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Proactive interference slows recognition by eliminating fast assessments of familiarity ☆

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Abstract

The response-signal speed–accuracy tradeoff (SAT) procedure was used to investigate how proactive interference (PI) affects retrieval from working memory. Participants were presented with 6-item study lists, followed immediately by a recognition probe. A variant of a release from PI design was used: All items in a list were from the same semantic category (e.g., fruits), and the category was changed (e.g., tools) after three consecutive trials with the same category. Analysis of the retrieval functions demonstrated that PI decreased asymptotic accuracy and, crucially, also decreased the growth of accuracy over retrieval time, indicating that PI slowed retrieval speed. Analysis of false alarms to recent negatives (lures drawn from the previous study list) and distant negatives (lures not studied for 168+ trials) suggests that PI slowed retrieval by selectively eliminating fast assessments based on familiarity. There was no evidence indicating that PI affected slow processes involved with the recovery of detailed episodic information.

Keywords: Memory retrieval; Proactive interference; Cue overload; Working memory; Familiarity and recollection; Speed–accuracy tradeoff procedure

Introduction

The successful execution of complex cognitive skills often requires gaining access to the products of prior perceptual and cognitive analyses. Whenever these products are outside the span of focal attention, they must be retrieved from either working memory or from more durable long-term memory representations. A major determinant of successful retrieval is the amount of interference in the retrieval context (e.g., Anderson & Neely, 1996; Crowder, 1976), either retroactive interference (RI) arising from interfering material occurring between encoding and retrieval or proactive interference (PI) arising from material occurring prior to initial encoding.

The reported experiment investigates how PI affects the recognition of recently presented events. We used the response-signal speed–accuracy tradeoff (SAT) procedure to conjointly measure the effects of PI on recognition accuracy and the speed of memory retrieval in a classic probe recognition task (e.g., Sternberg, 1975). We document that, in addition to reducing recognition accuracy, PI slows retrieval speed. Our analyses of the retrieval functions for items from different serial positions in the list and for lures of different types suggests that PI slows retrieval speed by selectively decreasing

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the contribution of fast assessments of familiarity, without concomitant effects on the recovery of specific episodic information, which occurs later in retrieval.

Classic PI effects

Peterson and Peterson (1959; see also Brown, 1958) presented participants with a verbal item for 500 ms and found that recall accuracy decreased as the retention period was increased across an 18-s interval. Using the same procedure, Keppel and Underwood (1962) found that recall accuracy declined as the number of study items increased when, crucially, the retention interval was held constant. They concluded that forgetting could be induced by the buildup of PI alone. The results indicated a sharp difference in proportion correct between the first and second trials in all retention intervals (3, 9, and 18 s). This finding provided the first systematic evidence implicating PI as a major determinant in recall, and it suggests a single trial is sufficient to produce PI.

"Release from PI" phenomena (Watkins & Watkins, 1975; Wickens, 1970) demonstrate that the effect of PI on memory is a function of the psychological similarity of the interfering material to the target item. For instance, when items from the same category are presented for several trials, PI gradually builds up. If items from a different category are then presented, PI is "released" in that performance returns to its original level (Watkins & Watkins, 1975). There are two broad classes of explanations for this phenomenon. One claims that the buildup and release effects of PI results from factors related to memory encoding. According to this view, changing the nature of the items results in better encoding (Watkins & Watkins, 1975; Wickens, 1970). The alternative explanation posits that PI affects retrieval. According to this view, items could be equally well encoded in memory, but they become increasingly difficult to retrieve with increasing PI. Changing the type of items provides unique retrieval cues, which then results in more efficient retrieval. Watkins and Watkins (1975) dubbed this view the "cue overload" explanation, suggesting that the efficiency of a retrieval cue decreases as the number of items it selects increases.

Several findings suggest that PI selectively affects retrieval, with little or no effect upon memory encoding or storage. For instance, Gardiner, Craik, and Birstwistle (1972), using a cue overload paradigm (e.g., Watkins & Watkins, 1975; Wickens, 1970), presented participants with words from a subset of a category (e.g., garden flowers) during the build up trials and then switched to a complementary subset (e.g., wild flowers) on the release trial. All participants received the general category name (e.g., *flower*) as a cue at presentation in the first trial but not in the following buildup trials. On the release trial, one experimental group received the subset cue (e.g., *wild flowers*) before the presentation, another experimental group received the cue at retrieval, and the control group did not receive any cue. Both the experimental groups showed similar amounts of release from PI. The control group did not show the release effect, which provided evidence that participants were not aware of the subcategory distinction during encoding. Crucially, the comparable release effects for the two experimental groups suggest that PI impacts on retrieval rather than encoding. Watkins and Watkins (1975) report findings that point to a similar conclusion. They showed that the build up of PI across 3 same-category lists did not affect recall performance in a final cued recall task, where participants were given the category names as a recall cue and asked to recall all items from the three lists. Again, this suggests that the lists were equally well encoded, and that PI effects occurred during retrieval of the individual lists. Finally, Tehan and Humphreys (1996) demonstrated that PI effects occurred as a function of the uniqueness of retrieval cues (unique cues providing release from PI) when encoding conditions were otherwise equal.

Collectively, these studies suggest that PI has its primary effect on retrieval (but see Chechile & Butler, 1975 & Chechile, 1987, for arguments that PI may also induce changes in encoding). However, research has not clearly identified how PI negatively impacts on retrieval processes. A fundamental question we sought to address was whether PI simply decreases the likelihood of retrieving an item from memory or whether it also affects the dynamics of retrieval, slowing retrieval as it builds.

Effects of PI on retrieval

Most investigations of PI have used recall tasks. However, there is substantial evidence that PI also negatively affects recognition performance (e.g., Gorfein & Jacobson, 1972, 1973; Petrusic & Dillon, 1972). Because the production of an item not presented at retrieval may involve a series of operations to resample memory, possibly using modified sets of cues (e.g., Raaijmakers & Shiffrin, 1981), recall may be a less than optimal task for investigating how PI affects basic retrieval operations. We examined recognition performance to more directly assess how PI adversely affects the likelihood and speed of accessing memory representations.

An additional feature of most standard investigations of PI is that they typically measure PI after a filled retention interval (e.g., distractor task), and hence primarily assess the effects of PI on recall from long-term memory. However, interference is operative in tasks such as language comprehension (e.g., Fedorenko, Gibson, & Rohde, 2006; Gordon, Hendrick, & Levine, 2002; Lewis, Vasishth, & Van Dyke, in press; Van Dyke & Lewis, 2003; Van Dyke & McElree, 2006) and problem solving (e.g., Altmann & Trafton, 2002), which typically rely on the products of very recent perceptual and cognitive processing and little or no distracting activity has occurred prior to retrieval. To explore the effect of PI on recently processed information, we investigated its effect on the immediate recognition of items from a list of six sequentially presented items, with no distractor task between study and test. We examined recognition performance for each serial position to assess the effects of PI on items typically thought to be within working memory span (viz., serial positions 4–6; Cowan, 2001) and less recent items that may be beyond the limited span of working memory (viz., serial positions 1–3). Our analyses focused on both the speed and accuracy of recognition as a function of PI. We discuss how PI might affect both aspects of recognition within the context of current approaches to recognition.

Single process approaches

Many recognition models assume that a single direct-access, or content-addressable, retrieval operation mediates item recognition (see Clark & Gronlund, 1996). In these frameworks, contextual cues contact memory representations without the need for a search through irrelevant memories, and recognition judgments are based on a global assessment of the match between the recognition probe and representations in memory. Current evidence suggests that a direct-access mechanism mediates the recognition of information held in both short- and long-term memory. Although retrieval from short-term representations was once thought to involve a specialized search process (e.g., Sternberg, 1975; Theios, 1973; Treisman & Doctor, 1987), detailed measures of the dynamics of retrieval in tasks such as probe recognition indicate that both short- and long-term memories are recovered with the same type of direct-access mechanism (e.g., McElree, 1996, 1998, 2006; McElree and Dosher, 1989, 1993; Wickelgren et al., 1980). A summary of this evidence is presented in McElree (2006).

If, as in recall, PI decreases the effectiveness of a set of retrieval cues used to access representations in memory, making it less likely that the cues will provide direct access to the relevant representation, then we would expect it to lower recognition accuracy. However, certain ways of reducing the effectiveness of retrieval cues might also slow the comparison process, slowing the overall recognition of an item.

As an illustration, consider the diffusion model, which represents what is perhaps the most fully articulated and tested general model of the speed and accuracy of basic comparison processes, applicable to both short- and long-term memory judgments (e.g., Ratcliff, 1978; Ratcliff, Van Zandt, & McKoon, 1999). In Ratcliff's (1978) treatment of recognition in tasks such as probe recognition, accuracy is determined by the degree of match between retrieval cues at test and the current state of the memory representation. Degree of match is represented as a mean resonance value between retrieval cues and the set of items in a particular condition. Higher resonance values lead to a higher probability of retrieval. If PI lowers resonance, following a cue overload or related principle, then it will lower the probability that a retrieval probe resonates with an element in memory, decreasing the overall accuracy of the judgment. Retrieval speed is conceptualized as the rate at which evidence accrues over time. It is unaffected by differences in mean resonance, which instantiates the principle that a content-addressable operation enables memory representations of differing quality to be retrieved with comparable speed. However, Ratcliff (1978) demonstrated that differences in the variance of the resonance values across conditions can engender differences in the rate of information accrual: Specifically, higher variance can produce faster rates of accrual, with other parameters held constant. In this framework, PI might affect retrieval speed if it decreases the variance of the distribution of resonance values, perhaps by attenuating high values.

Dual-process approaches

Several alternative approaches propose that recognition judgments can sometimes be mediated by information other than a global match between the probe and memory. Dual-process theories assume that recognition reflects a mixture of judgments based on familiarity and recollection (e.g. Atkinson & Juola, 1974; Jacoby, 1991; Mandler, 1980; Yonelinas, 1994, 2002). Familiarity can be viewed as a global assessment of the probes match to items in memory, whereas recollection is often conceptualized as a different process, one that is based on the recovery of more specific episodic information (e.g., source information; Jacoby, 1991; McElree, Dolan, & Jacoby, 1999; Yonelinas, 2002). Dual processes are often thought to underlie the recognition of items in long-term memory, but several studies indicate that they may also be operative in the retrieval of short-term representations (McElree, 1996, 1998, 2001; McElree & Dosher, 1989).

Dual-process approaches raise the possibility that PI might selectively affect one process only, or that it might affect the two processes in different ways. Jacoby, Debner, and Hay (2001) used the process-dissociation procedure (e.g., Jacoby, 1991) to estimate the effects of PI on familiarity and recollection in a fragment completion task. Participants were first given pairs of related words in a training phase, in which one word was paired with two associates (e.g., ale-beer and ale-brew). To manipulate PI, Jacoby et al., varied the frequency with which words were paired together in this training phase (75, 50, or 25% of the time). The training phase was followed by a study phase, in which participants were given one of the pairs to study (e.g., ale-brew). In a final test phase, participants were given a fragment (e.g., ale-b_e_) and instructed to complete it with the word that was presented in the study phase. Process-dissociation logic was used to derive estimates of how familiarity stemming from the frequency manipulation in the training phase and recollection of the specific pairs presented in the study phase jointly contributed to performance on the fragment completion task. Interestingly, Jacoby et al., found that PI affected the estimates of familiarity only. The familiarity estimates showed evidence of probability matching, in that they were nearly equal to the frequencies in the training phase. This pattern suggested to Jacoby et al., that PI did not lower the likelihood of recollecting the pairs from the study phases but only functioned as a form of bias when recollection failed. That is, prior learning exerted its influence on performance only when participants failed to recover specific episodic information from the study phase. In these cases, participants incorrectly completed the fragment in a manner consistent with prior training, and the frequency of doing so approximately matched the amount of prior training.

The experimental protocol used by Jacoby et al. (2001) differs in many ways from a classic cue overload paradigm, and there is no compelling reason to assume that results from this type of task will generalize to the operations that are used in simpler recognition tasks. Nonetheless, the results raise the intriguing possibility that PI may selectively affect the recovery of different forms of information on which recognition can be based.

In a classic cue overload paradigm, PI could selectively reduce the diagnosticity of a general assessment of familiarity or it could selectively impair the recovery of source information. In either case, it would lower the overall recognition accuracy, which in most circumstances is thought to rely on a mixture of the two forms of information. PI might also directly slow the retrieval of either type of information, in ways analogous to what was outlined in the section above. Interestingly, however, several studies, discussed more fully below, have demonstrated that the two forms of information are retrieved with different time courses. Familiarity information has been found to be available before source and other more specific episodic information (e.g., Curran, 2000; Hintzman & Curran, 1994; McElree, 1998, 2001; McElree et al., 1999; McElree & Dosher, 1989). This raises the possibility that PI could affect retrieval speed by simply altering the relative contribution of each type of information. For example, if PI selectively lowers the diagnosticity of familiarity information, it might slow overall retrieval speed because participants would be less able or less inclined to rely on relatively fast assessments of familiarity, and their judgments would have to wait upon slower accruing episodic information.

In the reported work, we used an experimental procedure that conjointly measures retrieval speed and accuracy to assess how PI affects recognition, and we employed manipulations that enabled us to separately estimate effects of PI on the recovery of familiarity and more specific episodic information.

The present study

Measuring the effect of PI on retrieval speed and accuracy

Reaction time (RT) paradigms are often used to investigate potential differences in the speed of memory retrieval. However, RT is not a pure measure of retrieval speed. Although, barring speed–accuracy tradeoffs, there is little doubt that a difference in retrieval speed will be reflected in RTs, the converse does not necessarily follow: We cannot infer a difference in retrieval speed from a difference in RT, because differences in the quality of the match between the probe and the memory representation alone can affect RT even if the underlying speed of information accrual is constant (e.g., Dosher, 1976, 1981; McElree & Dosher, 1989; Murdock, 1971; Ratcliff, 1978; Wickelgren, 1977; Wickelgren, Corbett, & Dosher, 1980). As PI is thought to affect the quality of the memory match, differences in RT do not entail that PI affects retrieval. What is required is a procedure that enables separate assessments of probability and speed of correctly identifying a recognition probe.

To conjointly measure the effects of PI on recognition speed and accuracy, we used an SAT variant of a probe recognition task (e.g., McElree, 1996, 1998; McElree & Dosher, 1989; Reed, 1976). Fig. 1 illustrates the basic procedure: participants studied 6-word lists, which were immediately followed by a recognition probe. We used an immediate test, rather than having a long retention interval and a distracter task between study and test, to directly measure effects of PI on representations that vary in recency over the short-term. Crucially, participants were cued to respond to a response signal (a tone) presented at 43, 200, 300, 500, 800, 1500 or 3000 ms after the onset of the recognition probe, and they were required to respond within 100–300 ms of the tone. Varying the response signal across this range of times enabled us to measure the full time-course of retrieval, from times when accuracy was at chance to times when accuracy reached its asymptotic level.

General effects of PI on accuracy and retrieval dynamics

Fig. 2 illustrates how we induced PI. For three consecutive trials, participants received three lists from the same semantic category. After the third trial, a different category was used for the next three trials, and so on throughout a session of the experiment. We expected PI to build up across the three trials using the same category and to be released when the category was switched. We assessed the effects of PI on the full time-course of retrieval by comparing functions from the three consecutive same-category trials.

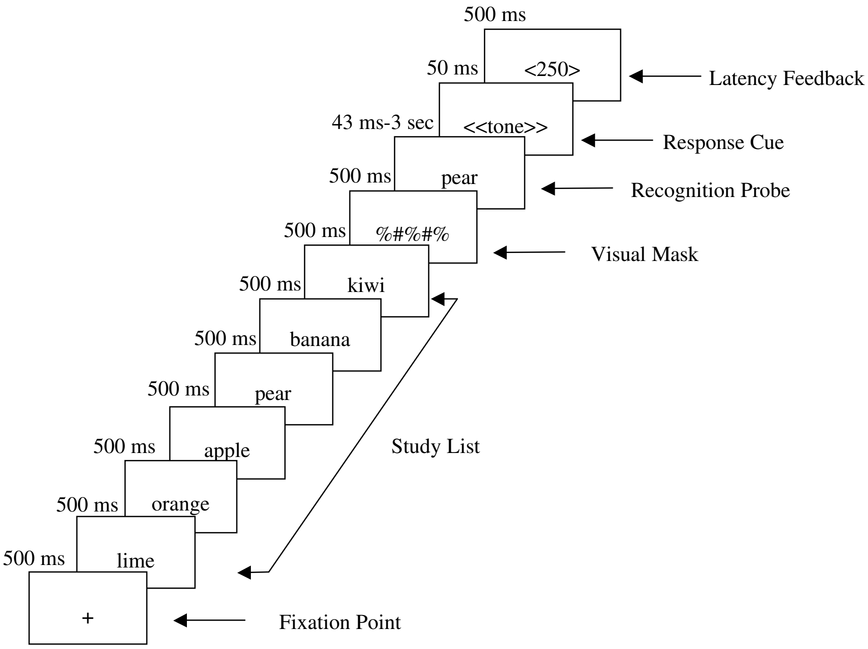

Fig. 1. A sample trial sequence and timing.

The asymptote of the SAT time-course function provides a measure of overall recognition accuracy. Based on previous findings (e.g., Gorfein & Jacobson, 1972, 1973; Petrusic & Dillon, 1972), we expected that PI would impact on recognition accuracy, and hence that it would lower the SAT asymptotes across the three lists as it builds. Our primary interest was in retrieval dynamics. Retrieval speed is jointly measured by when accuracy first departs from chance, the intercept of the SAT function, and the rate at which accuracy grows from chance to asymptote, the SAT rate. If PI slows retrieval, then it should either shift the SAT intercept towards longer times or slow the growth of accuracy over retrieval time. In either case, SAT functions will display disproportional dynamics: That is, the functions will reach a given proportion of their respective asymptotes at different times. Disproportional dynamics, whether due to differences in either intercept or rate, indicate underlying differences in either the rate of continuous information accrual if retrieval is continuous or the distribution of finishing times if retrieval is discrete (Dosher, 1976, 1979, 1981, 1982, 1984; Meyer, Irwin, Osman, & Kounois, 1988; Ratcliff, 1988).

Proactive interference has not been investigated with the SAT method, but there are indications that other forms of interference may affect retrieval speed. Dosher (1981) used an SAT procedure to investigate associative interference. Participants studied a series of word pairs that either contained an interference relation (AB, DE, and AC) or did not (AB, DE, and FC). At either a short delay or a long delay, they were presented with a word pair to recognize. Asymptotic accuracy was lower for pairs with interference relations. Additionally, however, associative interference appeared to slow retrieval speed (SAT rate), although the effects were moderate and did not reach significance.

Effects of PI on serial position

We also assessed how PI varies with recency within each of the three consecutive lists. Positive test probes were drawn equally often from each of the six serial positions in a list, which enabled us to derive a time-course function for each serial position. Studies of retrieval dynamics in the probe recognition task (McElree, 1996, 1998; McElree & Dosher, 1989, 1993; Wickelgren et al., 1980) have shown that asymptotic accuracy displays typical bowed serial position functions, with accuracy decreasing as the probe is drawn from more remote serial positions coupled with a small primacy advantage for the first position. In contrast, however, retrieval speed does not vary with recency but rather shows a sharply dichotomous pattern. Retrieval speed is exceptionally fast for the last item or group of items studied, with all other positions being slower and associated with the same speed. The retrieval advantage for the last chunk is thought to reflect the fact that it remains active in focal attention when no mental activity intervenes between study and test (see McElree, 2006 for a review of the evidence for this claim). Because the test probe can be matched to the contents of focal attention, no retrieval operation may be required for this type of trial. An analysis of the serial position functions

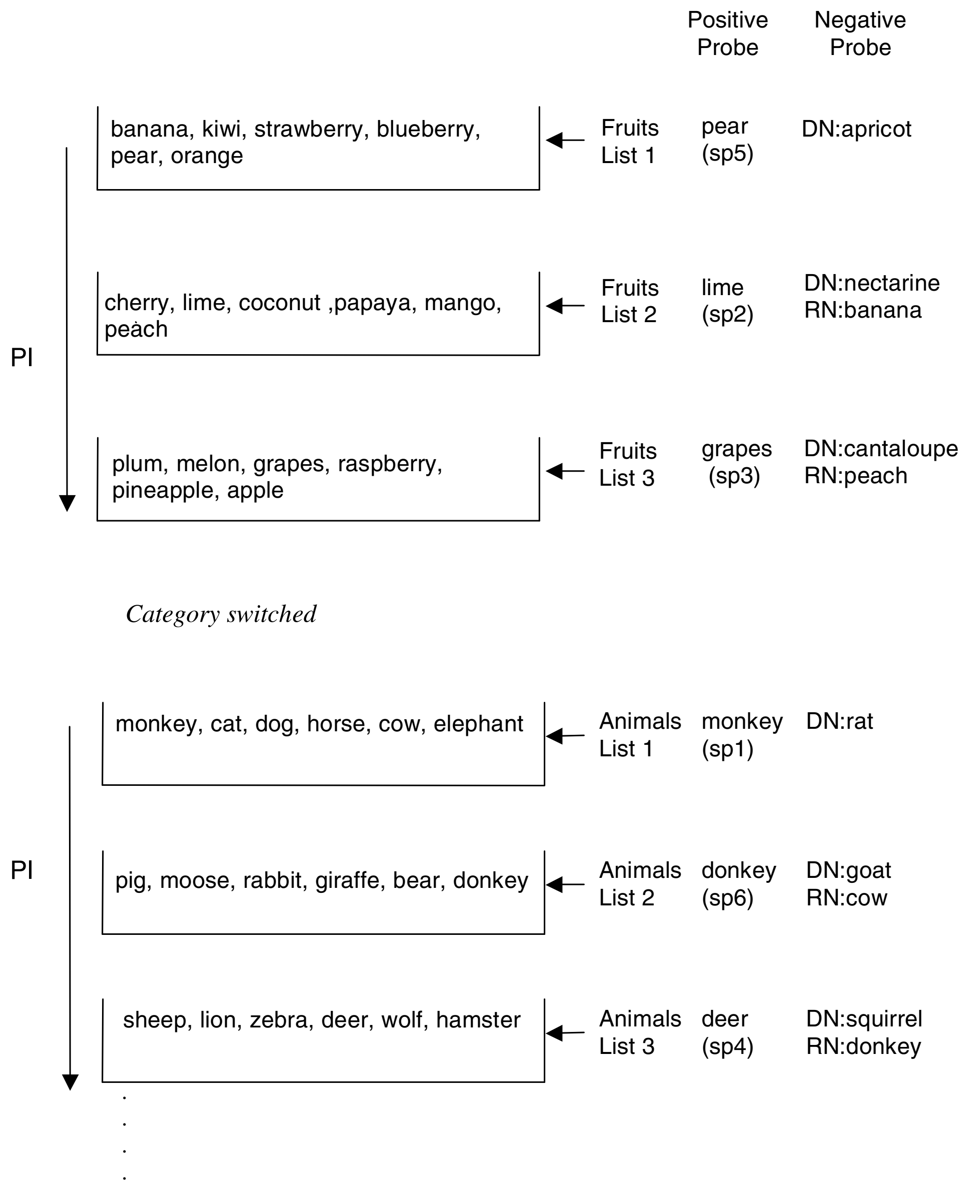

Fig. 2. PI manipulation and the list structures. *Note:* sp, serial position; DN, distant negative (lure from the same category from at least 168 trails back); RN, recent negative (lure from the previous trial).

enabled us to examine whether the effect of PI was operative across all items in a list or whether it was restricted to only cases that require retrieval. The former may be the case if PI affects encoding. However, if PI primarily affects retrieval, then we would not expect it to influence cases where the probe could be directly matched to items in focal attention.

Effects of PI on familiarity and recollective processes

Finally, we sought to examine the potential effects of PI on familiarity and the recovery of more specific episodic information. We did so by isolating the retrieval time-course for each type of information. The two types of information are often highly correlated, and factors (repetition, recency, etc.) that lead to high familiarity values also lead to detailed recovery of episodic and source information. Hence, it can be difficult to uniquely identify the contribution of each type of information to any overall judgment. However, the two forms of information can be isolated by placing them in opposition to one another, such that one provides evidence antithetical to the evidence provided by the other (e.g., Jacoby, 1999; McElree, 1998; McElree et al., 1999; McElree & Dosher, 1989).

One means of doing so is to examine false alarm (FA) rates to lures that vary in their recency (e.g., McElree, 1998, 2001; McElree & Dosher, 1989) or other factors that affect an item's familiarity (e.g., repetition, McElree et al., 1999). In a probe recognition task, recent lures will have a higher FA rate than more distant lures, presumably because they have higher familiarity due to more recent study. Crucially, previous SAT studies have found that recent lures engender FA rates that are non-monotonic across retrieval time. For example, in a probe recognition task, McElree and Dosher (1989) found that, relative to temporally distant lures (negative probes drawn from 3 or more trials back), lures that were members of the previous study list induced high FA rates early in retrieval (response-signal times < 900 ms), suggesting that recent lures had higher familiarity. With additional retrieval time (response-signal times > 900 ms), FA rates for recent lures decreased, approaching the level observed for distant lures. These non-monotonic FA functions were argued to result from an early, fast assessment of familiarity, which was attenuated later in retrieval by the recovery of list—specific information.

Hintzman and Curran (1994) reported a related pattern in an SAT study that contrasted easy and difficult item discriminations, where difficult discriminations required participants to reject the plural form of a word that was studied in a singular form. Consistent with McElree and Dosher (1989), they found that difficult lures produced high FA rates early in retrieval that were attenuated later in retrieval. McElree (1998) extended these findings by showing that both episodic familiarity and semantic similarity intrude early in the course of recognizing items from categorized lists. Recently studied lures and lures from the semantic categories studied in the list both produced high FA rates early in retrieval when compared against a baseline FA rate for less recently studied, semantically unrelated lures. Finally, in an experimental design following Jacoby (1999), McElree et al. (1999) found a similar FA profile for lures repeated for either 3 or 5 times versus lures presented only once.

The biphasic FA functions provide relatively direct evidence for the retrieval of two types of information (see McElree et al., 1999). Minimally, these results indicate that information on which recognition judgments are based shifts from a general assessment of familiarity early in retrieval to more specific episodic information later in retrieval. Dual-process approaches to recognition interpret this pattern as reflecting the contribution of two distinct processes, namely a familiarity process and a recollective process. Event-related brain potential (ERP) research has provided additional support for the two-process interpretation of these biphasic FA functions by demonstrating unique ERP components associated with the early and late phases of the SAT time-course functions (Curran, 2000).

That the same type of biphasic retrieval functions are found in paradigms using small list sizes and immediate recognition tests (e.g., McElree & Dosher, 1989) as in other paradigms with longer lists (McElree, 1998) and delayed tests (e.g., Hintzman & Curran, 1994; McElree et al., 1999) suggests that dual processes are operative in both short- and long-term recognition. This claim is generally consistent with other evidence indicating that the same type of retrieval mechanism mediates the recognition of both short- and long-term events (see McElree, 2006).

In the current experiment, we used two types of negative conditions to examine the potential effects of PI on familiarity and the recovery of source information. Analogous to McElree and Dosher (1989), we presented participants with recent negatives (RN), which were lures that were members of the previous study trial, and distant negatives (DN), which occurred at least 168 trials back. If PI affects familiarity, differences should emerge early in retrieval. Conversely, if PI affects the retrieval of more specific episodic information, then differences should emerge later in retrieval. Specifically, if PI selectively influences familiarity, then we would expect the high FA rate early in retrieval typically found with RNs to diminish as PI builds up across the three trials. Alternatively or additionally, if PI impacts on the recovery of more specific episodic information, then it should affect the degree to which this information attenuates the high FA rates for RNs later in retrieval.

Method

Participants

Eight students from New York University participated in the study. Each participant completed 14 105-min sessions, and an additional 15-min practice session to train for the SAT procedure. One participant was affiliated with the lab, and volunteered her time. All remaining participants were paid for their time.

Materials

The stimuli consisted of 21 instances of 56 categories. We used all categories from the category norms of Van Overschelde, Rawson, and Dunlosky (2004) that had 21 or more instances, supplementing these with a few experimenter-generated sets.

Design and procedure

Stimulus presentation and response collection were controlled by a personal computer. For each 3-trial sequence, which we will refer to as a set, a category was pseudo-randomly selected from the 56 categories.

A category was not repeated until a set from all 56 categories was presented (a total of 168 trials). For each trial in the set, a study list was constructed by randomly selecting (without replacement) 6 words from 21 words of the category. Positive probes were drawn from one of the 6 serial positions of the current study list equally often. For List 2 and List 3, half of the negative probes were distant negatives (DN), and half were recent negatives (RN). DNs were selected from members of the same category, but were studied at least 168 trials back. RNs were selected randomly from the 6 serial positions of the previous trial. List 1 trials use DNs only, since they involved the first presentation of a category.

Each participant performed 14 sessions. Each session consisted of 756 trials divided into three blocks, yielding 84 sets (three trials each) per block. For the positive conditions, this resulted in a total of 42 trials at each of the seven response deadlines (lags) for each of the 6 serial positions per list. For the negative conditions, there were 252 DN trials per lag for List 1, 126 DN trials per lag for List 2 and List 3, and 126 RN trials per lag for List 2 and for List 3.

Fig. 1 illustrates that the sequence of events in a single trial was as follows: (a) A centered, solid square fixation point was presented for 500 ms. (b) Study words were presented successively for 500 ms each. (c) After the presentation of the last study word, a mask consisting of non-letter symbols was presented in the same region as the study list for 500 ms. (d) Following the mask, the test word was presented at the same region as the study list and the mask. The test word remained on the screen for the duration of the lag. (e) At 43, 200, 300, 500, 800, 1500 or 3000 ms after the onset of the test item, a 50-ms tone sounded to cue the participants to respond. (f) Participants gave a yes–no recognition response as quickly as possible after the onset of the tone by pressing a key. (g) After the participant responded, feedback was given on the participant's latency to respond. Participants were trained to respond within 300 ms of the tone. They were informed that responses longer than 300 ms were too long and that responses under 100 ms were anticipations, and that both should be avoided. (h) Following the latency feedback, the participant was asked to give a confidence rating ranging from 1 to 3 ("3" indicating strong confidence, "1" indicating weak confidence). The confidence ratings primarily served as means of enabling participants to self-pace themselves through the trials. They were not analyzed further. Participants initiated the next trial by pressing a key. Participants were allowed to rest between blocks.

Results

Practice data was excluded from analysis. For positive trials, each participants' hit rates were scaled against the false alarm rates to distant negatives (DN) to obtain (equal-variance Gaussian) d' measures. To ensure d's were measurable, perfect performance in any condition was adjusted with a minimal corrections procedure: Hit rates higher than .99 were adjusted to .98, and false alarm rates lower than .01 were adjusted to .02. This adjustment approximates the correction suggested by Snodgrass and Corwin (1988). This correction was necessary for approximately 7% of the trials to obtain measurable d's.

Analysis of time-course data has typically been conducted on d' measures, to avoid possible distortions of the shape of the functions caused by response biases. To demonstrate that the results reported below were not particular to the d' transform, we performed analogous fits on the (untransformed) proportion correct data for the individual subjects' and the average (over subjects) data.[1] The results are reported in Appendix A and show the same effects found in the d' analyses. The Appendix also includes a table which reports the average hits, false alarm, and proportion correct data corresponding to the d' analyses reported below.

Because collecting enough data to derive stable functions for each of the 8 subjects required running each subject for 25.5 h, one could be concerned that subjects might have adopted radically different response strategies across the 14 sessions. To examine this issue, we collapsed and compared the data for the first half (the first 7 sessions) and the second half (the remaining 7 sessions) of the experiment for each participant. A 2 (1st or second half of sessions) × 3 (list) × 8 (lag) repeated measures ANOVA conducted on the proportion correct data (averaging over serial position) for each list and per lag revealed a significant effect of list, $F(2,14) = 9.640$, $p < .01$. As is documented below, this list effect reflects the build up of PI across the 3 lists. There was a marginal effect of session, $F(1,7) = 4.610$, $p < .069$, and a significant session by lag interaction, $F(2,14) = 2.573$, $p < .05$. The significant interaction was due to lower accuracy scores in the second half of the sessions than the first half at longer interruption lags. This could have arisen from the fact that motivation declined across the sessions, but it could also reflect the long-term build up of PI as the categories and exemplars became increasingly more familiar. Crucially, however, there was no indication of an interaction of list and session ($p < .01$). This lack of an interaction indicates that PI effects were consistent across sessions.

[1] We performed all analyses except fits of the dual-process model. We could not fit a dual-process model to the proportion correct data because it required anchoring the fits of the false alarm functions to the corresponding proportion correct functions, which unfortunately are on a different scale.

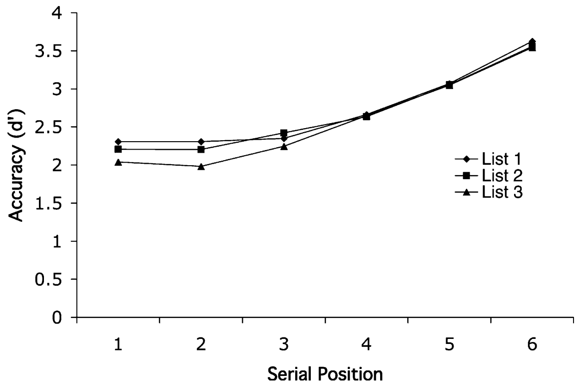

Fig. 3. Average asymptotic d' for the lists as a function of serial position of the test probe.

Consequently, we report below analyses that use the complete multi-session data.

Asymptotic accuracy

We averaged the d's for the last two interruption lags to obtain an empirical measure of asymptotic recognition accuracy (e.g. McElree & Dosher, 1989, 1993; McElree, 1998, 2001). Fig. 3 shows the average asymptotic d' for six serial positions of the three lists (Fig. A1 in the Appendix A shows the analogous proportion correct functions). A 3 (list) × 6 (serial position) repeated-measures ANOVA conducted on the asymptotic d's indicated that accuracy increased significantly as the test probe was drawn from more recent serial positions, $F(5,35) = 37.551$, $MS_e = 7.456$, $p < .01$. Main effect of list was marginally significant, $F(2,14) = 2.958$, $MS_e = .394$, $p < .085$. This is not surprising since Fig. 3 shows that PI has decreased accuracy for the first three serial positions, but not for the more recent serial positions.

To confirm that PI impacted more on less recent serial positions, we conducted an interaction contrast for the effect of list within each serial position. The results revealed that PI significantly decreased accuracy for serial position 1, $F(2,14) = 7.17$, $MS_e = .23$, $p < .01$ and serial position 2, $F(2,14) = 4.19$, $MS_e = .22$, $p < .05$. The more recent serial positions did not show a significant decrease in accuracy ($p > .1$). The post hoc comparisons between the lists were not significant for either serial position 1, $p > .1$, or serial position 2, $p > .1$. PI's effects on asymptotic accuracy on lists, and on separate serial positions will be discussed further in the analysis of the SAT curve fits.

Retrieval dynamics

To estimate the retrieval dynamics, the individual participants' data and the average data (d' values averaged across participants) were fit with an exponential approach to a limit:

$$d'(t) = \lambda(1 - e^{-\beta(t-\delta)}), t > \delta, \quad \text{else } 0. \tag{1}$$

In Eq. (1), d' (t) is the predicted d' at time t; λ is the asymptotic accuracy level reflecting the overall probability of recognition; δ is the intercept reflecting the discrete point in time when accuracy departs from chance ($d' = 0$); β is the rate parameter, which indexes the speed at which accuracy grows from chance to asymptote. Previous studies have shown that this equation provides a good quantitative summary of the shape of the SAT functions (e.g., Dosher, 1981; McElree, 1996, 1998, 2001; McElree & Dosher, 1989, 1993; Wickelgren & Corbett, 1977; Wickelgren et al., 1980).

Retrieval dynamics within lists

To verify that SAT functions within each list showed the same essential pattern that has been observed in other studies (e.g., McElree, 1996, 1998; McElree & Dosher, 1989, 1993; Wickelgren et al., 1980), the SAT functions for the 6 serial positions within each list were fit with sets of nested models that systematically varied the three parameters of Eq. (1). These models ranged from a null model in which all functions were fit with a single asymptote (λ), rate (β), and intercept (δ) to a fully saturated (18-parameter) model in which each function was fit with a unique asymptote (λ), rate (β), and intercept (δ). The quality of the fits was examined by three criteria, which have been used in prior research (e.g., Dosher, 1981; McElree, 1996, 1998, 2001; McElree & Dosher, 1989, 1993; Wickelgren & Corbett, 1977; Wickelgren et al., 1980): (1) The value of an adjusted R^2 statistic, which reflects the proportion of variance accounted for by a model, adjusted by the number of free parameters (Reed, 1973); (2) The consistency of the parameter estimates across participants; (3) Evaluation of whether the fit yielded systematic deviations that could be accounted for by additional parameters.

Models that did not allocate separate asymptotes (λs) for serial positions produced poor fits to the empirical SAT data. Allocating separate λs to each serial position increased the adjusted-R^2 from .76 to .96 in List 1; from .70 to .93 in List 2; from .67 to .95 in List 3 on the average data. Comparable differences were seen in the individual fits of all participants' data. However, consistent with prior studies, there was also clear evidence for dynamics differences. These differences were due to fast rising functions for serial position 6. A 6λ-2β-1δ model provided the best fit of the empirical data for each of the three lists. This model allocated a separate asymptote (λ) to each serial position, one rate (β) for serial positions 1 through 5, another rate (β) for serial position 6 (the most recently studied item), and a common intercept (δ) for all the six serial positions for all lists. This two-rate model increased adjusted-R^2 value from a 6λ-1β-1δ model from .95 to .98 for List 1, from .93 to .96 for List 2, and from .95 to .98 for List 3. A 6λ-2β-1δ model improved the R^2 in the all fits of the individual participants' data for each of the three lists. The increase in adjusted-R^2 value resulted from a faster rate parameter for the last serial position. The rate in $1/\beta$ ms-units was 115 ms for serial position 6 versus 223 ms for other serial positions in List 1, 126 versus 254 ms in List 2, and 126 versus 248 in List 3. The difference between the two rate parameters was statistically significant in all three lists: $t(7) = -4.168$, $p < .01$, for List 1; $t(7) = -5.749$, $p < .01$, for List 2; $t(7) = -8.316$, $p < .01$, for List 3. Fig. 4 shows the SAT functions of the 6 serial positions for the lists, with smooth curves showing fitted exponential functions (Fig. A2 shows the corresponding fits of the proportion correct data).

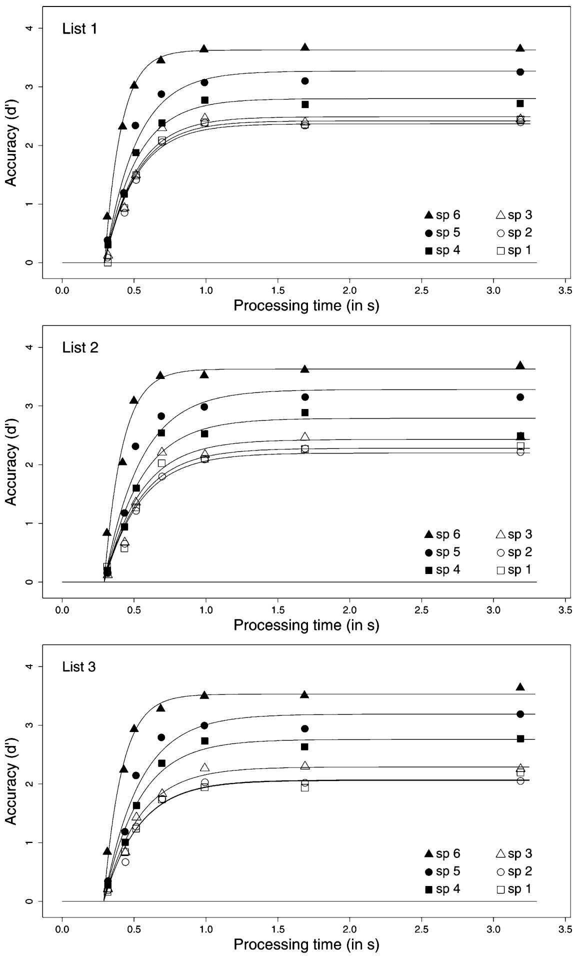

Fig. 4. Average d' (symbols) as a function of processing time (time of the response cue plus latency to respond to the cue) for each serial position (sp) for the three lists. Smooth curves show the best fits (6λ-2β-1δ model) of Eq. (1).

In summary, we replicated previous findings (McElree, 1996, 1998; McElree & Dosher, 1989) regarding serial position effects on both asymptotic accuracy and retrieval dynamics within all of the 3 lists. We now turn to the question of how retrieval dynamics varied as a function of proactive interference.

General effects of PI on retrieval dynamics

To examine the overall effect of PI across the lists, d's were computed for each list by averaging over serial position. We again fit the average and individual participants' retrieval functions with Eq. (1) using a nested model scheme. Competitive model fits found a 2λ-2β-1δ model to be the best fit to the data. The fit of this model to the average data is shown in Fig. 5. (Fig. A3 shows the corresponding fits of the proportion correct data.) This model allocated one asymptote (λ) and one rate (β) to List 1, and another asymptote and rate to Lists 2 and 3, with all three lists sharing a common intercept (δ). The asymptotes for Lists 2 and 3 were significantly lower than the asymptotes for List 1, 2.74 versus 2.60 (respectively) in the average data, $t(7) = 4.72$, $p < .01$. This decline in the asymptotes demonstrated that PI affected the probability of retrieval. This suggests that PI primarily built up across Lists 1 and 2, but it did not generally decrease performance further. However, 4 participants show some evidence of a further decline in the asymptote for List 3, which did engender some measurable differences in asymptotic performance (see below).

Differences in retrieval speed mirrored the pattern observed in the asymptotes. These differences were best captured in rate. The rate (β) declined from List 1 to Lists 2 and 3, 206 versus 224 ms $1/\beta$ units, and this difference in the parameter estimates was significant, $t(7) = 3.04$, $p < .05$. All participants showed a decrease in both the asymptote and the rate parameters from List

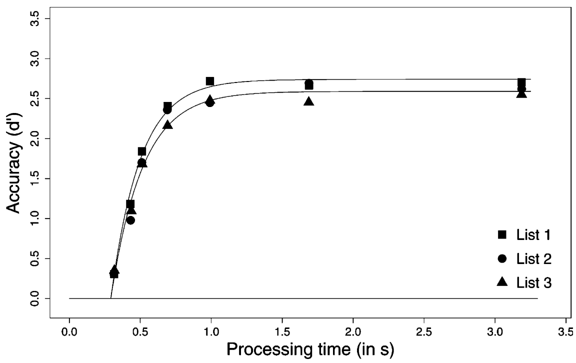

Fig. 5. Average d' values (symbols) averaged over serial position for each list as a function of total processing time. Smooth curves show the best fit (2λ-2β-1δ model) of Eq. (1) with the average parameters listed in Table 1.

1 to Lists 2 and 3, except one participant who did not show any asymptotic differences. Table 1 shows the adjusted-R^2 values and estimated parameters of the 2λ-2β-1δ fit for the average data and all participants.

In summary, the model fits provided clear evidence that PI lowered the likelihood of retrieving the test probe from memory. More importantly, they provide the first reported evidence that PI negatively impacts on the speed of retrieval.

Effects of PI on serial position

Our analysis of asymptotic patterns indicated that PI affected the first few items in the list, but not more recent serial positions. We analyzed the full retrieval functions to determine whether PI affected retrieval speed in a similar fashion. Consistent with other studies (McElree, 1996, 1998; McElree & Dosher, 1989, 1993; Wickelgren et al., 1980), adequately modeling the retrieval functions for the serial positions within each of the individual lists (see *Retrieval dynamics within lists* section above) required allocating separate asymptotic (λ) parameters to each serial position to capture the fact that asymptotic accuracy varied with recency, and a separate rate (β) parameter to the last serial position to capture the fast dynamics for the condition that was maintained in focal attention. To examine how PI affected this pattern across the lists, we fit an 18λ-6β-1δ model to 18 functions (6 serial positions within 3 lists) for the average data and the individual participant's data. For each list, this model allocated a separate asymptote (λ) to each of the 6 serial positions, and a separate rate (β) parameter to the last serial position in each list and another rate (β) parameter to each of the remaining serial positions. All three lists were fit with a common intercept (δ). Table 2 lists the resulting parameter estimates.

With this model, we found clear evidence that PI lowered asymptotic accuracy for serial positions 1–3, but it did not affect the asymptotes for more recent positions. A 6 (serial position) × 3 (list) repeated-measures ANOVA on the asymptotic parameters showed a main effect of serial position, $F(5,35) = 42.778$, $MSe = 8.476$, $p < .05$, with accuracy increasing in more recent serial positions, and a main effect of list, indicating that overall the asymptote declined across the lists, $F(2,14) = 4.424$, $MSe = .383$, $p < .05$. However, the interaction was also significant, $F(10,70) = 2.999$, $MSe = .034$, $p < .05$. Interaction contrasts revealed a significant decline in the asymptote for serial position 1 from List 1 to List 2, $F(1,7) = 11.23$, $MSe = .27$, $p < .05$, and a marginal decline from List 2 to List 3, $F(1,7) = 11.23$, $MSe = .19$, $p = .086$. For serial position 2, there was a reliable decline from List 1 to List 2, $F(1,7) = 28.84$, $MSe = .30$, $p < .05$, and from List 2 to List 3, $F(1,7) = 6.04$, $MSe = .09$, $p < .05$. For serial position 3, there was a significant decline in the asymptote from List 1 to List 2, $F(1,7) = 6.70$, $MSe = .07$, $p < .05$, but not from List 2 to List 3 ($p > .1$). The comparisons for the more recent serial positions were not significant. The marginal differences between List 2 and List 3 reflect the fact that PI was essentially asymptotic at List 2 for half the participants.

In terms of retrieval dynamics, there was clear evidence that PI affects the rate of retrieval for serial positions 1–5, but not for serial position 6, the most recently studied item. In ms ($1/\beta$) units, the average rate for serial positions 1–5 in List 1 was 390 ms, as compared to 426 ms in List 2 and 408 ms in List 3. The β estimates were reliably faster for List 1 than List 2, $t(7) = 2.93$, $p < .02$, but there were no significant differences between Lists 2 and 3, $t(7) = -0.98$, $p < .36$. Like the general trend in the asymptotes, PI appeared to build up primarily between Lists 1 and 2, with no further impact in List 3. In contrast, the average rate for serial position 6 in List 1 was 254 ms, as compared to 258 ms in List 2 and 257 ms in List 3, and there were no significant differences among the β estimates for the lists: $t(7) = 0.29$, $p < .78$, for List 1 versus List 2; $t(7) = 0.17$, $p < .89$, for List 2 versus List 3. Hence, the most recent serial position appeared to be immune to PI both in terms of accuracy and retrieval speed.

The absence of an effect of PI on the most recent serial position is consistent with other time-course data showing that this item remains in focal attention, which effectively circumvents the need for a retrieval process (for a review, see McElree, 2006). Collectively, the fits of the serial position functions provide further evidence

Table 1
Parameter estimates for PI across the lists (2λ-2β-1δ model)

Parameter	Average	Participant							
		1	2	3	4	5	6	7	8
λ_1	2.74	2.33	2.93	4.15	2.17	2.70	2.72	2.31	2.51
λ_2	2.60	2.19	2.70	3.92	2.00	2.60	2.56	2.23	2.53
β_1	4.84	6.19	4.33	5.70	9.28	5.14	4.29	4.29	5.06
β_2	4.47	5.41	4.26	5.21	7.72	5.05	3.96	4.09	4.30
Common δ	.293	.390	.245	.286	.311	.292	.333	.283	.306
R^2	.982	.979	.967	.982	.897	.909	.940	.885	.942

Table 2
Parameter estimates for the 18λ-6β-1δ1 model

Parameter	Average	Participant							
		1	2	3	4	5	6	7	8
List 1									
λ_1	2.49	1.88	2.81	4.26	1.67	2.53	2.55	1.64	2.48
λ	2.45	1.95	2.37	4.20	1.71	2.42	2.42	2.12	2.33
λ_3	2.57	2.32	2.72	3.92	1.82	2.65	2.70	2.11	2.46
λ_4	2.90	2.65	3.09	4.03	2.53	2.83	2.98	2.51	2.46
λ_5	3.39	3.00	3.84	4.48	3.35	3.07	3.39	2.88	3.00
λ_6	3.77	3.74	3.94	4.24	3.78	3.72	3.93	3.58	3.30
β_1	2.56	2.60	2.93	3.36	2.97	2.81	2.05	2.60	2.65
β_2	3.93	2.93	4.61	6.56	5.82	3.31	3.34	4.07	4.28
List 2									
λ_1	2.36	1.55	2.48	3.91	1.56	2.83	2.27	1.87	2.40
λ_2	2.28	1.75	2.19	3.97	1.43	2.56	2.26	1.90	2.16
λ_3	2.51	2.20	2.58	3.80	1.94	2.73	2.34	1.96	2.57
λ_4	2.85	2.45	2.84	3.94	2.14	3.08	2.81	2.78	2.78
λ_5	3.39	2.81	3.90	4.45	3.06	3.57	3.30	2.94	3.14
λ_6	3.75	3.29	3.90	4.22	3.85	3.74	3.80	3.77	3.38
β_1	2.35	2.51	2.83	3.08	2.86	2.19	1.89	2.59	2.04
β_2	3.87	3.72	5.52	5.30	5.02	4.46	3.75	2.93	3.37
List 3									
λ_1	2.14	1.76	2.03	3.86	1.31	2.04	2.25	1.57	2.32
λ_2	2.13	1.77	2.10	3.72	1.17	2.17	2.08	1.67	2.32
λ_3	2.37	2.37	2.54	3.48	1.49	2.32	2.38	1.82	2.61
λ_4	2.85	2.72	2.87	3.98	2.15	2.64	2.98	2.56	2.89
λ_5	3.29	3.18	3.67	4.41	2.76	3.14	3.37	2.66	3.19
λ_6	3.66	3.33	3.74	4.24	3.78	3.48	3.90	3.54	3.38
β_1	2.45	2.11	3.07	3.40	3.27	2.83	1.83	2.26	2.27
β_2	3.89	2.82	5.45	5.78	4.37	4.96	2.93	3.60	3.84
Common δ	.188	.273	.187	.208	.188	.188	.187	.360	.188
R^2	.891	.871	.883	.853	.837	.831	.827	.807	.822

Note: SP, serial position.

that PI slowed retrieval speed, even in cases like serial positions 4 and 5 where its effect on accuracy may be weak or non-existent.

False alarm analysis

Our results indicate that PI slows retrieval. How does it do so? To determine whether PI has an across-the-board effect on retrieval speed or whether it selectively influences either familiarity or the recovery of more specific episodic information, we examined its effect on recent negatives (RN, a studied item from a previous trial), and distant negatives (DN, at least 168 trials back). As an RN probe has high familiarity, it should lead to high FA rates early in retrieval (e.g., McElree, 1998; McElree et al., 1999; McElree & Dosher, 1989). However, participants should also be better able to recover specific source information for a RN than a DN probe (viz., that the RN probe occurred on the previous trials). As this information accrues later in retrieval, it should serve to correct or attenuate the FA rates for the RN probe based on familiarity (e.g., McElree, 1998; McElree et al., 1999; McElree & Dosher, 1989). Hence, we can examine the effect of PI on the two forms of information by comparing *changes* in the FA functions as PI builds.

To do so, we constructed a d' measure, d'_{FA}, that scaled the relative degree to which RN trials induced a higher FA rate than DN trials (e.g., Dosher, McElree, Hood, & Rosedale, 1989; McElree, 1998, 2001; McElree et al., 1999; McElree & Dosher, 1989). For both Lists 2 and 3, the z-score of FA rates to RNs were scaled against z-score of FA to DN, viz., $d'_{\mathrm{FA}} = z(\mathrm{FA}_{\mathrm{RN}}) - z(\mathrm{FA}_{\mathrm{DN}})$, at each of the response lags. This allowed an unbiased measure of performance by factoring out participants' bias to judge an item as old (e.g., tendency to respond yes more often than no), and it also factors out any general tendency to false alarm to a semantically similar lure, as both DN and RN probes are from the same semantic category as the study list. Thus, the resulting score is a pure measure of residual tendency

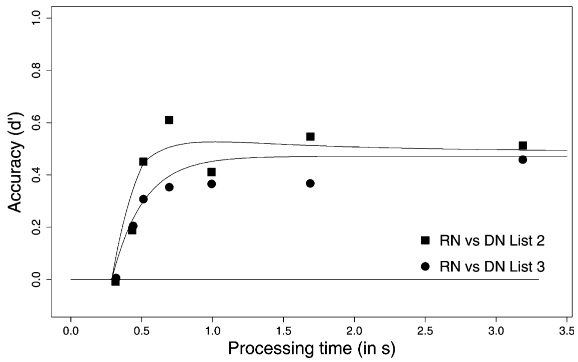

Fig. 6. Average d'_{FA} values (symbols) for recent negatives (RN) for Lists 2 and 3 as a function of total processing time. Smooth curves show the best fit of Eq. (2) with the average parameters listed in Table 4.

to false alarm induced by recently studying the RN probe. Importantly, with this scaling, higher d'_{FA} values indicate *lower* performance due to an increased tendency to false alarm. Fig. 6 shows the $d'_{FA}$for Lists 2 and 3 for the average data.

Of particular interest was how the d'_{FA} pattern changed over response lags across the lists. Crucially, the RNs tested in List 2 were studied in List 1, where PI was low. In contrast, the RNs tested in List 3 were studied in List 2, where, as the analysis above demonstrates, PI was operative. Hence, by comparing the respective FA rates for Lists 2 and 3, we can assess how the build up of PI affected the ability to reject lures with high familiarity.

Fig. 6 shows that in List 2, we obtained the general pattern for RNs that has been reported in previous studies (e.g. McElree, 1998; McElree et al., 1999; McElree & Dosher, 1989): The d'_{FA} values increase early in retrieval and then diminish later in retrieval. This type of non-monotonic pattern indicates that the information basis for a judgment shifted across retrieval, and it is what is predicted from dual-process models of recognition memory (see McElree et al., 1999). Specifically, a fast assessment of familiarity is available early in retrieval and induces a high FA rate for RNs as compared to DNs. Later in retrieval, this high FA rate diminishes. The attenuation of the early FA rate reflects the accrual of new information, presumably recollective source information (either the source of the lure or that lure was not in the study list).

Table 3 presents the d'_{FA} values for the 8 individual participants, along with the average d'_{FA} values plotted in Fig. 6. Six of the eight subjects (S1, S2, S3, S4, S6, and S7) show a peak FA rate early in retrieval at interruption times between 200 and 500 ms, which is larger than the FA values at the final three interruption times ranging from 800 to 3000 ms. The peak value occurs at 500 ms for all these subjects except S3, who shows higher values at 200 and 300 ms. Only 2 subjects, S5 and S8, show no clear evidence for a non-monotonic time-course function.[2]

Strikingly, Fig. 6 and the corresponding values in Table 3 show that the non-monotonicity evident in List 2 and in all other investigation of RN manipulations was absent in List 3, and that List 3 lacked the high FA rate early in retrieval found in List 2 and other studies. This suggests that the PI that has built up from Lists 1 to 2 has diminished the familiarity of the RNs. Furthermore; the d'_{FA} values for List 3 at the longest lags were indistinguishable from those in List 2. This suggests that PI has no effect on the retrieval of more specific episodic information, which is assumed to occur later in retrieval.

One way to quantify this pattern and to test these claims further is to fit the d'_{FA} values with model that explicitly assumes that retrieval shifts from one source of information to another source across retrieval time. This type of model is formally equivalent to a two-process retrieval model. Ratcliff (1980) proposed one such two-process SAT model, and McElree and Dosher (1989; see also Dosher et al., 1989; McElree, 1998, 2001; McElree et al., 1999) adapted this model to the exponential form:

$$d'(t) = \begin{cases} \lambda(1 - e^{-\beta(t-\delta)}), & \text{for } \delta_1 < t < \delta_2 \\ \lambda_2 + (\lambda_1 - \lambda_2)(\delta_2 - \delta_1)/(t - \delta_1) \times (1 - e^{-\beta(t-\delta 1)}), & \text{for } t \geqslant \delta_2. \end{cases} \quad (2)$$

Eq. (2) states that during the initial retrieval period ($\delta_1 < t < \delta_2$), accuracy depends on accrual of one type of information, which, in this application, we assume is familiarity. During this initial period, accuracy is modeled by the top portion of Eq. (2), a simple exponential approach to an asymptote (λ_1). At time δ_2, a second source of information starts to contribute to the response. This source of information could arise from the output from a second process, e.g., a recollective operation in dual-process models. Alternatively, as developed more fully in the Discussion section, this parameter could simply reflect that the retrieval process is modified over time so that more list-specific source information begins to be recovered. In either case, the change in retrieval shifts the asymptote from λ_1 to λ_2. The bottom portion of Eq. (2) states that response accuracy gradually shifts to the new asymptote (λ_2) starting at time δ_2.

[2] In the average d'_{FA} function, the 5th interruption lag at 800 ms is lower (.411) than both the previous lag (0.6106) and the two following lags (0.5468 and 0.5128). Although this could reflect a higher-order non-monotonicity—e.g., a high value at 500 ms that is overcorrected at 800 ms and then upwardly adjusted again at 1500 and 3000 ms—it is more likely that this average value simply reflects the contribution of what might be an unduly low value at lag 800 for S6 (−0.3962) and S3 (−0.0842) only.

Table 3
d'_{FA} (recent negative versus distant negative) values for the average and individual participants

	Interruption Lag (ms)						
	43	200	300	500	800	1500	3000
Average							
d'_{FA} List 2	−0.0084	0.1882	0.4507	0.6106	0.4111	0.5468	0.5128
d'_{FA} List 3	0.0056	0.2052	0.3076	0.3532	0.3656	0.3678	0.4586
Subject 1							
d'_{FA} List 2	−0.0914	−0.1278	0.4211	0.9014	0.4845	0.6868	0.3803
d'_{FA} List 3	−0.2847	−0.1005	0.1469	0.1187	0.1760	0.4424	0.5823
Subject 2							
d'_{FA} List 2	−0.0914	−0.1278	0.4211	0.9014	0.4845	0.6868	0.3803
d'_{FA} List 3	−0.2847	−0.1005	0.1469	0.1187	0.1760	0.4424	0.5823
Subject 3							
d'_{FA} List 2	0.1420	0.7687	0.2358	0.0764	−0.0842	0.0000	0.0974
d'_{FA} List 3	0.1274	0.5295	0.6872	0.4646	0.1642	0.0000	0.0000
Subject 4							
d'_{FA} List 2	−0.0436	0.2004	0.5222	0.7223	0.3453	1.1342	0.2614
d'_{FA} List 3	−0.2309	0.2184	−0.0040	0.2731	0.4504	0.0708	0.5470
Subject 5							
d'_{FA} List 2	0.2476	0.2806	0.4962	0.5634	0.4317	0.9929	1.1894
d'_{FA} List 3	0.1907	0.1533	0.5295	0.4299	0.4354	0.3963	0.4843
Subject 6							
d'_{FA} List 2	−0.0574	0.0487	0.2726	0.4876	−0.3962	0.3068	0.3349
d'_{FA} List 3	0.0948	0.3198	−0.0486	0.2119	0.6825	0.3931	0.2042
Subject 7							
d'_{FA} List 2	−0.0152	−0.2330	0.4942	1.0300	0.8285	0.3238	0.0967
d'_{FA} List 3	0.1021	−0.1486	0.2012	0.0445	0.1902	0.5068	0.3726
Subject 8							
d'_{FA} List 2	0.0822	0.2351	0.3517	0.3829	0.6584	0.1979	1.0585
d'_{FA} List 3	0.0617	0.2069	0.6281	0.7243	0.5673	0.3948	0.7913

To test whether the effects of PI can be modeled as a difference in either familiarity, the recovery of more detailed episodic information, or a combination of the two operations, we can fit and compare the asymptote parameters λ_1 and λ_2 for Lists 2 and 3. If PI only impacts on familiarity, we should be able to model the differences between the d'_{FA} values for Lists 2 and 3 as a difference in λ_1 only. Conversely, if PI also affects the recovery of detailed episodic information, then the fits will require different λ_2 parameters for Lists 2 and 3.

To anchor the fits to the overall time-course patterns, and to thereby insure that the fits of the d'_{FA} functions were consistent with the standard d' functions, the dual process model was fit to the five functions, *viz.,* the two the d'_{FA} functions in Fig. 6, and the three regular d' functions for List 1 (scaled against $z(FA_{DN})$), List 2 (scaled against $z(FA_{RN})$), and List 3 (scaled against $z(FA_{RN})$). In this way, we modeled the differences in the standard d' function in the same fashion as the d'_{FA} functions, either a difference in λ_1 and λ_2. We fit both the average and individual participants' data allowing both λ_1 and λ_2 to vary across Lists 2 and 3. Table 4 lists the parameter estimates from the fits of the average and individual participants' data, and the smooth functions in Fig. 6 show the fits to the average data points.

For List 2, the average λ_1, the asymptote reflecting familiarity, was estimated at 0.697 (in d' units), whereas for λ_2, the asymptote reflecting the accrual of specific episodic information, was estimated at 0.494. Six of the eight participants showed this ordering, and the difference in parameters estimates was significant, $t(7) = 2.970$, $p < .05$. The higher λ_1 captures the non-monotonic nature of the functions, and it suggests an early intrusion of familiarity information that is corrected later in retrieval. The two intercepts, λ_1 and λ_2, indicate that, in the average data, familiarity began to be operative at 290 ms and the correction based on more specific episodic information began at

Table 4
Parameter estimates for the dual process model

Parameter	Average	Participant							
		1	2	3	4	5	6	7	8
List 2 λ_1	.697	1.41	1.03	1.31	.381	2.00	1.35	.785	.597
List 3 λ_1	.499	−2.49	.595	1.35	−.911	−2.00	.191	.193	.743
List 2 λ_2	.494	.678	.694	−.185	.632	.776	.267	.069	.701
List 3 λ_2	.472	.454	.863	.051	.474	.554	.427	.637	.503
Common β	4.56	5.30	4.04	5.65	8.23	5.66	3.93	4.22	4.66
Familiarity δ	.289	.386	.240	.290	.310	.304	.329	.280	.304
Recollection δ	.531	.397	.800	.422	.339	.300	.320	.800	.747
R^2	.988	.957	.944	.984	.905	.960	.953	.940	.944

516 ms. Paired-t tests on the two intercepts confirmed that familiarity was operative earlier in retrieval, $t(7) = -2.359$, $p < .05$.[3]

In contrast, for List 3, the average λ_2 was estimated at 0.499 and λ_2 was estimated at 0.472, only slightly lower. No consistent differences were seen across participants, and the differences were not significant, $t(7) = -1.560$, $p > .1$. There was no evidence for a non-monotonic form, and hence no evidence of an early intrusion of familiarity.

Crucially, a direct comparison of λ_1 estimates for Lists 2 and 3 (0.697 versus 0.499 in the average data) demonstrated that the familiarity estimate was significantly higher in List 2 than List 3, $t(7) = 2.39$, $p < .05$. However, there was no evidence that these conditions differed later in retrieval, when more detailed episodic information, possibly due to a recollective process, was assumed to be operative. There was no consistent trend across participants in the λ_2 estimates, and a direct comparison of the estimates (0.494 versus 0.472 in the average data) was not significant, $p > .1$. This fit suggests that PI selectively impacted on fast assessments of familiarity operative early in retrieval, but there was no evidence to indicate that it affected later retrieval processes.

A viable method to evaluate the non-monotonicity of a function is to fit the data with both dual process and single process models (e.g., Rotello & Heit, 1999). To further demonstrate that a dual process model better explains our data, we fit the average and individual data with a single process model as described in Eq. (1). Adjusted-R^2 comparisons of the single (R^2 ranging from .86 to .92) versus dual process model fits (R^2 ranging from .90 to .98) yielded a higher R^2 for the dual process model fit than the single process model fit, $t(6) = 6.032$, $p < .01$. This was consistent across participants. Thus, a dual process model better accounts for our data than a single process model. In summary, the intrusion analysis suggests that PI affects early assessments of familiarity, but it does not impact on the recovery of detailed episodic information later in retrieval.

Discussion

Before discussing how PI affected retrieval, we briefly summarize general properties of the observed time-course functions. Within each list, our findings replicated previous findings on the effects of serial position on retrieval speed and accuracy (e.g. McElree, 1996, 1998; McElree & Dosher, 1989, 1993; Wickelgren et al., 1980). Both the analyses of the empirical asymptotic d's and the model fits demonstrated that asymptotic accuracy declined as the positive test item was drawn from less recent serial positions, except for a small primacy advantage. This pattern indicates the likelihood of retrieving memory representations decreases with intervening study events and possibly the passage of time. Indeed, McElree and Dosher (1989) showed that a simple forgetting model—the acquisition-primacy model of Wickelgren and Norman (1966)—could fully account for asymptotic profiles of this form. Consistent with other studies of retrieval dynamics for items of varying recency, summarized in McElree (2006), we found that retrieval dynamics show a sharply dichotomous pattern: Retrieval speed is faster for the most recently studied item than all other positions, and positions beyond the most recent do not differ in retrieval speed. This pattern suggests that the last item remained in focal attention at test time, hence could be rapidly matched to the test probe. All other items required a slower retrieval process to verify their list status.

[3] The estimated λ_1 value for the List 2 data likely underestimates its true value to the degree to which the value at the 4th point is unduly low (see Footnote 1). This is because fitting routine essentially splits the differences between 3rd, 4th, and 5th points. If the 4th data point were more in line with the 3rd and 5th, non-monotonicity would be stronger because the fitted function would have higher values earlier in retrieval than those shown in Fig. 6.

General effects of PI

Analysis of the composite retrieval functions (averaged across serial position) for each of the three lists indicated that PI decreased the likelihood of retrieving an item and, crucially, slowed retrieval speed. Model fits indicated that asymptotic accuracy reliably declined from List 1 to List 2, as did retrieval speed estimated by either SAT rate or intercept. In our experimental paradigm, PI built up rapidly between Lists 1 and 2. For half the participants, the effects of PI were asymptotic by List 2.

More fine-grained analyses of the individual serial position functions across the three lists indicated that the overall decline in asymptotic accuracy was primarily due to the effects of PI on the first 3 serial positions. No measurable effects of PI on asymptotic accuracy were observed for the other, more recent serial positions. However, PI had a more ubiquitous effect on retrieval speed, in that it slowed retrieval for all serial positions except the most recent one.

That PI had no measurable effect on the last serial position, either in terms of retrieval speed or accuracy, is consistent with the hypothesis that the most recent item remains in the current focus of attention when no activity intervenes between study and test. McElree (2006) reviewed findings from several experimental paradigms that provide independent support that the last study event remains in a special state within focal attention, including the finding, replicated here, that the overall retrieval dynamics for this item is markedly faster than any other serial position. Accordingly, we believe that the explanation for why PI did not impact on the final serial position is a simple one: This item is immune to PI because no retrieval process is needed to execute a response; rather, participants could simply match the test probe to the current contents of focal attention.

Immunity to PI

Several researchers have suggested that PI is operative only in long term memory, and that items that are in working memory are immune to PI induced by semantic similarity (e.g. Cowan, 2001; Craik & Birtwistle, 1971; Davelaar, Goshen-Gottstein, Ashkenazi, Haarmann, & Usher, 2005; Tehan & Humphreys, 1995). A common finding is that on an immediate test (mostly recall tests), the 3–4 most recent items are immune to PI. We applied an immediate test to systematically investigate and localize PI effects on the recognition of items of varying recency. Analogous to previous findings, our results show an effect of PI on asymptotic accuracy for the first 3 items in a 6-item study list. However, contrary to traditional findings that show the most recent 3–4 items are immune to PI, our data show that PI slowed retrieval dynamics for serial positions 4 and 5, which are typically thought to be maintained in working memory (e.g., Cowan, 2001). The only item we found to be immune to PI, in terms of both speed and accuracy, was the last item, a case where no other material intervened between study and test. Hence, we believe that immunity from PI results from information being maintained in the current focus of attention, not because items are maintained in a specialized 3–4 item working memory store.

Immunity from PI does not extend to the broader set of items that many researchers have argued are stored in working memory because, we believe, these items require a retrieval process to be restored to active processing. To assert that items in working memory are immune to PI requires postulating that retrieval from working memory is qualitatively different than retrieval from long-term memory. McElree (2006) reviewed the evidence from several investigations of the dynamics of memory retrieval from standard working memory paradigms. Although there are solid grounds on which to draw a distinction between representations in the focus of attention and those stored in memory, there is no compelling evidence for either qualitative or quantitative differences in retrieval for items that are argued to be within or outside the span of a working memory system.

However, when the possibility of chunking is acknowledged, we note that there may be less discrepancy between our findings and other studies that have found immunity for the last 3–4 items. If information is chunked by some organizing principle, then it is possible that more than one nominal item can remain in focal attention and thereby be immune to PI. For example, in 9-item lists consisting of 3 instances from 3 semantic categories, McElree (1998) found that the last three items show the retrieval speed advantage for the last item on the list observed here and in other studies (McElree, 1996; McElree & Dosher, 1989, 1993; Wickelgren et al., 1980). McElree (2006) also found that the last three items from a 6-item list consisting to 3 instances from 2 semantic categories showed a retrieval advantage. In studies that show no PI effects for the last 3–4 items, it is possible that these items may have been encoded into a chunk and maintained in focal attention at test time. In our study, however, the retrieval dynamics advantage was restricted to only the most recent position in all three lists (see *Serial position effects section* above), which provides independent evidence that only the most recent item was maintained in focal attention at test time.

It may appear odd that our data showed that PI slowed retrieval speed for serial positions such as 4 and 5, but it did not measurably lower asymptotic accuracy at these positions. This could simply indicate that SAT response dynamics provide a more sensitive measure of PI than asymptotic accuracy. Alternatively, however, if we are correct in claiming that PI affects global assessments of familiarity and not the recovery of detailed episodic information (see below), then the absence of asymptotic effects in these cases might reflect the fact that the recovery of source information compensated late in retrieval for the early impact of PI on familiarity. In contrast, recovery of detailed episodic information would be expected to be poorer for less recent serial positions (e.g., positions 1–3), and therefore may contribute less to the asymptotes for these items. Hence, in these cases, the asymptotes might partly reflect the influences of PI on familiarity.

Localizing the effects of PI

Our analyses of negative trials indicated that recent negatives (RNs) drawn from List 1, where the effects of PI are minimal, induced a high rate of false alarms early in retrieval, relative to the rates observed for distant negatives (DNs). These early false alarm rates are most readily interpreted as arising from the fact that RNs have high residual familiarity (strength or related constructs) as a consequence of recent study. The analysis showed that the false alarm rate diminished later in retrieval. The late-occurring reduction in the tendency to false alarm to RNs appears to reflect the recovery of more list-specific information, either that the test probe was from an earlier list or that the current study list did not contain the test probe. This type of pattern has been found in several studies (e.g., Curran, 2000; Dosher et al., 1989; Hintzman & Curran, 1994; McElree, 1998; McElree et al., 1999; McElree & Dosher, 1989). The model fits reported here, as well as in other studies (e.g., McElree, 1998; McElree et al., 1999; McElree & Dosher, 1989), demonstrate that these types of non-monotonic functions can be adequately modeled with the assumption that a general assessment of familiarity is available before more list-specific information is recovered.

Crucially, we found that RNs drawn from List 2 did not engender non-monotonic functions. This suggests that PI eliminated the high intrusion rate early in retrieval. Equally importantly, the false alarm rates for RNs in Lists 2 and 3 were nearly identical at the longest retrieval time. This suggests that PI simply attenuated familiarity, and thereby reduced the tendency to false alarm early in retrieval. There was no evidence in our data to indicate that PI affected the recovery of detailed episodic information. Had this been the case, participants would have been less likely to recover the source information necessary to reject a RN as having been in the current study list. And, as higher d'_{FA} values reflect a higher tendency to false alarm, we should have observed functions in which the d'_{FA} asymptote for RNs from List 3 were higher than d'_{FA} asymptote for RNs from List 2.

We believe that the most consistent interpretation of the false alarm data is that PI selectively affected a global assessment of familiarity. Interestingly, if this interpretation of the negative data is correct, it suggests a principled explanation for how PI might slow the retrieval of a positive test probe (viz., slow the dynamics of the standard d' functions in Figs. 3 and 4). Assuming that recognition memory performance is typically based on two types of information—a familiarity assessment, which is available early in retrieval, and the recovery of more detailed episodic information, which becomes available later in retrieval—the slowing of retrieval as PI builds follows directly from the assumption that PI eliminates a proportion of the fast assessments of familiarity early in retrieval. Eliminating fast assessments that would otherwise lead to a correct positive response at early times will depress the overall rate of rise of the SAT function relative to conditions like List 1 where those assessments positively contribute to performance at early retrieval times.

Other properties of the time-course data are also consistent with this interpretation. Notably, selectively eliminating responses based on familiarity can accommodate the finding that asymptotic performance was lower in Lists 2 and 3 than in List 1. A dual-process account assumes that recognition performance reflects a mixture of the two types of information, and Eq. (2) explicitly assumes that familiarity continues to contribute to performance throughout the full time-course of retrieval.[4] Hence, if PI decreases familiarity it can be expected to decrease asymptotic performance, particularly when participants are less able to recover source information later in retrieval, as in test probes drawn from less recent serial positions.

Of course, full acceptance of our interpretation that PI selectively affects fast assessments of familiarity should be contingent on further studies employing convergent measures. However, this interpretation is generally consistent with Crowder's (1976) contention that retrieval discriminability provides the most viable explanation of the detrimental effects of PI on memory. This hypothesis asserts that PI lowers the probability of retrieval by decreasing the discriminability of items in memory. In the classical release-from-PI paradigm (and in our study), this is established by presenting words from the same semantic category, resulting in the semantic category being an

[4] There are two ways in which this is true. First, performance is a weighted mixture of λ_1 and λ_2 after the output from recollection first becomes available, *viz.*, times after δ_2, with the mixture being determined by t. Secondly, δ_2, the late asymptote, is not a pure estimate of recollection, but rather it reflects the *contribution* of recollection to performance at later phases of retrieval. No assumptions are made about how the different types of information combine to form λ_2. The model is compatible with the independence assumption made in the process-dissociation framework, but it is also compatible with other means of combining information (McElree et al., 1999).

insufficient cue for retrieval. Our claim is that PI reduces performance by reducing the distinctiveness of items when the judgment depends primarily on familiarity. When items from the same category are presented for three consecutive trials, all items from the category may have quite similar familiarity values when presented as recognition probes. This may make it difficult to discriminate studied from unstudied items based on item familiarity alone. Hence, we are in general agreement with accounts that emphasize the importance of (temporal or positional) distinctiveness (e.g., Nairne, Neath, Serra, & Byun, 1997; Neath, 1993; Neath & Knoedler, 1994). However, our interpretation of the false alarm findings goes beyond Crowder's original hypothesis in assuming that the loss of discriminability in recognition is particularly detrimental to general familiarity assessments. The non-monotonic functions for RNs suggest to us that it is possible to partially compensate for the loss of discriminability by recovering distinctive information associated with the test probe if the recollective operations are engaged by retrieval cues other than the semantic category.

Finally, although we found no evidence that PI affects processes that recover detailed episodic information late in retrieval, it is possible that other manipulations or procedures could produce results that indicate otherwise. This may be the case if the PI manipulation somehow decreases the discriminability of this type of information, perhaps, for example, by decreasing the distinctiveness of source information. As familiarity and source information are often correlated, this type of manipulation might engender the same type of retrieval speed differences observed here, but rather different false alarm functions, ones that show influences of PI at later retrieval times.

Single- versus dual-process accounts

Do our findings necessitate a dual-process account of recognition? We have reported two major findings: First, that PI slows overall retrieval speed, and second that it appears to lessen the reliance on familiarity information early in retrieval, which otherwise would engender non-monotonic false alarm functions for recent negatives. As noted in the Introduction, single-process accounts might be able to model the observed slowing of retrieval by adopting specific assumptions about how PI might impact on the comparison process. For example, a diffusion model (Ratcliff, 1978) could explain this pattern by assuming that PI decreases the variance of the resonance values. However, it is unclear whether a single process model can provide a plausible explanation of the non-monotonic functions in Fig. 6 and in related time-course studies (e.g., Dosher et al., 1989; Hintzman, Caulton, & Levitin, 1998; Hintzman & Curran, 1994; McElree & Dosher, 1993; McElree, 1998; McElree et al., 1999). Single-process models may find it particularly difficult to accommodate non-monotonic functions that show crossover relations, where parametric manipulations of a variable (e.g., repetition in McElree et al., 1999) systematically engender *higher* false alarm rates early in retrieval but *lower* false alarm rates later in retrieval. These types of non-monotonic functions follow naturally from dual-process models of recognition. Nonetheless, McElree et al. (1999) noted that single-process models might be able to accommodate these findings by assuming that a single retrieval process recovers both familiarity information and more detail episodic (e.g., source) information at different phases of retrieval, possibly by using different sets of retrieval cues coupled to different decision rules. McElree et al. (1999) illustrate how one might be able to instantiate such an account in a global memory model such as SAM (Gillund & Shiffrin, 1984).

Consequently, it remains to be determined whether single-process accounts can adequately model extant timecourse patterns or whether these data require a dual-process account. Importantly, however, our time-course data suggest that PI may slow retrieval speed and reduce asymptotic performance by selectively eliminating fast assessments of familiarity whether or not familiarity information is retrieved with the same retrieval process as later-accruing source information.

Generality of the results

Our study documents the detrimental effects of PI on the recognition of items that are temporally extended over a relatively short-term period. We believe the results are relevant to any situation in which successful performance depends upon accessing the products of recent processing. However, most research on PI has used recall tasks with delayed tests, and it is not entirely clear how the effects documented here generalize to these tasks. The primary difficulty is that recall, which is often modeled as a series of operations to resample memory, with cues being dynamically modified by the output of previous operations, may involve operations quite distinct from recognition (e.g., Murdock, 1982, 1993; Raaijmakers & Shiffrin, 1981). Hence, it remains to be determined whether both the findings documented here will extend to situations where recall is required. Nonetheless, it appears as if both findings bear some similarity to results in recall tasks.

There is evidence that PI slows recall, although it is not entirely clear how it does so. Wixted and Rohrer (1993) report that PI slows overall recall latency by increasing the rightward tail (positive skew) of the latency distributions. They suggest that this might indicate that the retrieval process used to recover items from the list slows as PI builds up. This claim is based on the assumption that the rightward tails of the distributions (specifically, the exponential process in an ex-Gaussian fit of the latency distributions) reflects changes in retrieval time. To the degree that this assumption is correct, these recall results would correspond well to our SAT results. However, that PI affects the positive skew of a distribution without inducing concomitant shifts of the leading edge (the mean and/or variance of the Gaussian in a ex-Gaussian fit), suggests that PI only impacts on a proportion of trials but not on the bulk of trials within a condition (Ratcliff & Murdock, 1976). An alternative account of this finding is that PI only increases the proportion of resampling operations in difficult to recall items, rather than inducing a general slowing of the retrieval for all items from a list. Our SAT findings are prima facie more consistent with an across-the-board slowing of retrieval processes. This stems from the fact that SAT dynamics differences, either in SAT intercept or rate, tend to be associated with shifts of the entire response time distribution (e.g., McElree, 1998; McElree & Carrasco, 1999; McElree & Dosher, 1993). In contrast, manipulations that induce shifts in the positive skew alone typically engender differences in SAT asymptotes (e.g., McElree & Dosher, 1989). To the degree that this generalization is correct, the slowing of responses in the two tasks could reflect different underlying effects of PI. Clearly, additional research is needed to determine whether PI has comparable dynamics effects on both tasks.

Our more tentative claim that PI only affects familiarity assessments also finds support in the recall literature. As noted, Jacoby et al. (2001) found that process-dissociation estimates indicated that PI did not affect recollection but rather familiarity in a task requiring recall, albeit cued fragment completion rather than free recall. Prior learning exerted its influence on recall when participants failed to recover specific episodic information and incorrectly completed the fragment in a manner consistent with their prior learning. This effect is analogous to our increased tendency to false alarm to familiar lures early in retrieval when, presumably, there was not sufficient time for additional list-specific information to accrue. For recent lures, the build up of PI actually has an advantageous effect, decreasing this tendency to false alarm by diminishing overall familiarity. For positive probes, however, the build up of PI has the detrimental effect of rendering fast assessments of familiarity as less distinctive. We have suggested that this may cause the observed overall slowing of retrieval speed.

Conclusion

Our findings indicate that proactive interference negatively affects recognition performance by slowing retrieval speed and reducing overall accuracy. The analysis of false alarms to lures with high familiarity suggested that PI slows retrieval speed by selectively eliminating familiarity, leaving the recovery of detailed episodic information unaffected. The selective affect of PI on familiarity is consistent with Crowder's (1976) retrieval discriminability account, and it suggests that PI renders familiarity judgments ineffective by reducing the distinctiveness of items from the same category. Our finding that PI did not impact on the recovery of source memory is also consistent with this account: If the recovery of source information is driven by retrieval cues other than an item's semantic category, it may provide distinctive information with the potential to attenuate the negative impact of PI on performance. Finally, our analysis of the serial positions functions showed that PI slows retrieval for all serial positions except the most recent one. In line with previous research, this finding suggests that the last item on the study list remains in the current focus of attention. We suggest that items in focal attention are immune to PI because they do not need to be retrieved from memory.

Appendix A. Analyses on proportion correct data

This appendix reports analyses on the proportion correct data corresponding to the analyses presented in the Result section, to address possible concerns about the use of an equal-variance Gaussian d' measures. Table A1 presents the average latency, hit rate, and proportion correct at each interruption lag for each of the 6 serial positions in each of the 3 lists, as well as the latency and false alarm data for distant and recent negative lures for each interruption lag.

Asymptotic accuracy

We averaged the proportion correct for the last two interruption lags to obtain an empirical measure of asymptotic recognition accuracy, which is shown in Fig. A1. A 3 (list) by 6 (serial position) repeated measures ANOVA indicated a significant main effect of list, $F(2,14) = 6.405$, $p < .01$, revealing the overall effect of PI on asymptotic proportion correct across the lists. Effect of serial position was also significant, $F(5,35) = 21.258$, $p < .01$, indicating that asymptotic accuracy increased as the test probe was drawn from more recent positions of the memory lists. The interaction of list and serial position was also significant, $F(5,35) = 2.244$, $p < .05$. As Fig. A1 illustrates, this interaction resulted from PI's selective impact on the earlier test probes (probes 1–3) compared to more recent positions (probes 4–6).

Retrieval dynamics within the three lists

The fitting routine described in *Retrieval dynamics within the lists* subsection of the Results section was carried out to investigate dynamics differences on proportion correct data across serial positions in each of the three lists. Consistent with our reported results, a 6λ-2β-1δ model provided the best fit of the empirical data for each of the three lists. This model allocated a separate asymptote (λ) to each serial position, one rate (β) for serial positions 1 through 5, another rate (β) for serial position 6 (the most recently studied item), and a common intercept

Table A1
Hits and false alarm rates

Item	Interruption lag						
	1	2	3	4	5	6	7
List 1							
Positive trials							
Average (across SP)							
Latency	0.315	0.432	0.520	0.698	0.990	1.687	3.188
Hit rate	0.249	0.488	0.650	0.781	0.789	0.811	0.845
Serial position 1							
Latency	0.315	0.432	0.520	0.698	0.990	1.687	3.188
Hit rate	0.293	0.431	0.535	0.667	0.683	0.712	0.724
Serial position 2							
Latency	0.310	0.436	0.520	0.699	0.992	1.686	3.188
Hit rate	0.307	0.407	0.516	0.651	0.686	0.706	0.728
Serial position 3							
Latency	0.319	0.435	0.516	0.700	0.993	1.689	3.187
Hit rate	0.322	0.435	0.545	0.740	0.717	0.745	0.744
Serial position 4							
Latency	0.318	0.431	0.517	0.697	0.992	1.690	3.184
Hit rate	0.373	0.521	0.686	0.780	0.818	0.821	0.830
Serial position 5							
Latency	0.310	0.424	0.510	0.689	0.987	1.687	3.184
Hit rate	0.404	0.527	0.797	0.888	0.894	0.909	0.927
Serial position 6							
Latency	0.307	0.408	0.493	0.681	0.980	1.687	3.183
Hit rate	0.541	0.837	0.941	0.975	0.974	0.986	0.986
Negative trials							
Distant negative							
Latency	0.318	0.434	0.510	0.693	0.994	1.692	3.189
False alarm rate	0.282	0.159	0.098	0.066	0.040	0.049	0.051
List 2							
Positive trials							
Average (across SP)							
Latency	0.291	0.410	0.497	0.680	0.977	1.680	3.179
Hit rate	0.351	0.352	0.469	0.635	0.648	0.657	0.680
Serial position 1							
Latency	0.309	0.434	0.521	0.696	0.992	1.688	3.189
Hit rate	0.543	0.591	0.688	0.787	0.795	0.804	0.820
Serial position 2							
Latency	0.319	0.438	0.520	0.703	0.988	1.690	3.187
Hit rate	0.326	0.383	0.449	0.554	0.634	0.669	0.647
Serial position 3							
Latency	0.318	0.438	0.517	0.700	0.994	1.689	3.189
Hit rate	0.306	0.385	0.497	0.675	0.689	0.734	0.738
Serial position 4							
Latency	0.314	0.435	0.522	0.693	0.988	1.687	3.186
Hit rate	0.340	0.482	0.587	0.796	0.791	0.847	0.755
Serial position 5							
Latency	0.307	0.434	0.512	0.691	0.985	1.690	3.183
Hit rate	0.333	0.574	0.807	0.857	0.894	0.902	0.908
Serial position 6							
Latency	0.306	0.407	0.490	0.677	0.983	1.685	3.183
Hit rate	0.553	0.811	0.941	0.971	0.977	0.976	0.983
Negative trials							
Distant negative							
Latency	0.315	0.434	0.509	0.690	0.995	1.691	3.189
False alarm rate	0.266	0.177	0.101	0.066	0.058	0.053	0.037

(*continued on next page*)

Table A1 (*continued*)

Item	Interruption lag						
	1	2	3	4	5	6	7
Recent negative							
Latency	0.315	0.436	0.517	0.700	0.995	1.691	3.191
False alarm rate	0.271	0.226	0.200	0.183	0.146	0.133	0.127
List 3							
Positive trials							
Average (across SP)							
Latency	0.311	0.430	0.519	0.696	0.989	1.688	3.187
Hit rate	0.293	0.477	0.615	0.746	0.778	0.771	0.778
Serial position 1							
Latency	0.315	0.437	0.514	0.694	0.991	1.688	3.188
Hit rate	0.327	0.432	0.477	0.597	0.605	0.586	0.654
Serial position 2							
Latency	0.319	0.435	0.522	0.701	0.993	1.689	3.187
Hit rate	0.322	0.367	0.490	0.595	0.614	0.609	0.623
Serial position 3							
Latency	0.317	0.435	0.525	0.699	0.991	1.690	3.188
Hit rate	0.336	0.423	0.547	0.644	0.720	0.715	0.685
Serial position 4							
Latency	0.317	0.433	0.524	0.694	0.990	1.684	3.187
Hit rate	0.351	0.487	0.623	0.789	0.844	0.829	0.830
Serial position 5							
Latency	0.317	0.428	0.518	0.688	0.986	1.687	3.184
Hit rate	0.378	0.550	0.789	0.881	0.899	0.879	0.925
Serial position 6							
Latency	0.308	0.413	0.492	0.678	0.986	1.682	3.183
Hit rate	0.553	0.859	0.935	0.974	0.974	0.974	0.983
Negative trials							
Distant negative							
Latency	0.317	0.433	0.510	0.695	0.995	1.691	3.190
False alarm rate	0.261	0.170	0.111	0.086	0.064	0.051	0.046
Recent negative							
Latency	0.317	0.435	0.518	0.701	0.996	1.692	3.190
False alarm rate	0.278	0.215	0.194	0.160	0.120	0.122	0.122

Note: SP, serial position.

(δ) for all the six serial positions for all lists. Initially, allocating unique asymptotes to each serial position with a 6λ-1β-1δ model increased adjusted-R^2 value from a 1λ-1β-1δ model from .76 to .93 for List 1, from .70 to .91 for List 2, and from .67 to .93 for List 3. Furthermore, allocating two rates with a 6λ-2β-1δ model increased adjusted-R^2 value from a 6λ-1β-1δ model from .93 to .97 for List 1, from .91 to .96 for List 2, and from .93 to .98 for List 3. The fit of the 6λ-2β-1δ model to the average data is presented in Fig. A2.

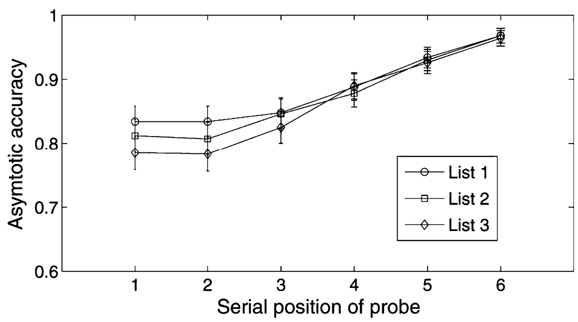

Fig. A1. Average asymptotic proportion correct data for the three lists as a function of serial position of the test probe. (Error bars show the 95% confidence intervals.)

Retrieval dynamics of PI across the lists

To investigate the overall effects of PI on performance in each of the 3 lists, proportion correct data for each list was computed by averaging over serial position. We performed the same fitting routine outlined in the *General effects of PI on retrieval dynamics* subsection of the Results section. We replicated the findings reported in that section. Competitive model fits found a 2λ-2β-1δ model to be the best fit to the data. This model allocated one asymptote (λ) and one rate (β) to List 1, and another asymptote and rate to Lists 2 and 3, with all three lists sharing a common intercept (δ). The asymptotes for Lists 2 and 3 (0.87 on the average data) were significantly

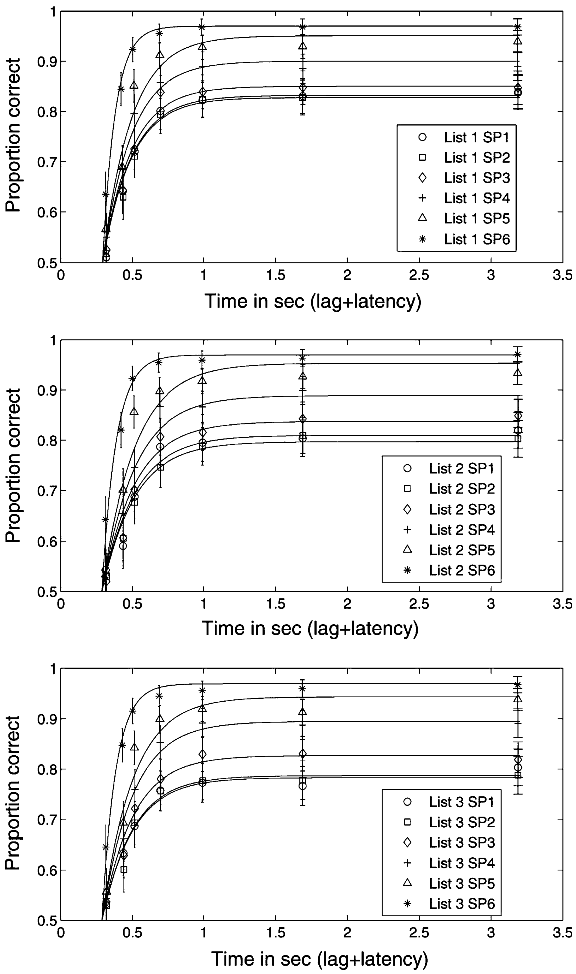

Fig. A2. Average proportion correct (symbols) as a function of total processing time (time of the response cue plus latency) for each serial position for the three lists. Smooth curves indicate the best fits (6λ-2β-1δ) model. (Error bars show the 95% confidence intervals.)

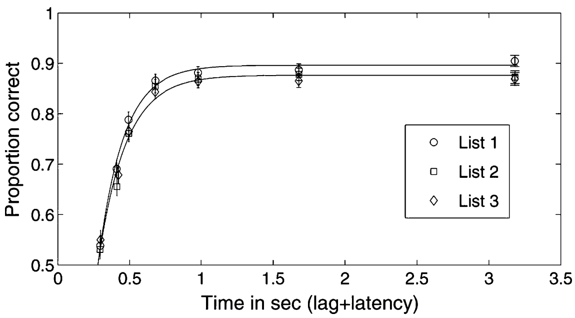

Fig. A3. Average proportion correct (symbols) averaged over serial position for the three lists as a function of processing time. Smooth curves indicate the best fit (2λ-2β-1δ) model. Error bars show the 95% confidence intervals.

lower than the asymptotes for List 1 (0.89 on the average data), $t(7) = 3.491$, $p < .05$. The rate decline from List 1 (160 ms on the average data) to Lists 2 and 3 (173 ms on the average data) was marginally significant, $t(7) = -2.204$, $p < .063$. Fig. A3 presents the proportion correct functions for the 3 lists, with smooth curves showing fitted exponential functions.

Effects of PI on serial position

To investigate the effects of PI on the different serial positions, we fit an 18λ-6β-1δ model to 18 functions (6 serial positions within 3 lists) for the average data and the individual participant's data. For each list, this model allocated a separate asymptote (λ) to each of the 6 serial positions, and a separate rate (β) parameter to the last serial position in each list and another rate (β) parameter to each of the remaining serial positions. All three lists were fit with a common intercept (δ). The results of this fit replicated our reported findings on the *Effects of PI on serial position* subsection in the Results section. In terms of asymptotic accuracy, the asymptote parameter showed a decline across the lists for serial position 1, $F(2,14) = 6.813$, $p < .01$, for serial position 2, $F(2,14) = 20.034$, $p < .01$, and for serial position 3, $F(2,14) = 5.925$, $p < .05$. The asymptote parameters did not show a reliable decline for the more recent positions, serial positions 4–6, $p > .05$. Analysis on the rate parameters indicated that the rate parameter for serial positions 1–5 showed a significant decline from List1 to List2, $t(7) = 2.733$, $p < .029$, but not from Lists 2 to 3, $p > .05$, consistent with our findings in the Result section indicating that PI's effects were asymptotic at List 2. The pattern for the rate parameter of serial position 6, the most recently studied item, also replicated our reported findings on the d' data. The rate decline for this position was not reliable across Lists 1–2, or Lists 2–3, $p > .05$.

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