A Single-System Account of the Relationship Between Priming, Recognition, and Fluency

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A single-system computational model of priming and recognition was applied to studies that have looked at the relationship between priming, recognition, and fluency in continuous identification paradigms. The model was applied to 3 findings that have been interpreted as evidence for a multiple-systems account: (a) priming can occur for items not recognized; (b) the pattern of identification reaction times (RTs) to hits, misses, correct rejections, and false alarms can change as a function of recognition performance; and (c) fluency effects (shorter RTs to words judged old vs. judged new) and priming effects (shorter RTs to old vs. new words) can be observed in amnesic patients at levels comparable with healthy adults despite impaired or near-chance recognition. The authors' simulations suggest, contrary to previous interpretations, that these results are consistent with a single-system account.

Keywords: fluency, repetition priming, recognition, computational model

The question of whether repetition priming and recognition are mediated by independent or related memory processes has received much attention and has played a key role in the development of theories of the organization of memory. *Repetition priming* is the term used to refer to a change in identification, detection, or production of an item (e.g., a word) as a result of prior exposure to the same or a similar item, whereas *recognition memory* typically refers to the capacity to judge whether an item has been previously presented in a particular context.

An influential view is that priming and recognition are mediated by functionally and neurally distinct memory systems (e.g., Gabrieli, 1998; Schacter & Tulving, 1994; Squire, 1994, 2004). Findings from patients provide compelling evidence in favor of this view: Priming is relatively intact in amnesic patients despite severely impaired, and sometimes chance, recognition performance (Hamann & Squire, 1997). Furthermore, individuals with damage to right occipital brain regions show impaired priming and spared recognition (e.g., patient M. S.; Gabrieli, Fleischman, Keane, Reminger, & Morrell, 1995), constituting a double dissociation. Findings from imaging studies also converge on this notion: In a recent example, Schott et al. (2005; see also Schott et al., 2006) found that priming and recognition were associated with distinct patterns of functional magnetic resonance imaging activation. Functional dissociations in behavioral performance have also been

reported in normal adults (see Roediger & McDermott, 1993, for a review); for example, semantic versus nonsemantic processing of stimuli at study has large benefits on recognition performance but little or no effect on priming (e.g., Jacoby & Dallas, 1981), and changes in perceptual form between study and test can have opposite effects on priming and recognition performance (Wagner, Gabrieli, & Verfaellie, 1997). Dissociations, such as these, have been interpreted as evidence for distinct memorial bases of priming and recognition (e.g., Wagner & Gabrieli, 1998; Wagner et al., 1997).

An alternative view is that priming and recognition are, to some extent, mediated by a common memory representation. For example, the double dissociation shown by amnesic patients and occipital lobe patients has been reproduced by the simple recurrent network (SRN), a connectionist model in which a single memory representation mediates priming and recognition (Kinder & Shanks, 2001, 2003). Other simulation studies have shown that certain types of dissociations are consistent with a single-system perspective (see, e.g., Berry, Henson, & Shanks, 2006; Shanks, Wilkinson, & Channon, 2003; Zaki, Nosofsky, Jessup, & Unverzagt, 2003). Similarly, and contrary to the aforementioned imaging studies, some studies have found evidence in support of the notion that priming and recognition depend on a common representation. For example, Turk-Browne, Yi, and Chun (2006) found commonalities in the neural correlates of the encoding processes leading to priming and recognition memory.

Certain dual process theories of recognition also posit a common memory source in priming and recognition. One view is that the facilitation in processing, or fluency, from priming can give rise to a feeling of familiarity that can serve as a basis for recognition (Jacoby & Dallas, 1981; Mandler, 1980; Yonelinas, Regehr, & Jacoby, 1995; for a review of studies concerned with attributions of fluency, see Kelley & Rhodes, 2002). It has been shown that recognition judgments can be influenced by manipulations designed to enhance fluency or speed of processing, suggesting that fluency can indeed serve as a basis for recognition. For

example, Whittlesea, Jacoby, and Girard (1990) showed that an item presented in a low masking condition at test was more likely to be judged old than an item presented in a high masking condition. Presumably items presented in low levels of masking were easier to read and were processed more fluently than those presented in high masking. Whittlesea et al. argued that this enhanced fluency was misattributed to prior exposure of the word.

Studies that look at the contribution of fluency, or priming, to recognition often use gradual clarification procedures to present each item (e.g., by presenting a stimulus for successively longer durations, Stark & McClelland, 2000; or by slowly unmasking a stimulus, Conroy, Hopkins, & Squire, 2005; see also Johnston, Dark, & Jacoby, 1985; Johnston, Hawley, & Elliot, 1991; Verfaellie & Cermak, 1999). Typically, the participant's task is to identify each item and then to make a recognition judgment to the item. Repetition priming is reflected in faster identification reaction times (RTs) to old than new items. The *fluency effect* is the term usually used to describe the shorter RTs to items *judged* old than items *judged* new, independent of actual old–new status (Conroy et al., 2005; Johnston et al., 1985). Thus, the task permits concurrent assessment of recognition, priming, and fluency, providing a measure of each for every item. Indeed, RTs can be compared across all four possible outcomes—that is, hits (old items judged old), misses (old items judged new), false alarms (new items judged old), and correct rejections (new items judged new).

Three findings from this paradigm have been interpreted as evidence for distinct memorial bases of priming and recognition. Briefly, they are that (a) priming can occur for items not overtly recognized (Stark & McClelland, 2000), (b) RTs to false alarms are faster than RTs to misses when recognition is poor, and vice versa when recognition is relatively good (Johnston et al., 1985), and (c) amnesic patients show relatively intact fluency and priming effects despite impaired recognition performance (Conroy et al., 2005; Verfaellie & Cermak 1999).

In this article, we aim to consider each of these findings in turn and to account for each one using a computational model in which priming and recognition performance depend on a single source of memorial evidence but are subject to independent sources of noise. We present for the first time a formal quantitative model of priming, recognition, and fluency. It is our hope that this model may serve as a useful benchmark for evaluating multiple- versus single-system theories and, via its testable predictions, may present a falsification challenge to researchers. We regard it as important that before a multiple-systems approach is advanced, researchers can show that a single-system model is unable to account for their data patterns or has critical limitations.

A Single-System Model of Priming and Recognition

The model presented here is conceptually very similar to standard signal detection models of recognition judgments and their latencies (Pike, 1973; Ratcliff & Murdock, 1976; Stretch & Wixted, 1998), and it extends previous work with this type of model (Berry, Henson, & Shanks, 2006; Shanks et al., 2003). It should be noted from the outset that the model is one simply of the *influence of memory* on performance in priming and recognition tasks rather than a detailed mechanistic account of the processes involved in these tasks. The model starts with the assumption that, at test, both old and new items are associated with a memory

variable called familiarity *f*. *f* is a normally distributed random variable:

$$f \sim N(\mu, \sigma_f), \quad (1)$$

which, because of prior exposure, is assumed to have a greater mean value for old items (μ_{old}) than for new items (μ_{new}). For a given item, the same value of *f* contributes to both recognition and priming tasks (which is what makes it a single-system model). The judgment made during a recognition task depends on the variable J_r:

$$J_r = f + e_r \quad (2)$$

$$e_r \sim N(0, \sigma_r),$$

where e_r is another normally distributed random variable with a mean of zero and a standard deviation of σ_r that represents task-specific sources of noise in the recognition task.

Similar to signal detection theory of recognition (see, e.g., Macmillan & Creelman, 2005), accuracy is simulated in the recognition task by comparing the value of J_r against a criterion value (*C*). If the value of J_r for a given item exceeds the criterion, then the item will be judged "old," otherwise it will be judged "new." In principle *C* is free to vary; however, for the sake of simplicity, *C* is set here to the midpoint between the means of the old and new familiarity distributions, that is, ($\mu_{new} + \mu_{old}$)/2.

To simulate an identification RT for the clarification task, we assume that RT is a decreasing function of *f* but with the addition of another independent source of noise:

$$RT = b - sf + e_p \quad (3)$$

$$e_p \sim N(0, \sigma_p),$$

where the parameters *b* and *s* are merely scaling parameters that represent the RT intercept and slope (rate of change of RT with *f*), respectively. The noise associated with the priming task, e_p, represents measurement error, or the influence of nonmemorial factors on performance in priming tasks (Ostergaard, 1992). This method of simulating the influence of memory on RTs is similar to previous applications of the model (Shanks & Perruchet, 2002; Shanks et al., 2003; although other linear transformations of *f* can be used to simulate performance in other tasks, e.g., perceptual identification accuracy—see Berry, Henson, & Shanks, 2006). Thus, greater values of *f* lead to a greater likelihood of an old response and shorter RTs. In sum, the central assumption in the model is that a single familiarity signal drives priming and recognition tasks but is scaled differently and is subjected to different sources of noise for each task.

We now turn to the data from Stark and McClelland (2000), which was taken as evidence for multiple bases of recognition and priming. Stark and McClelland used the continuous identification with recognition (CID-R) task (Feustel, Shiffrin, & Salasoo, 1983) to investigate the relationship between priming and recognition. On a study trial of this task, an item is presented for a brief duration (e.g., 17 ms) and is then followed by a mask (####) for the remainder of a presentation block (e.g., 233 ms). The item is then re-presented, at a slightly longer duration (e.g., 34 ms), and is again replaced with the mask for the remainder of the presentation block (e.g., 216 ms). Presentation continues in this way, with the item being presented for longer and longer durations until it is identified (or until the presentation duration of the word equals the

duration of a presentation block). The same procedure is used in a second test phase (in which some items are repeated from the study phase), except that participants make a recognition judgment following each identification.

Of key interest for these simulations is Stark and McClelland's (2000) observation that the identification RTs for misses (old items judged new) were faster than those for correct rejections (new items judged new). In other words, even though certain items were not remembered, a priming effect still occurred for these items. Stark and McClelland argued that this result supports the notion that the sources of recognition memory and priming are independent, because if priming and recognition depend on the same memory source, then priming should not occur when recognition is absent. Furthermore, they found that performance in the two tasks was not significantly correlated, bolstering the case for independence.

Experiment 1

The aim of Experiment 1 was to replicate Stark and McClelland's (2000) finding of priming for items judged new and then apply the model to the data. An experimental replication was conducted rather than simply fitting the model to Stark and McClelland's data because robust demonstrations of priming in the absence of awareness remain elusive, and independent replications of such effects are therefore important.[1] We presented words at study using the CID procedure; participants pressed a button when they could identify the word and then named the word aloud. At test, we presented old and new words to participants using the CID-R procedure.

Method

Participants. Twenty-four individuals were recruited through a University College London participant database. Their ages ranged from 19 to 38 years, with a mean of 23.3 years. All participants reported normal or corrected-to-normal vision, reported English as their first language, were tested individually in sound-dampened cubicles, and were paid £4 (approximately $7) in return for taking part. The experiment was fully automated, and the experimenter was not present in the room during the course of the experiment.

Materials. A total of 120 words were selected with similar constraints to Stark and McClelland (2000): All words had four letters, had a frequency of occurrence of 10–200 per million (Kucera & Francis, 1967), and had a maximum score of 500 on the Imagability and Concreteness scales in the Medical Research Council Psycholinguistic database (Coltheart, 1981). All words were presented in white 20-pt Courier font. Two 50-word lists were constructed. Each word list acted as the old or new stimuli, counterbalanced across participants.

Procedure. At study, a single word was presented on each CID trial. At the start of each trial, a mask (a row of hash marks ####) was presented for 500 ms to orient the participant. Next, a word was presented in lowercase 20-pt Courier font for 17 ms. The mask was then presented in 26-pt Courier font for 233 ms, forming a 250-ms presentation block. The word was then immediately presented again, but this time the exposure duration was increased by 17 ms, and the mask followed for the remainder of the 250-ms presentation block. Presentation continued in this way, with the

total stimulus plus mask time remaining constant in each block, until the mask duration was 0 ms (15 blocks). When a response was made (by clicking the left mouse button), the mask was immediately presented for 2,000 ms. Participants then clicked a button that was presented below the stimulus presentation area to advance to the next trial.

There were 70 study trials in total. The first and last 10 trials were considered primacy and recency filler trials, and none of the words from these trials appeared at test. The RTs from these filler trials were not included in any subsequent analysis. The remaining 50 trials contained the stimuli that would later appear at test. For the study phase, participants were told that a word would flash on the screen for longer and longer durations and that this would make it appear clearer over time. They were told that they must click the left mouse button when they knew the identity of the word and then read it aloud. On each trial, the time from the onset of the stimuli to the onset of the button press was recorded. The importance of speed was emphasized; however, errors were discouraged: Participants were told that they should click the mouse button only when they were confident that they could identify the word correctly. If the word had not been identified by the end of the trial, then a message appeared to the participants asking them to try to be faster on the next trial. RTs longer than 3,750 ms (the time that had elapsed by the end of the last stimulus presentation block) were not recorded. No indication of the upcoming recognition test was given.

After the study phase, the instructions for the test phase were presented. We presented a single word using the CID procedure on each test trial. Participants were again instructed to press the mouse button when they could identify the word and then read the word aloud; they were additionally told that after identifying each word they would have to make a judgment about the word. After each identification, the probe "old or new?" appeared on the screen, and two buttons labeled "old" and "new" were also presented on the screen below this probe. Participants were instructed to click the button labeled "old" if they thought that the word they had just identified was one from the study phase. They were told to click the "new" button if they thought that the word had not been presented in the study phase. There were 100 test trials in total (50 old and 50 new trials). The selection of a word for each trial was randomly determined. Misidentification trials at study or test were excluded from all subsequent analysis. Responses were recorded on a tape recorder and later checked for accuracy.

An alpha level of .05 was used for statistical tests, and *t* tests were two-tailed. We used the Greenhouse–Geisser correction to correct for nonsphericity on tests involving repeated measures factors with more than two levels.

Results

Study phase. The number of errors made was very low ($M <$ 1% errors across participants), and as a result, no further analysis of the errors was conducted. The mean RT to the study words was 1,441 ms ($SEM = 41$ ms).

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[1] Stark and McClelland's (2000) other main results of (a) repetition priming for nonwords and (b) differences in the magnitude of priming for words, nonwords, and pseudowords were not of interest for present purposes because they were not used to argue for independent memorial bases of priming and recognition.
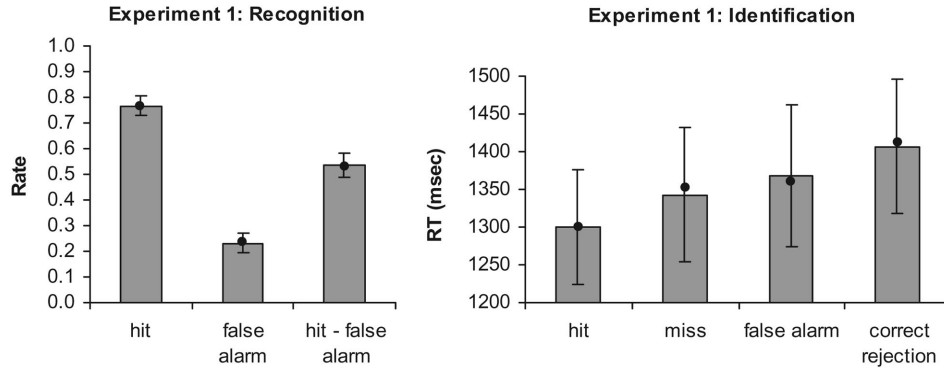
Experiment 1: Recognition

Experiment 1: Identification

Figure 1. Left panel: hit and false alarm rates for the recognition task in Experiment 1. Right panel: Continuous identification with recognition (CID-R) reaction times (in milliseconds). In the CID-R task, a word flashed on the screen for longer and longer durations, each time followed by a mask. Reaction times are the time from the onset of the presentation to the time taken to press a button to indicate that the participant knew what the item was (for correct trials only). After identification, an old–new recognition judgment was made. Gray bars indicate data; error bars indicate 95% confidence intervals of the data. Circles indicate model results. Each simulated data point is based on 50 observations for each old–new stimulus type and for 10,000 participants. Hit = an old word judged old; false alarm = a new word judged old; miss = an old word judged new; correct rejection = a new word judged new.

Test phase. Recognition accuracy, as measured by d', was significantly greater than chance overall, $t(23) = 18.38$, $p < .001$ (mean $d' = 1.53$, $SEM = 0.08$; mean hit rate = 0.77, $SEM = 0.02$; mean false alarm rate = 0.23, $SEM = 0.02$).

For every participant, priming was calculated as the mean RT for new items minus the mean RT for old items. Priming was significantly greater than zero overall, $t(23) = 5.70$, $p < .001$ ($M = 85$ ms, $SEM = 15$), indicating that old items were identified more quickly at test than new items (new items $M = 1,397$ ms, $SEM = 46$; old items $M = 1,312$ ms, $SEM = 40$). Consistent with Stark and McClelland (2000), no significant correlation was found between this priming effect and recognition accuracy (d'), $r(23) = -.25$, $p = .24$. As has been observed in previous studies, a significant fluency effect was also obtained (judged old mean RT = 1,315 ms vs. judged new mean RT = 1,392 ms), $t(23) = 7.77$, $p < .001$, $SEM = 10$.

The RTs to correct rejections, misses, false alarms, and hits are shown in Figure 1. A repeated measures analysis of variance, comparing the RTs for these recognition outcomes, revealed a significant difference between the RTs in these four categories, $F(3, 69) = 11.25$, $p < .001$. Of primary interest for this experiment, RTs to misses were significantly faster than RTs to correct rejections, $t(23) = 3.55$, $p = .002$ (mean priming for items judged new = 63 ms, $SEM = 18$), replicating Stark and McClelland (2000). Furthermore, additional comparisons (t tests, Bonferroni corrected) revealed that the RTs to hits were faster than those to correct rejections, $t(23) = 7.34$, $p < .05$, and false alarms, $t(23) = 2.97$, $p < .05$. No other significant comparisons were found.

In summary, the key result from this experiment was that a priming effect for items judged new was obtained, replicating Stark and McClelland (2000). Repetition priming and recognition were also found to be at levels significantly greater than that expected by chance and not significantly correlated.

Simulation Study 1

For the simulation of Experiment 1, as in a prior application of the model (Berry, Henson, & Shanks, 2006), the model was simplified by setting $\mu_{new} = 0$, and $\mu_{old} = \mu$, with no loss of generality (i.e., μ represents the difference in the means of the old and new distributions). The other parameters of the model (see Equations 1–3) are the standard deviation of the distribution of familiarity values across items, σ_f, the standard deviation of the noise associated with the recognition task, σ_r, the standard deviation of the noise associated with identification, σ_p, the RT intercept, b, and the familiarity slope, s, associated with the generation of the RTs.

There were some a priori constraints imposed on the parameter values to be consistent with previous applications of the model to normal adults (Berry, Henson, & Shanks, 2006), namely that $\sigma_r = \sigma_f = 0.2$.[2,3] Also, the criterion, C, for both recognition and priming judgments was fixed as the midpoint of the old and new distribu-

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[2] Models of recognition memory often allow the variance of the old item "strength" distribution to be larger than that of the new distribution, but here we make a simpler assumption of equal variances. In our model, the standard deviation of recognition strength, σ_{Jr}, depends on σ_f and σ_r. The simulations were repeated with $\sigma_{Jr}(new) = 0.8 \times \sigma_{Jr}(old)$ for all nonamnesic conditions by lowering $\sigma_f(new)$ to 0.10583. It was not possible to lower $\sigma_f(new)$ to the point where $\sigma_{Jr}(new) = 0.8 \times \sigma_{Jr}(old)$ for the hippocampal lesions and medial temporal lobe lesions groups (in Simulation Study 3), because even when $\sigma_f(new) = 0$, $\sigma_{Jr}(new) > 0.8 \times \sigma_{Jr}(old)$, therefore, these simulations were repeated with $\sigma_{Jr}(new) = 0.9 \times \sigma_{Jr}(old)$, and $\sigma_{Jr}(new) = 0.95 \times \sigma_{Jr}(old)$, respectively, by setting $\sigma_f(new) = 0.188266$ (hippocampal lesions group), and $\sigma_f(new) = 0.355422$ (medial temporal lobe lesions group). The critical predictions of the model were not qualitatively affected by these changes.

[3] The value of σ_f can be set arbitrarily (to a nonzero value) and the other parameters rescaled accordingly. In terms of signal detection theory, the standard would have been to set $\sigma_{Jr} = 1$, and hence $\sigma_r = \sigma_f = 1/\sqrt{2}$.

Table 1
Parameters of the Model

		Value								
			Johnston et al. (1985)		Conroy et al. (2005)					
		Exp. 1	Exp. 1	Exp. 2	Exp. 2 CON	Exp. 2 H	Exp. 2 MTL	Exp. 1 CON	Exp. 1 H	Exp. 1 MTL
Symbol	Meaning	Figure 1	Figure 2		Figures 3–4			Figure 5		
σ_f	Standard deviation of familiarity distributions (new/old)	0.20	0.20	0.20	0.20	**0.32**	**0.70**	0.20	0.32	0.70
σ_r	Standard deviation of recognition noise	0.20	0.20	0.20	0.20	**0.50**	**1.80**	0.20	0.50	1.80
σ_p	Standard deviation of priming noise	**290**	290	290	**1,000**	1,000	1,000	1,000	1,000	1,000
μ	Mean familiarity of old items	**0.42**	**0.54**	**0.12**	**0.37**	0.37	0.37	0	0	0
b	RT intercept	**1,400**	**4,150**	**4,950**	**8,770**	**7,650**	**9,500**	8,770	7,650	9,500
s	RT–familiarity slope	**210**	**550**	550	**1,450**	1,450	1,450	1,450	1,450	1,450

Note. Bold font indicates that the parameter was varied to fit the data. Exp. = Experiment; CON = control group; H = hippocampal lesions group; MTL = medial temporal lobe lesions group; RT = reaction time (in milliseconds).

tions of familiarity (i.e., $C = \mu/2$). This left four free parameters: μ, σ_p, s, and b. There were eight degrees of freedom in the data (RT to hits, misses, false alarms, and correct rejections; the hit and false alarm rates for the recognition task; the mean item RT variance; and the Pearson correlation between priming and recognition).[4] The values of the parameters (in this and subsequent simulations) are shown in Table 1. They were chosen by a hand-search process: First μ was varied to fit the recognition data, next the free parameters relating to the priming task (in Equation 3) were varied to fit the RT data.

For each old and new item, a single value of f was randomly sampled on each trial from the relevant distribution. The value of f was then scaled and combined with one source of noise (Equation 3) to derive an RT that formed the basis of the fluency and priming data. The same value of f was then combined with another source of noise (Equation 2) to determine the recognition response. We emphasize that the same memory signal (familiarity) contributed to priming, recognition, and fluency.

We simulated the data using the same number of trials as in Experiment 1 (50 old, 50 new trials) and using 10,000 simulated participants. The large number of participants means that the error bars on the simulation results are negligible. The simulation results for the RTs to hits, misses, false alarms, and correct rejections are shown in the right panel of Figure 1, and for recognition performance in the left panel of Figure 1. The error bars on the experimental data are 95% confidence intervals. It can be seen from Figure 1 that the model results are within these intervals for all cases.[5]

To determine whether the variability in RTs predicted by the model is realistic, we calculated the variance of each participant's RTs to items at test. This variance was fit by the model: Mean item standard deviation of RTs (within-subject) in Experiment 1 = 277 ms, 95% + CI = 302 ms, 95% − CI = 252 ms; mean item standard deviation of RTs (within-subject) predicted by the model = 296 ms. The primary reason for fitting this variance was to ensure that RTs were generated within the appropriate intervals and to constrain the σ_p free parameter.

Lastly, the model predicts a near zero correlation between priming and recognition, $r = .07$, which is also within the 95% confidence interval of the correlation observed in Experiment 1 ($r = -.25$, 95% + CI = .17, 95% − CI = −.68).

Discussion

The single-system model predicted that priming would occur for items judged "new," suggesting that this result is not necessarily indicative of independent memorial bases of priming and recognition. In fact, the prediction of RT(misses) < RT(correct rejections) falls quite naturally out of the model, which assumes a signal-detection-like process in recognition: Because an old item's value of J_r must exceed C for an old judgment to occur (see Equation 2), values of f will tend to be greater for misses than correct rejections. RTs for misses will tend to be faster than correct

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[4] Correlations were simulated in a previous application of the model by drawing a value of μ randomly from a normal distribution for each participant, i:

$$\mu_i \sim N(\mu, \sigma_\mu), \qquad (4)$$

where σ_μ is the standard deviation of the mean familiarity across participants and is a free parameter (Berry, Henson, & Shanks, 2006). σ_μ was not included in this simulation study to improve the ratio of free parameters to degrees of freedom in the data, and, moreover, only one correlation is being simulated here rather than several (as was the case in Berry, Henson, & Shanks, 2006). It should be noted that when the simulation was repeated with μ_i included (and σ_μ was set at 0.028 as in Berry, Henson, & Shanks, 2006), the predicted correlation was very similar to the one obtained in this simulation and was still within the 95% confidence interval ($r = .10$ with μ_i included vs. $r = .07$ without).

[5] Because the parameter values were chosen by hand (for this simulation study and the subsequent ones), it is likely that better fits could have been obtained by using a more formal fitting procedure. However, our main goal in these simulations was to show that the model can produce sufficiently close qualitative and quantitative fits to the data.

rejections simply because RTs are a decreasing function of f (see Equation 3). In fact, the model would even predict this qualitative pattern if no task-specific sources of noise were included (i.e., $e_r = e_p = 0$ in Equations 2 and 3). Without these sources of noise f(hits) > f(false alarms) > f(misses) > f(correct rejections) (as predicted by signal detection theory) and RTs will inversely correspond to f such that RT(correct rejections) > RT(misses) > RT(false alarms) > RT(hits).

Yet in the simulation of Experiment 1, the inclusion of the noise parameters results in the pattern of RTs being RT(correct rejections) > RT(false alarms) > RT(misses) > RT(hits). Consistent with this, there was a numerical trend for RT(false alarm) > RT(miss) in the experimental data, but this difference was not significant. It should be noted though that this pattern has been found in some studies: Johnston et al. (1985; Experiment 1) found that RTs to false alarms were indeed significantly slower than RTs to misses (see ahead to the Simulation 2 section). Stark and McClelland (2000) also observed numerical trends for RT(false alarms) > RT(misses) for word stimuli (but reported no statistical comparisons).

Why does the model predict, correctly, that (in some cases) RT(false alarms) > RT(misses)? Consider a new item that has an "average" f and is combined with a high value of e_r (to generate J_r in Equation 2); this item will still have the same average value of f when its RT is generated (in Equation 3), and it will be unlikely to again be combined with a large value of e_p. Thus, a new item with a J_r value that exceeds C can be classified as a false alarm, but it will not necessarily have a comparably short RT, because it is unlikely that e_r and e_p will both be large for the same item. The reverse scenario occurs for misses: An old item with an average f that is combined with a large negative value of e_r lowering its value of J_r below C will be classified as a miss. When that same value of f is used to predict the item's RT, it will be unlikely to again be combined with a large negative value of e_p, meaning that misses will not necessarily result in comparably long RTs, and the RTs can be shorter than those of false alarms. (This property is related to the phenomenon of regression to the mean.) Thus, the inclusion of noise parameters in the model is important for it to explain this result.

In the next simulation study, we turn to another set of results that have been taken as evidence for distinct bases of priming and recognition. In this case, we will show how the relative sizes of RT(misses) and RT(false alarms) vary with μ, and again, it is the inclusion of the noise parameters that is critical in increasing the model's explanatory power.

Simulation Study 2: Johnston et al. (1985)

In a classic study by Johnston et al. (1985), participants read items at study and identified ones that gradually clarified from a mask at test. In their Experiment 1, the stimuli were words, and recognition and priming were at levels greater than chance. The order of RTs was RT(correct rejections) > RT(false alarms) > RT(misses) > RT(hits). In Experiment 2, the stimuli were nonwords, recognition and repetition priming were at levels lower than those of Experiment 1, and the order of RTs changed to RT(correct rejections) > RT(misses) > RT(false alarms) > RT(hits). Thus, the pattern of RTs in Experiment 2 resembled that predicted by a model of priming and recognition similar to the one presented here but with no noise parameters (as discussed above). The results of

Experiment 2 were interpreted as evidence that recognition relied primarily on a single memory signal when recognition performance was poor. However, because the pattern of RTs in Experiment 1 did not conform to the predictions of such a model, Johnston et al. (1985, 1991) interpreted the RT(false alarm) > RT(miss) pattern as evidence that an additional memory factor contributed to recognition when overall recognition performance was higher. This article has been cited as evidence that priming and recognition are mediated by different memory bases.

As shown in the simulation of our Experiment 1, inclusion of decision noise allows the model to predict the RT(false alarm) > RT(miss) pattern. However, what is not clear is whether the model predicts RT(false alarm) < RT(miss) when recognition is poor. To investigate this, we applied the model to Experiments 1 and 2 of Johnston et al. (1985). The values of σ_r, σ_f, and σ_p were kept from the previous simulation, leaving μ, s, and b as the three free parameters for Experiment 1. The parameter s was held constant across experiments, but it was necessary to change b (as well as μ) between experiments, resulting in two free parameters for Experiment 2. The change in b can be justified by the generally slower RTs in Experiment 2 than Experiment 1. There were six degrees of freedom in the data for each experiment (hit rate; false alarm rate; RTs to hits, misses, false alarms, and correct rejections). The parameter values are shown in Table 1, and the model results for RTs are shown in Figure 2.

It can be seen that all of the model results for the RTs to hits, misses, false alarms, and correct rejections are within the empirical range. For the recognition task, the model results for the hit and false alarm rates in Experiment 1 were .83 and .17, respectively (Johnston et al.'s, 1985, hit rate = .70, 95% CI = .04; false alarm rate = .21, 95% CI = .04). In Experiment 2, the model hit and false alarm rates were .58 and .42, respectively (Johnston et al.'s, 1985, hit rate = .57, 95% CI = .04; false alarm rate = .29, 95% CI = .04). Although the fits for two of the four hit and false alarm rates were outside of the empirical range, the crucial aspect of these results is that the model predicted RT(false alarms) > RT(miss) when recognition was high (in Experiment 1), and RT(false alarm) < RT(miss) when recognition was low (in Experiment 2).

Furthermore, Johnston et al. (1985) also reported that the fluency effect (i.e., shorter RTs for hits and false alarms vs. misses and correct rejections) was attenuated by recognition performance: In Experiment 1, the effect was 310 ms, but in Experiment 2, the effect was lower at 122 ms. The model also predicted this trend: In Experiment 1, the fluency effect was 275 ms, whereas in Experiment 2, the fluency effect was 133 ms.

Why does the model predict a reversal in the RTs to misses and false alarms at different levels of recognition performance? To answer this question, we distinguish between two ways in which a new item can have a value of J_r that exceeds C and be classified as a false alarm. First, an item can have a relatively high value of f that exceeds C even after being combined with e_r (to form J_r in Equation 2). When a false alarm occurs in this way, an item's RT will tend to be comparably short because its value of f will still be relatively high when its RT is generated (by combining it with e_p in Equation 3). Second, an item's value of f may not exceed C initially, but it does exceed C when it is combined with a high value of e_r. As explained in the previous *Discussion* section, when false alarms occur in this way, an item's RT will not necessarily be comparably short because when the same (relatively average or
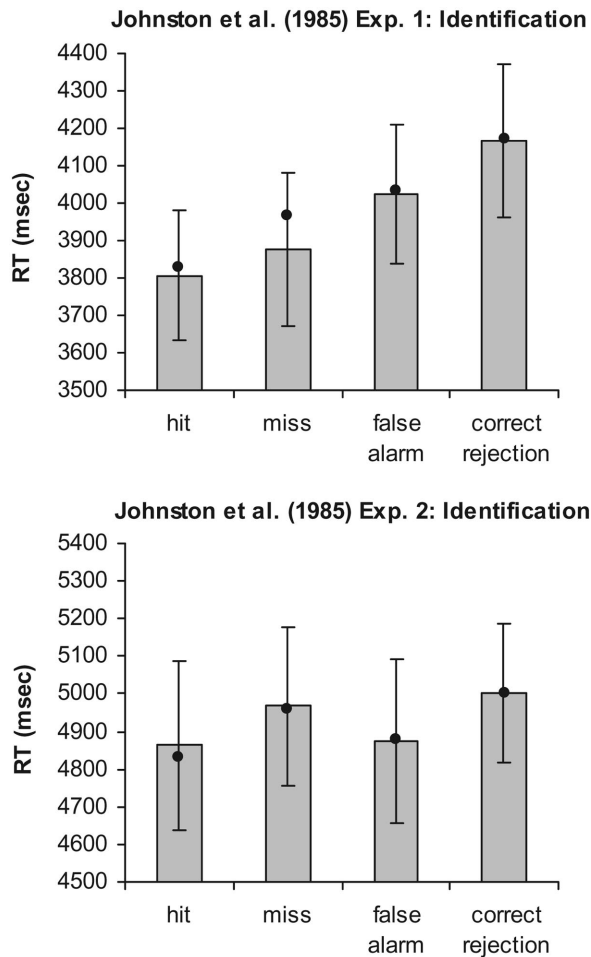
Johnston et al. (1985) Exp. 1: Identification

Johnston et al. (1985) Exp. 2: Identification

Figure 2. Simulated and empirical data of Johnston et al.'s (1985) Experiments 1 and 2. Top panel: identification reaction times (RTs) for Experiment 1. Bottom panel: identification RTs for Experiment 2. Each simulated data point is based on 88 observations for each old–new stimulus type and for 10,000 participants. Error bars indicate 95% confidence intervals (estimated from Johnston et al., 1985). Hit = an old word judged old; miss = an old word judged new; false alarm = a new word judged old; correct rejection = a new word judged new.

low) f is used to generate its RT, it is unlikely to again be combined with another large value of noise (e_p).

When μ is low, the distributions of f for old and new items are closer together, and there will be many more items with values of f that initially exceed C (because the mean of the new item distribution is closer to C). So when μ is low, the first cause of false alarms (above; i.e., high f) will dominate, and false alarms will have comparably short RTs. However, when μ is high, the distributions of f are further apart, and there will be a much lower number of items that have values of f that initially exceed C (because the mean of the new item distribution is further from C). Thus, when μ is high, false alarms will mainly arise through the second cause (above; i.e., high e_r), and the RTs to false alarms will not be comparably short. The reverse process occurs for old items: When μ is low, misses will have comparably long RTs because many more old items will have values of f that are initially below C. When μ is high, misses will not tend to have comparably long

RTs because there will be relatively fewer old items that have values of f that are initially below C. Thus, when μ is low, RTs to false alarms can be shorter than RTs to misses and vice versa when μ is high. As was the case in the previous simulation study, the inclusion of the noise parameters in the model is crucial for its capacity to account for this pattern of results.

In sum, this simulation study showed that the model predicts that the difference between RTs to misses and false alarms changes as a function of recognition strength, as was observed by Johnston et al. (1985). Thus, this finding also does not seem to compel an account in which priming and recognition are mediated by distinct memorial bases.

Simulation Study 3: Conroy et al. (2005)

The simulation studies reported above have been concerned with priming, recognition, and fluency in healthy adults. Next, we turn to some recent and seemingly compelling evidence for distinct memorial bases of priming and recognition in amnesia. Conroy et al. (2005) investigated the contribution of fluency to recognition judgments in two groups of amnesic patients: One had medial temporal lobe lesions (MTL group, $n = 2$); the other had just hippocampal lesions (H group, $n = 3$). In the study phase of Conroy et al.'s Experiment 1, participants were told that words would be presented but too briefly for conscious perception. In fact, no words were presented. At test, words clarified from a mask, and a recognition judgment was made after every identification. A fluency effect was found for the MTL and H groups (i.e., RT[items judged old] < RT[items judged new]), which was comparable in size to a control group (CON group, $n = 8$). In addition, as an alternative method of measuring fluency, Conroy et al. took a median split of the RTs and looked at the percentage of old judgments in each half. More old judgments were made to words identified in the quick half than in the slow half, and this effect did not differ across groups. These results suggest that recognition judgments in amnesic patients and the controls were influenced by fluency of identification.

The study phase of Experiment 2 was genuine: Words were presented, and participants read them aloud. The test phase of Experiment 2 was the same as Experiment 1 except that the stimuli were old or new. Relative to the control group, the H group was impaired at recognition, and performance in the MTL group was very close to chance. Despite this impairment in recognition, amnesic patients showed levels of fluency and priming (faster RTs for old than new words) that were comparable with the CON group.

To the extent that fluency can give rise to a feeling of familiarity and act as a basis of recognition (as suggested by, e.g., Jacoby & Dallas, 1981; Mandler, 1980), Conroy et al. (2005) reasoned that fluency from priming should contribute to recognition in amnesia, yet clearly this was not the case. In a further test of this hypothesis, Conroy et al. derived an estimate of recognition for each group, given the observed magnitude of fluency and priming. They found that the estimate of recognition was much lower than was actually observed, suggesting that fluency from priming did not contribute to recognition (see also Poldrack & Logan, 1997, for a related finding). This, coupled with the dissociation between fluency and priming on the one hand and recognition on the other in amnesia, led Conroy et al. to argue for the independence of the memorial bases of priming and recognition (see also Stark & Squire, 2000).

Is it necessary to interpret the results from Conroy et al. (2005) with a multiple-systems view, or can they be explained by a single-system account? Accordingly we attempted to simulate their findings with the single-system model. Furthermore, one of the MTL patients in Conroy et al.'s study, E. P., showed priming in the absence of recognition (e.g., Conroy et al., 2005; Hamann & Squire, 1997), presenting an additional challenge for the model.

How can the effects of amnesia be simulated with the model? We simulated the performance of amnesic patients in Conroy et al.'s (2005) Experiments 1 and 2 by assuming that, relative to controls, there is a larger amount of noise in the encoded memory signal and also in the assessment of that signal. More specifically, the values of σ_f and σ_r were greater for our simulations of the amnesic groups than the control group; the values of these parameters were also associated with the severity of the amnesia such that they were greater in the more severe MTL group than the H group. In more psychological terms, the greater value of σ_f in amnesic patients represents greater variability in the degree to which an item resonates with an underlying memory representation at test. The psychological meaning of σ_r can be described as follows: The addition of e_r to f in Equation 2 is, in fact, formally equivalent to adding e_r to the decision criterion C.[6] Signal detection modelers have added variability to the decision criterion as far back as Wickelgren (1968) and more recently to simulate the receiver-operating characteristic slope of remember–know judgments (Wixted & Stretch, 2004). In this sense, a greater value of σ_r in amnesia represents a greater amount of variability in the placement of the decision criterion from item-to-item, relative to controls.[7]

Others have also modeled amnesic performance by introducing greater amounts of noise into their simulations: For example, using the retrieving-effectively-from-memory modeling framework, Malmberg, Zeelenberg, and Shiffrin (2004) simulated the effects of Midazolam-induced amnesia on recognition by assuming that the storage of memory traces is noisier in a Midazolam group than a control group. By varying the parameter c (the probability that an item gets stored accurately) between groups, they were able to reproduce patterns of results that had previously been taken as evidence for a dual-process account of recognition memory.

The following simulations were carried out in a similar manner to Simulation Studies 1 and 2 except that for Experiment 2, f depended on whether an item was old or new, whereas in Experiment 1, all item values came from a single (new item) distribution. The CON group data from Experiment 2 were chosen as a point of departure for these simulations because these results bear the most resemblance to the previous simulation studies (i.e., normal adult participants who performed at levels greater than chance in priming and recognition). There were four free parameters for the simulation of the CON group data: σ_p, s, μ, and b. The values of the parameters are shown in Table 1. Changes in σ_p and s from the previous simulations were necessary to characterize the ensuing effects of Conroy et al.'s (2005) different clarification task on RTs; that is, there is bound to be greater variability in RTs as a result of the longer clarification duration used (11 s; requiring an increase in σ_p), and priming/fluency effects in general were larger than in the previous simulated studies (requiring an increase in s). Changes in the b parameter across groups can be justified simply by the different baseline levels of responding in each of the groups (e.g., the H group produced the fastest RTs overall, and therefore b is lowest here). The parameter values of σ_p, s, and μ were then set for

the simulation of the MTL and H groups of this experiment. To then simulate the increased noise associated with the encoding and assessment of the memory signal in amnesia relative to the CON group, we varied σ_f and σ_r according to the severity of amnesia (greater for the MTL group). There were eight degrees of freedom in the data for each condition (RTs to judged old and new items, RTs to actual old and new items, percent correct in recognition, d' for recognition, and the percentage of items judged old in the fast and slow identification medians).

We simulated the data using the same number of trials as in the experiments (40 trials per old–new stimulus type in Experiments 1 and 2) and using 10,000 simulated participants. The simulation results for priming, fluency, and recognition for Experiment 2 are shown in Figure 3. The error bars for the CON data are 95% confidence intervals (estimated from Conroy et al., 2005), and those for the MTL and H data are the range of data from the patients in those groups (estimated from Conroy et al., 2005; the range was used because of the limited amount of participant data in the MTL and H groups). It can be seen from Figure 3 that the model results lie within these intervals for all data points in Experiment 2 and that the model gives very close fits to the (mean) RTs for actual old–new and judged old–new items as shown in Figure 4 (where error bars are unknown).

Conroy et al. (2005) also analyzed their recognition data with d'. These results and those of the simulations are presented in Table 2. It can be seen that there is a very close correspondence between the data and simulation results.

In Experiment 2, Conroy et al. (2005) also looked at whether a fluency effect was present within the subset of items that were new (i.e., whether RT[false alarm] < RT[correct rejection]). The CON group did not show this fluency effect for new items (false alarms: 8,839 ms; correct rejections: 8,831 ms), but the MTL group did (false alarms: 9,180 ms; correct rejections: 9,706 ms). Conroy et al. took this finding to mean that recognition was primarily based on declarative memory in healthy adults (i.e., that responding was not based on fluency), but that declarative memory did not affect fluency-based responding in the MTL group (because the declarative memory necessary for recognition was lacking). (Conroy et al., 2005, did not report these results for the H group.) Consistent with Conroy et al.'s (2005) data, the model also predicted that there would be a large fluency effect for new items in the MTL group (false alarms: 9,182 ms; correct rejections: 9,767 ms), but contrary to Conroy et al., the model predicted that there would be a fluency effect—albeit a smaller one—for new items in the CON group (false alarms: 8,505 ms; correct rejections: 8,861 ms). We return to this difference between the prediction of the model and the result of Conroy et al. in the *Discussion* section.

As found by Conroy et al. (2005), the model predicted that a greater percentage of items identified quickly (items with RTs less than the median) would be judged old than items identified slowly (items with RTs greater than the median). These results are pre-

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[6] We are grateful to John Dunn for pointing this out.

[7] We could have equally assumed that σ_p is greater in amnesic patients relative to controls. However, increasing σ_p would have resulted in little quantitative change in the simulation results, and the qualitative pattern of results would not have been crucially altered. Therefore, σ_p is kept constant across simulations of the amnesic and control groups.
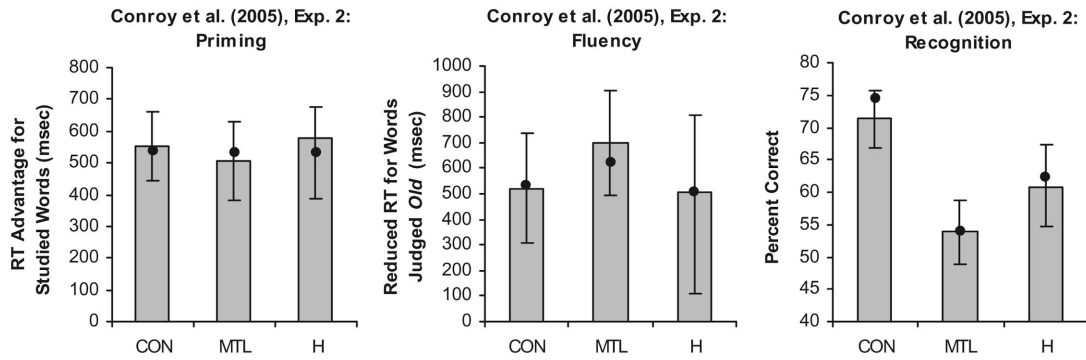
Figure 3. Priming, fluency, and recognition in Conroy et al.'s (2005) Experiment 2. Left panel: Priming effect (identification time for new words minus identification time for old words). Center panel: Fluency effect (identification time for words judged new minus the identification time for words judged old). Right panel: Percentage of correct responses (hits plus correct rejections) in the recognition task. Error bars show 95% confidence intervals of the means for controls (CON) and ranges of scores (estimated from Conroy et al., 2005) for patients with medial temporal lobe lesions (MTL) or damage limited to the hippocampal regions (H). Circles indicate model results. Each simulated data point is based on 40 observations for each old–new stimulus type and for 10,000 participants. *Note.* From "On the Contribution of Perceptual Fluency and Priming to Recognition Memory," by M. A. Conroy, R. O Hopkins, and L. R. Squire, *Cognitive, Affective, & Behavioral Neuroscience,* Volume 5, pp. 14–20. Copyright (2005) by the Psychonomic Society. Adapted with permission.

sented in Table 3, and again it can be seen that the simulation results are comparable with those of Conroy et al.

To estimate the role of fluency in recognition judgments, Conroy et al. (2005) asked what recognition performance would have been had all of the items from the quick median half been judged old and all of those in the slow median half been judged new. These results are presented in Table 4. The low estimates of percentage correct and d' were taken as evidence that even if judgments were entirely based on RTs, the RTs could not have been a strong cue for recognition accuracy. A striking finding is that when we performed the same analysis on our simulated data, the estimates of recognition were also comparably low (see Table 4).

Conroy et al. (2005) then conducted an analysis that was intended to give an estimate of the contribution of fluency from priming to recognition. This involved calculating an estimate of percentage correct based on the magnitude of the priming and fluency effects for old and new words (for details, see Conroy et al., 2005, p. 19). The recognition percentage correct estimates for each group are presented in Table 5. These low estimates were taken to indicate that priming and fluency do not significantly contribute to recognition and that recognition must therefore be based on some other memorial source. Again, we performed the same analysis on the simulated data, the results of which are also presented in Table 5. The percentage correct estimates were also very low. Thus, the low levels of recognition accuracy estimated
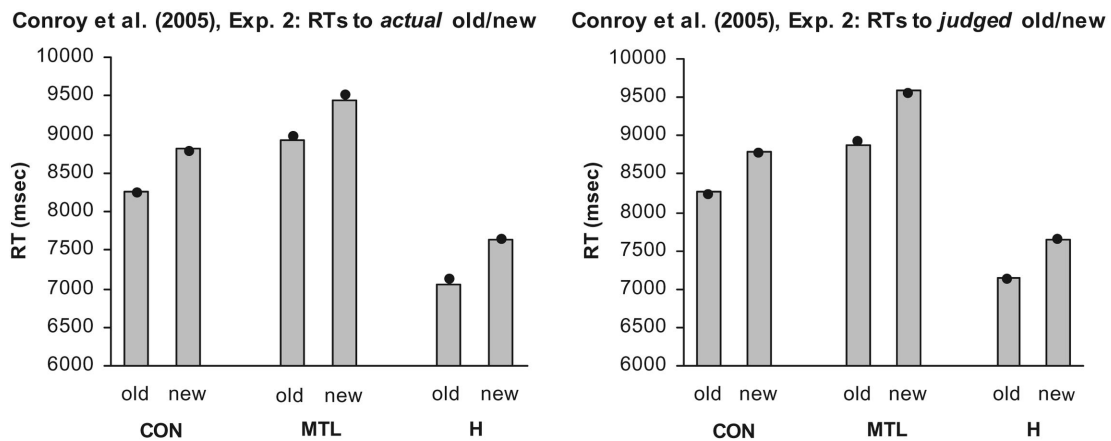

Figure 4. Reaction times (RTs) to actual old–new words (left panel) and judged old–new (right panel) words in Conroy et al.'s (2005) Experiment 2. Gray bars indicate Conroy et al.'s data, and circles indicate model results. Each simulated data point is based on 40 observations for each old–new stimulus type and 10,000 simulated participants. CON = control group; MTL = medial temporal lobe lesions group; H = hippocampal lesions group.

Table 2
Recognition Performance (d′) in Conroy et al.'s (2005) Experiment 2

| Group | Recognition accuracy (d′) | |
	Conroy et al.'s (2005) Experiment 2	Simulation Experiment 2
CON	1.31	1.31
H	0.59	0.62
MTL	0.19	0.19

Note. CON = control group; H = hippocampal lesions group; MTL = medial temporal lobe lesions group.

from the fluency effects calculated by Conroy et al. are not inconsistent with a model in which a single memory strength variable mediates priming and recognition. Because this variable is subjected to independent sources of noise for each task, it can appear as if there is a lack of relationship between priming and recognition, even though they are driven by the same memory strength signal.

Although our primary concern was to simulate the results of Experiment 2, further support for the robustness of the model was sought by applying it to Experiment 1. For all groups, the same parameter values were retained from simulation of Experiment 2, except for μ, which was decreased from 0.37 to 0 (because there was no study phase and therefore no influence of memory at test in Experiment 1). The model results for the fluency effects in each group, and also for the RT values from which they were derived, are presented with Conroy et al.'s (2005) data in Figure 5. With the exception of the fluency effect for the MTL group, all the model results lie within the range of results observed by Conroy et al.

In Experiment 1, Conroy et al. (2005) also found that more old judgments were made to words identified in the quick half than in the slow half, and this effect did not differ significantly across groups. These results are presented with the simulation results in Table 6. This shows that the model predicts fluency effects for all groups even when all items at test are new.

Discussion

The model presented here reproduces the dissociations between priming, recognition, and fluency in amnesia reported by Conroy et al. (2005). By assuming that there is a larger degree of noise in

the encoding and assessment of the memory signal in amnesic patients than controls, the model predicted fluency and priming effects for the amnesic groups that were comparable with controls, despite impaired recognition in the H group relative to the CON group, and near chance recognition in the MTL group. Furthermore, as calculated by Conroy et al., the model also predicted that, even if judgments were based solely on speed of identification, recognition would be low. The same parameter values were then applied to Conroy et al.'s Experiment 1, in which there was no influence of memory, and the model still predicted fluency effects in all three groups of participants.

Conroy et al. (2005) found that the RTs for false alarms were shorter than correct rejections for the MTL group in both experiments, indicating a relationship between fluency and recognition judgments; however, this was only the case for the CON group in Experiment 1, suggesting that the presence of declarative memory interferes with fluency-based responding (in Experiment 2). The model predicted an effect for the CON group in both experiments (likewise for the MTL group). The evidence regarding this discrepancy in the CON data from other studies that have used comparable study/test conditions to Conroy et al. is mixed: Verfaellie and Cermak (1999) also found no difference in RTs for false alarms and correct rejections, whereas other studies have reported a numerical trend for false alarms to be faster than correct rejections (see, e.g., Johnston et al., 1985, 1991; Stark & McClelland, 2000). Indeed, in Experiment 1 of this article, there was a numerical trend for RTs to false alarms to be shorter than those of correct rejections (1,368 ms vs. 1,406 ms) when recognition memory was good.

In any case, the difference between the RTs to correct rejections and false alarms in Conroy et al.'s (2005) study was smaller in the CON group than the MTL group (−8 ms vs. 526 ms). In line with this trend, the model also predicts that this difference is smaller in the CON group than the MTL group (356 ms vs. 585 ms).

The model predicted very slightly lower priming effects in the MTL and H groups than the CON group. This is necessarily the case because priming and recognition depend on the same memory source in the model, and variables will therefore tend to have similar effects on performance in each task. This prediction therefore conflicts with the notion that priming is intact in amnesia (e.g., Hamann & Squire, 1997), an issue that has proven controversial (see, e.g., Ostergaard, 1999). It is relevant to note, however, that Verfaellie and Cermak (1999, Experiment 2), whose study has

Table 3
Percentage of Items Judged Old That Were Identified "Quickly" (Reaction Time < Median) and "Slowly" (Reaction Time > Median) in Conroy et al.'s (2005) Experiment 2

| Group | Percentage of items judged old | | | |
| | Identified quickly | | Identified slowly | |
	Conroy et al.'s (2005) Experiment 2	Simulation	Conroy et al.'s (2005) Experiment 2	Simulation
CON	57.8	59.9	38.7	40.0
H	62.5	58.9	49.0	40.9
MTL	66.3	58.6	46.2	41.5

Note. CON = control group; H = hippocampal lesions group; MTL = medial temporal lobe lesions group.

Table 4
Estimates of Recognition Performance If All Items Identified Quickly Were Judged Old and If Items Identified Slowly Were Judged New in Conroy et al.'s (2005) Experiment 2

	Percentage correct		d'	
Group	Conroy et al.'s (2005) Experiment 2	Simulation	Conroy et al.'s (2005) Experiment 2	Simulation
CON	61.6	60.0	0.59	0.51
H	55.8	59.3	0.29	0.47
MTL	61.3	57.2	0.57	0.37

Note. CON = control group; H = hippocampal lesions group; MTL = medial temporal lobe lesions group.

much in common with Conroy et al. (2005), did find that priming was impaired in amnesic patients relative to controls.

Despite the fact that priming and recognition are mediated by a common memory source in the model, it predicted a priming effect (of 530 ms) for the MTL group when recognition was, for all practical purposes, no different from chance (53.9% of the items were recognized correctly, $d' = 0.19$; see Figure 3). The severely amnesic individual E. P. is reported to perform normally in tests of priming despite chance performance in tests of recognition, and this pattern is typically regarded as compelling evidence for priming and recognition being mediated by multiple memory systems (e.g., Hamann & Squire, 1997; Stark & Squire, 2000). However, as the above simulation results show, this pattern is compatible with the single-system model (see also Kinder & Shanks, 2001): It would be difficult to achieve sufficient statistical power to detect an effect of the magnitude predicted (3.9% greater than chance). Even if it can be convincingly shown that E. P.'s recognition memory has been completely eliminated by his amnesia and yet his priming performance has been untouched (as some have argued), we are still wary about drawing strong conclusions from individual cases and would ideally like to see replications of this pattern in other patients.

General Discussion

The main aim of these studies was to present an alternative interpretation of three results that have been taken as evidence for distinct memory bases for priming and recognition. First, in Experiment 1, we replicated Stark and McClelland's (2000) observation of priming for old items that were not overtly recognized, and then we showed that this result is predicted by a single-system

Table 5
Estimates of Recognition Performance Given the Observed Magnitude of the Fluency Effect Within Each Group for Old and New Words

	Percentage correct estimate	
Group	Conroy et al.'s (2005) Experiment 2	Simulation
CON	52.2	52.0
H	50.8	51.7
MTL	52.6	51.3

Note. CON = control group; H = hippocampal lesions group; MTL = medial temporal lobe lesions group.

signal detection model in which one memory source drives priming and recognition. Second, the model was applied to the results of Johnston et al. (1985). As found by Johnston et al., the model predicted slower RTs to false alarms than misses when recognition performance was relatively good, but it predicted that RTs to false alarms would be quicker than RTs to misses when recognition was lower. Third, in Simulation Study 3, by assuming that there is a relatively large degree of noise in the encoding and assessment of the memory signal in amnesia, the model reproduced the pattern of intact fluency and priming on the one hand, and impaired recognition on the other, thus reproducing the dissociation between amnesic patients and controls reported in Conroy et al.'s (2005) study. The results of these simulations suggest that these three types of finding are not necessarily indicative of multiple memory sources in priming and recognition. The simulation results suggest an alternative account to those that propose that distinct memory bases mediate repetition priming and recognition (e.g., Squire, 1994; Wagner & Gabrieli, 1998; Wagner et al., 1997), namely that a single memory source drives priming and recognition.

The results also have implications for dual-process accounts of recognition that propose that fluency from priming can contribute to recognition (e.g., Jacoby & Dallas, 1981; Johnston et al., 1991; Mandler, 1980). As shown by Conroy et al. (2005), it is difficult to obtain direct evidence for this notion when one estimates the magnitude of recognition based on the identification of RTs to old and new items. A similar conclusion was reached by Poldrack and Logan (1997): Participants in their study made lexical decision judgments to old or new items and gave a recognition judgment after each decision. Discriminability between old and new items in the lexical decision task was measured with the distance between the standardized RT distributions for old and new items (dRT). Values of dRT were significantly less than the observed values of d' for the recognition task and could account for only a small proportion of recognition discrimination, suggesting that fluency (response speed) could not have been the sole factor in recognition judgments. Consistent with these findings, when we estimated recognition performance in the model in a similar manner to Conroy et al., the estimated contribution of fluency was also minimal. From the perspective of the model, the fluency from priming does not make a direct contribution to recognition, but rather a common memory source supports above-chance performance in each task (i.e., there is a common cause rather than a causal chain). Thus, although low estimates of the contribution of fluency to recognition seem to suggest a lack of a relationship between priming and recognition, this result is not inconsistent with a single-system account.
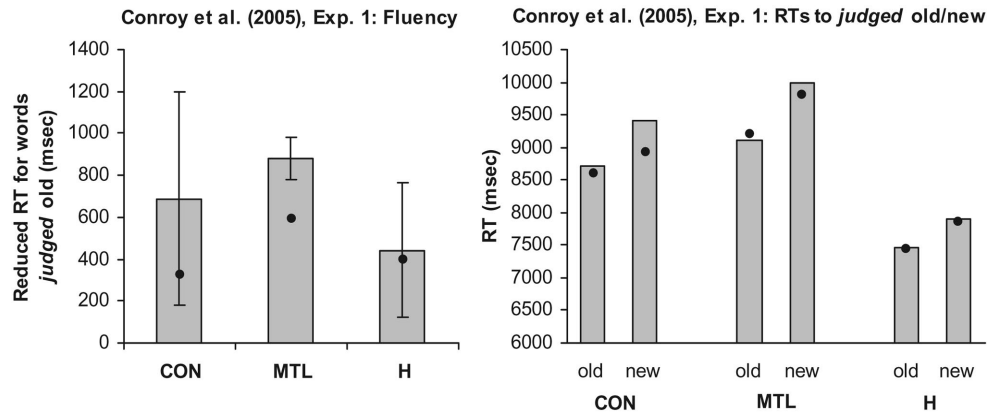
Figure 5. Fluency effects (left panel) and reaction times (RTs; right panel) to judged old and judged new words in Conroy et al.'s (2005) Experiment 1. Error bars show 95% confidence intervals of the means for the control (CON) group and ranges of individual scores (estimated from Conroy et al., 2005) for the hippocampal lesions (H) and medial temporal lobe lesions (MTL) groups. Circles indicate simulations based on 40 observations per stimulus type for 10,000 participants.

A limitation of the model concerns the use of fluency as a heuristic in recognition: For example, Johnston et al. (1991) found that when the identification and recognition trials were blocked, rather than interleaved, fluency effects did not occur. This was taken as evidence that interleaving the identification and recognition trials encouraged a reliance on speed of identification as a heuristic. The reason the model does not predict a difference between blocked and interleaved versions of the task is because the same value of *f* is used to determine an item's RT and its recognition judgment; in other words, there is a relationship between an item's RT and its likelihood of being judged old (see Equations 2 and 3). There is much evidence to suggest that other manipulations can affect the probability with which fluency is used as a cue for recognition (e.g., Jacoby & Whitehouse, 1989; Kinder, Shanks, Cock, & Tunney, 2003; Whittlesea et al., 1990), though the model in its current state does not speak to the use of fluency as a heuristic. It has been suggested (e.g., by Levy, Stark, & Squire, 2004) that because manipulations designed to enhance fluency tend to increase the proportion of old judgments to old and new items, such manipulations merely influence decision bias and not recognition accuracy. If this were the case, then the model would be able to account for this quite readily by allowing the decision criterion, *C*, to vary.

Dissociations between priming and recognition are widely taken as support for a multiple-systems view. For example, in normal adults, levels of processing manipulations have large effects on recognition but much smaller ones on priming (Brown & Mitchell, 1994; Jacoby & Dallas, 1981), and changes in modality between study and test have been shown to produce the opposite pattern—priming is reduced, but recognition is relatively unaffected. We have already shown that the model can account for the pattern produced by levels of processing manipulations: In another article (Berry, Henson, & Shanks, 2006), the model simulated large effects of an attentional manipulation on recognition but much smaller ones on priming (in a perceptual identification task). However, dissociations—such as the one produced by changes in modality—are more challenging for the model, and the model in its current state does not account for this. However, from a signal detection point of view, once one starts to take into account modality, a single dimension of strength may no longer be appropriate, and a multidimensional approach may be required.

Double dissociations have also been reported in patients: Individuals with damage to the right-occipital lobes show impaired priming despite relatively intact recognition, thus showing the reciprocal dissociation to amnesic patients (Gabrieli et al., 1995). Although, again, it is not clear how the model would be able to

Table 6

Percentage of Items Judged Old That Were Identified "Quickly" (Reaction Time < Median) and "Slowly" (Reaction Time > Median) in Conroy et al.'s (2005) Experiment 1

| | Percentage of items judged old | | | |
| | Identified quickly | | Identified slowly | |
Group	Conroy et al.'s (2005) Experiment 1	Simulation	Conroy et al.'s (2005) Experiment 1	Simulation
CON	64.4	56.3	48.4	43.8
H	59.2	57.0	50.0	42.7
MTL	61.3	58.4	35.0	41.8

Note. CON = control group; H = hippocampal lesions group; MTL = medial temporal lobe lesions group.

account for this dissociation, another single-system model, the SRN (Kinder & Shanks, 2003), has been shown to have some success at simulating this pattern. Kinder and Shanks (2003) assumed that individuals with amnesia had a generalized (rather than a specific) learning deficit, whereas individuals with right-occipital lobe damage had a deficit in visual processing. A double dissociation emerged from the SRN solely because of the way that the assumed nature of the deficits and differences in task procedures interacted with a single underlying memory representation. Moreover, it is relevant to note here that the use of double dissociations to infer distinct systems has been criticized, and their interpretation is widely debated (see, e.g., Dunn & Kirsner, 2003; Plaut, 1995). The findings from the studies that we have looked at in this article have analyzed identification RTs according to the recognition response, and as such, they constitute evidence from a different domain that does not rely on the logic of dissociation (at least in Simulation Studies 1 and 2).

Does the model make other predictions to those presented in this article that can be tested? As mentioned above, in Berry, Henson, and Shanks's (2006) study, by assuming that the variance of the noise associated with the perceptual identification task is greater than that of the recognition task, we showed how the model could simulate large effects of an attentional manipulation at study on recognition while simulating much smaller ones on priming. The model also correctly predicted that the reliability of the recognition task would be consistently greater than that of the priming task (as measured by split-half correlations; cf. Buchner & Wippich, 2000). In normal adults, the model also predicts that the sensitivity of the recognition task will not exceed that of the priming task (e.g., performance on the priming task will not exceed that of the recognition task when compared on the same response metric). This prediction held for all conditions of Berry, Henson, and Shanks. Similarly, Berry, Shanks, and Henson (2006) found that even when priming and recognition tasks were completely comparable in every way except for task instructions, and recognition was at chance, the sensitivity of the priming task never exceeded that of the recognition task.

Moreover, in unpublished simulations, we have applied the model to a modified CID-R paradigm in which, after every two identification trials, the items from those trials are re-presented for a two-alternative forced choice (2AFC) recognition judgment. Because the model assumes that greater values of f will lead to faster identification RTs and also to a greater likelihood of an old judgment, it predicts that the item judged old on a 2AFC trial will also tend to have the shorter identification RT. The single-system model makes this prediction, regardless of whether the items presented on the 2AFC trial are both new, both old, or one is old and the other is new. Different predictions are made by a "dual-system" version of the model, which is identical in all respects to the single-system model except that after an item's identification RT has been calculated, *another* value of f is sampled to calculate J_r. In other words, the value of f is different for priming and recognition (albeit sampled from the same distribution). In contrast to the single-system model, this dual-system version of the model predicts that on 2AFC trials in which both items are old or both are new, the item judged old will not tend to have the shorter identification RT. However, on 2AFC trials in which one item is old and the other is new, it predicts, like the single-system model, that the

item judged old will also tend to have the shorter identification RT (because of priming). This highlights an advantage of the approach we are using, which is that quantitative predictions of single- and dual-system versions of the model can be tested empirically.

Finally, another advantage of the approach that we are advocating is that it is based on signal detection theory. Signal detection theory is widely accepted as a plausible framework for theorizing about recognition, and this framework has been successful in accounting for a variety of phenomena (although there is debate as to the precise form that a signal detection model should take; e.g., Wixted, 2007, vs. Parks & Yonelinas, 2007). Many models of recognition have been proposed that also include a role for signal detection theory (e.g., Gillund & Shiffrin, 1984; Hintzman, 1984, 1988; Murdock, 1982, 1983). However, these models have not been used to also account for priming (one exception is the retrieving-effectively-from-memory modeling framework; see Schooler, Shiffrin, & Raaijmakers, 2001). Kinder and Shanks's (2001, 2003) model has been applied to priming and recognition but has never been shown to be compatible with a broad range of recognition phenomena. From a single-system perspective, a logical step is to use signal detection theory to also account for priming; we have tried to do this here by assuming that the same memory strength variable that drives recognition also drives priming. The model that we propose is simple, is based on general principles, and is relatively easy to implement.

In conclusion, the results from studies discussed in this article that have been taken as evidence for distinct memory bases of priming and recognition are not inconsistent with a single-system account in which one memory signal drives priming and recognition and is subjected to different nonmemorial sources of noise. We regard it as important that before a multiple-systems approach is advanced, researchers need to show that a single-system model is unable to account for their data patterns or has critical limitations. Indeed, in a future project we plan to conduct a formal comparison of single- and dual-system versions of the model. Whether or not the model stands up to further tests, we do believe it is an important step forward to have a formal, quantitative model of priming, recognition, and fluency to use as a benchmark.

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