred before 200 ms or after 4000 ms were excluded (~1% of the data). Figure 3 gives the median response time of correct trials in the top panel and the probability of error in the bottom panel for pure-CM, Mixed CM/VM, and pure-VM conditions.

The pure-CM and pure-VM data are similar to those in previous studies with standard probe-recognition tasks (e.g. Nosofsky et al. 2014a): CM performance is faster, has lower error rate, and smaller effects of set size. In this side-paradigm short-term familiarity (due to study of the recent list) is the same for CM and VM (as was true for the standard paradigm). However in the side-paradigm long-term familiarity (from prior lists) of targets and foils is the same for targets and foils, and is the same for both for CM and VM (as was not the case for the standard paradigm). Thus the present pure-CM advantage cannot be attributed to use of a familiarity-based-only strategy for discriminating between targets and foils. Instead, the results suggest strongly that in CM picture-response learning to the left and right keys has taken place. Nevertheless, the pure-CM data still show some set-size effects, so responding in this condition is not governed entirely by long-term item-response learning; an influence of capacity-limited short-term memory search remains.

The mixed condition data show a different pattern of results: CM and VM items now show quite similar performance, although response time seems to be slightly longer for the VM items. Thus, mixing appears to have inhibited long-term item-response learning for the CM items.

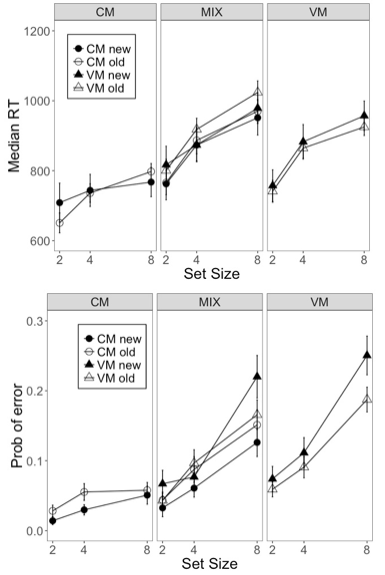


Figure 3 Median correct response times in milliseconds (top panel) and probability of error (bottom panel) for CM, MIX and VM, for old and new tests. Bars indicate between-

# Experiment 2

Experiment 2 was designed to explore the generality of the results by adding AN pictures to the design; these were used both in a pure-AN condition and a mixed condition. Because AN items have no long-term familiarity from prior trials, a comparison of that pure condition to pure VM and pure CM, both of which do have long-term familiarity, provides diagnostic information, as will become clear in the discussion of the results. Using a mixed condition with AN and CM pictures in the same list was meant to explore further and understand better the failure of learning in the first experiment: In the first study all items studied in the mixed condition had high long-term familiarity, possibly adding confusion, lessening the ability to distinguish CM from VM, and thus inhibiting learning. It should be far easier to distinguish AN from CM pictures in mixed lists. Finally, there were two mixed conditions, one using 8 CM pictures, 4 to each side (as in Experiment 1) and one using 16 CM pictures, 8 to each side. These mixed conditions varied long-term familiarity for the CM pictures in an attempt to understand better the effects of long-term familiarity upon CM performance, and to understand better the reasons for the inhibition of learning in the mixed conditions. Thus Experiment 2 used six conditions: pure-CM, pure-VM, pure-AN, a condition that alternated AN and CM across trials, and two conditions that mixed AN and CM within trials, one with 8 CM pictures assigned to each side, and one with 4 CM pictures assigned to each side.

**Method:**

The methods were the same as in Experiment 1 except for these changes. The test picture was presented on the side of presentation rather than centrally, in the hope of reducing possible confusion about the key to press. It used a new condition termed AN (for All-New): Every picture studied and all foils had never been seen before; pictures tested as targets had been seen only in the study list for that trial, and never on previous trials. It added a new condition in which trials alternated between AN and CM, the first trial in each block randomly selected to be AN or CM. A final new condition mixed CM and AN pictures in equal numbers on each study list, but there were 8 CM pictures assigned to each side instead of 4. Different groups of participants took part in CM, VM, AN, MIXED CM(8)/AN, MIXED CM(4)/AN, and Alternating CM/AN, with numbers participating and retained for analysis respectively 34(--), 35(--), 33(--), 32(--), 34(--), and 34(--). There were nine blocks of 24 trials each, the first not used for analysis.

**Results:**

Figure 4 gives the median response time of correct trials in the top panel and the probability of error in the bottom panel for the six main conditions. In each case, the data are plotted as a function of item type (CM-old, CM-new, VM-old, VM-new, AN-old, AN-new) and set size.

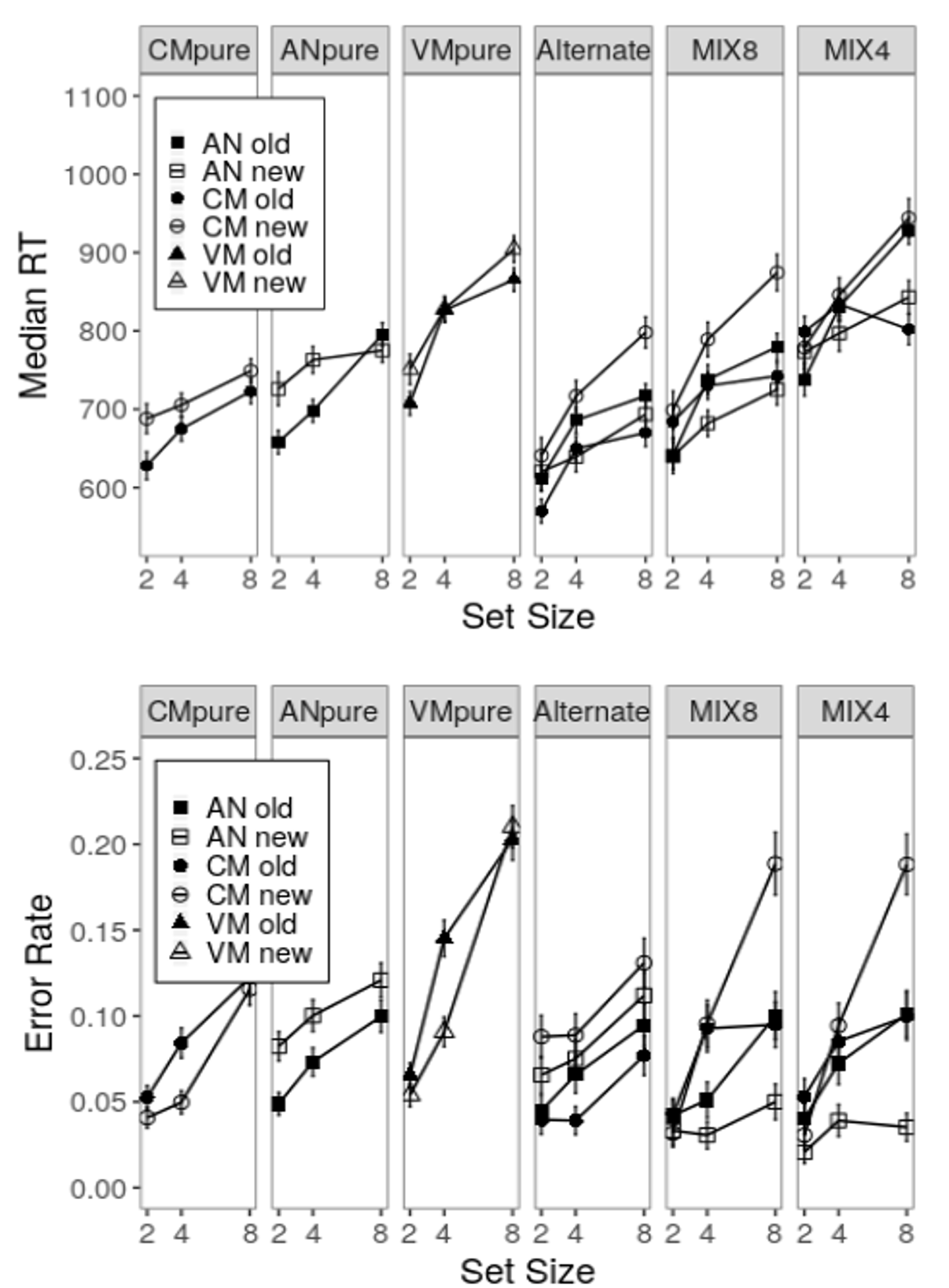


Figure4

For both accuracy and RT, pure-CM and pure-AN have much superior performance to pure-VM, with CM slightly superior to AN. AN and CM are qualitatively similar, having lowered set size effects. The superior performance of pure-CM to pure-VM replicates the results from Experiment 1 and again provides evidence of item-response-learning facilitating performance. However, the roughly equal performance for pure-CM and pure-AN could seem puzzling given that only CM can benefit from response learning. We propose that AN performance is based almost exclusively on short-term familiarity, but that CM performance is based on two additional factors that are opposing: Relative to AN, response learning helps CM but long-term familiarity harms CM, as described further in the discussion.

Mixing CM pictures together with AN pictures in the same study lists causes reduced CM performance, as seen in the comparison of MIX4 and MIX8 to pure-CM. This extends the similar findings in Experiment 1 in which mixing CM pictures with VM pictures harmed performance. Thus, the interfering effect of mixing on item-response learning for CM items appears to be a fairly general phenomenon, and is not due simply to confusion caused by mixing with inconsistently-mapped items. In addition, AN pictures should be easy to distinguish from CM pictures, so inability to distinguish different picture types in unlikely to be the primary cause of the inhibition of CM response learning.

Another result is also noteworthy: Mixing eight CM items produces better CM performance than mixing four CM items, whereas naïve intuition might suggest the opposite would have been observed due to additional item-response training given the smaller CM set of items. This result is explicable in terms of differences in long-term familiarity in these two conditions, as outlined in the discussion.

**Discussion**.

We describe informally a set of processes that can explain the patterns of results across the two experiments. It is reasonable to posit three primary sources of performance: 1) Short-term familiarity differences between targets and foils due to targets having been seen on the just-presented study list. 2) Long-term familiarity due to the test item having been seen on prior trials. 3) Long-term item response learning when items are consistently mapped to specific responses across trials.

Short-term familiarity can serve as a basis for good performance in every condition of these studies—that is the basis for the short-term recognition design. Long-term familiarity is likely a factor because there is ‘bleed over’ from prior trials. Participants are unlikely to be able to focus exclusively on only the recent list when retrieving from memory. Indeed researchers have obtained evidence demonstrating this factor in prior studies of short-term probe recognition (e.g., Monsell, 1978; Nosofsky et al., 2014). Long-term familiarity differs among conditions of the present side paradigm: Considering all trials, in both CM and VM every picture has been seen as both targets and foils equal numbers of times. In almost all reasonable models, the extra long-term familiarity for both targets and foils will degrade the ability to use their difference in short-term familiarity to make decisions. Without turning to quantitative modeling one can see this as a matter of familiarity operating on a ratio scale. Speaking qualitatively, if there are short-term familiarities on some scale of 10 vs 5 for targets vs foils, adding long-term familiarity of 10 to both will produce values of 20 vs 15, producing a much smaller ratio. Such degradation of performance due to long-term familiarity will not occur for AN pictures, because these have no long-term familiarity. In our toy examples the AN difference would remain 10 vs. 5. Thus familiarity alone (both short- and long-term together) would predict better performance for AN than both CM and VM, which would be equal.

However the third factor, response learning, benefits only CM. For CM this factor counters the interference caused by long-term familiarity and produces better performance for CM than VM. In addition, to the extent that it is used in CM it also reduces the set size effects, because it is a contribution from long-term memory, not from accessing information from the current memory set. Furthermore, the approximate equality of pure AN and pure CM is explicable if AN has no learning and no long-term familiarity costs, but CM has both, the two producing opposing effects on performance that tend to offset each other.

The above discussion pertains primarily to performance in the pure-list conditions. Another important result from Experiment 2 is better performance for CM pictures in the mixed-8 condition than the mixed-4 condition. This result also can be explained by the harm caused by long-term familiarity: Each mixed-8 CM picture is seen one half as often as each mixed-4 CM picture, and thus should have much less long-term familiarity. Less long-term familiarity should produce less harm and hence better performance.

The other major result observed in both of in our side studies, and in the prior regular study as well, is seen in the mixed-list conditions: CM performance is greatly harmed compared to pure-CM and is closer to VM performance. This occurs in both regular probe recognition and the side paradigm, and occurs whether mixing occurs with AN pictures or VM pictures. In the side paradigm, mixed CM performance was virtually the same as VM performance (Experiment 1), and worse than AN performance (Experiment 2). Hence, for reasons not yet clear, the mixed conditions appear to have inhibited, slowed, or prevented response learning for the CM items. Consistent practice has been shown to be a major route to achieving automaticity in wide varieties of cognitive tasks (e.g., Schneider & Shiffrin, 1977, Shiffrin & Schneider, 1977; Logan, 1988). The present results show that learning is not an automatic consequence of consistent training, but depends on the context in which such training occurs. Why mixing in short-term probe recognition inhibits learning is not yet clear. Possibly the need to use only short-term familiarity for the AN or VM items on a mixed list produces a tendency to do so for the CM items on that same list, thereby inhibiting learning. In any event, constraints upon the ability to learn from consistent training will be an important area for future research.

These ideas have been implemented in a quantitative model, based on the EBRW model we have used previously for the regular version of probe recognition. The qualitative features of the data can be captured quite well, but space does not permit presentation of the modeling.

Summary:

This study of short-term probe recognition allowed us to examine the contributions of short-term familiarity of the test picture due to study of the just presented list, long term familiarity of the test item due to presentations and tests on prior trials, and learning of pictures-to-responses due to consistent training. The key innovation, varying the side of presentation, allowed us to equate long-term familiarity for CM and VM items. Thus one key finding, the advantage of CM over VM could safely be ascribed to response learning. That was not a possible conclusion from our prior studies in which CM performance could have been due to differences in long-term familiarity. These studies also made clearer what was the role of long-term familiarity: It adds noise to the decision process when equal for targets and foils, explaining better performance for AN than VM, the relative performance levels among all three conditions, and the finding that in the mixed condition a four item CM set produced worse performance than an eight item CM set of pictures, due to higher long-term familiarity in the four item set.

The mixed results do not yet lend themselves to a clear understanding. In these studies mixing seems to prevent, inhibit or greatly slow response learning. It may be that the need to focus so strongly on the presence of a test item on the list, due to the presence on the list of VM and/or AN items, inhibits learning for the CM items on the same list. Such ideas would have to be pursued in future research.

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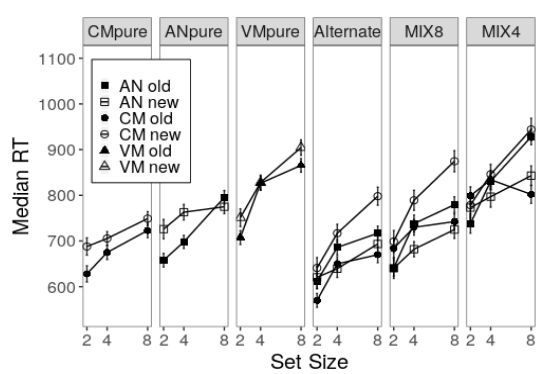
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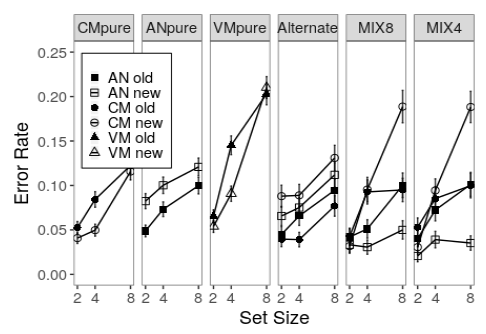
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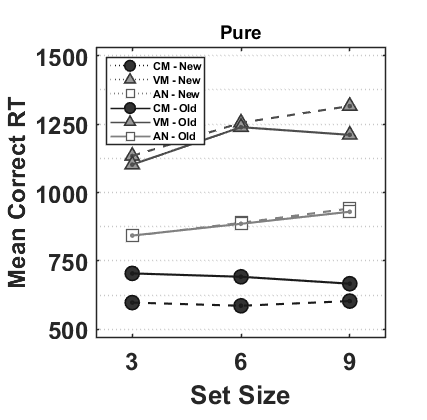
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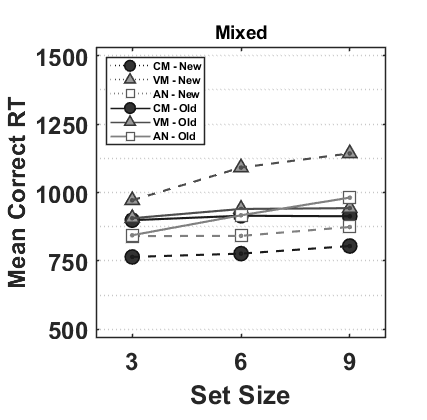
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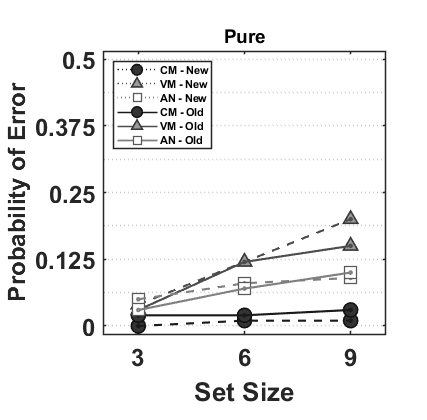
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