The Quarterly Journal of Experimental Psychology

ISSN: 1747-0218 (Print) 1747-0226 (Online) Journal homepage: https://www.tandfonline.com/loi/pqje20

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THE QUARTERLY JOURNAL OF EXPERIMENTAL PSYCHOLOGY
2012, 65 (8), 1449–1474

Psychology Press
Taylor & Francis Group

EPS Mid-Career Award 2011

Are there multiple memory systems? Tests of models of implicit and explicit memory

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This article reviews recent work aimed at developing a new framework, based on signal detection theory, for understanding the relationship between explicit (e.g., recognition) and implicit (e.g., priming) memory. Within this framework, different assumptions about sources of memorial evidence can be framed. Application to experimental results provides robust evidence for a single-system model in preference to multiple-systems models. This evidence comes from several sources including studies of the effects of amnesia and ageing on explicit and implicit memory. The framework allows a range of concepts in current memory research, such as familiarity, recollection, fluency, and source memory, to be linked to implicit memory. More generally, this work emphasizes the value of modern computational modelling techniques in the study of learning and memory.

Keywords: Memory; Signal detection theory; Priming; Recognition; Hippocampus.

Our understanding of learning and memory processes has been enormously advanced in recent years by the development, application, and testing of computational models. Across areas as diverse as conditioning and associative learning (e.g., Rescorla & Wagner, 1972), categorization

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The first author is deeply indebted to the Experimental Psychology Society for the Mid-Career Award. We gratefully acknowledge the support of the Economic and Social Research Council during the course of the research described here. We thank our many collaborators for their contributions to this work, in particular Rik Henson and Maarten Speekenbrink, and Tim Perfect for very helpful comments on the article.

http://www.psypress.com/qjep
http://dx.doi.org/10.1080/17470218.2012.691887

(e.g., Nosofsky, 1987), and memory retrieval (e.g., Brown, Neath, & Chater, 2007), formal models employing a range of processing assumptions (connectionist, exemplar-based, and so on) have provided deep explanations for characteristic behaviour in their domain of application, suggested novel research avenues, and made contact with neuroscientific research on the brain bases of learning and memory (see Lewandowsky & Farrell, 2011; Sun, 2008).

This article describes computational and experimental work directed at understanding the nature of, and relationship between, explicit and implicit memory/learning. Curiously, in regard to the important contributions that have been made by computational models, this area is an exception. The research agenda has been only very modestly influenced by such models. This is striking for at least two reasons. First, the topic itself—understanding the relationship between explicit and implicit memory/learning—has been the focus of very substantial research efforts over the past 30 or so years and indeed has been one of the core questions the field has addressed, so there has been no shortage of motivation to explore the value of such models. Secondly, there does not seem prima facie to be any great conceptual difficulty in developing and applying models to this domain. One speculation as to why this state of affairs has come about is that much of the research on implicit and explicit memory has been overly dominated by the logic of dissociation and specifically by attempts to show dissociations between explicit and implicit memory (Roediger & McDermott, 1993). The work described here seeks to redress this limitation.

The outline of the article is as follows. We begin by describing a single-system model of implicit and explicit memory, first described by Shanks and Perruchet (2002) and Shanks, Wilkinson, and Channon (2003), which builds on signal detection theory (SDT). This model assumes that only a single memory trace is created by exposure to some stimulus or event, and this trace forms the basis of responses in both types of test. The model makes a number of qualitative predictions, which we describe together with various tests of those predictions. For example, it predicts that priming can never occur at the level of a group or condition in the absence of recognition, and several tests (Berry, Shanks, & Henson, 2006; Berry, Shanks, Li, Sheridan Rains, & Henson, 2010) have tended to confirm this prediction. We next describe a more general memory framework (Berry, Shanks, Speekenbrink, & Henson, 2012), which takes a multiple-systems perspective and which assumes that separate systems can contribute to explicit and implicit memory. This framework is general in the sense that the single-system model is a special case of it. Another special case is a model that assumes strict independence of the systems. We describe model-selection results that indicate that for normal individuals, measures of overall fit favour the single-system model over those that add a second memory system. We extend this to include data from individuals with amnesia, showing a surprising degree of support for the single-system model. Finally, we consider some of the ways in which this framework may be expanded into a more general theory of memory.

Within any cognitive architecture, a "system" is an identifiable set of procedures for acquiring, representing, maintaining, and retrieving information specific to a particular type of behavioural goal. Overall, the aim of the work described here is to use computational models to inform our psychological and neural understanding of memory systems.

A single-system model

Shanks and Perruchet (2002) and Shanks et al. (2003) described a formal, single-system model of explicit and implicit memory. Later versions (e.g., Berry, Henson, & Shanks, 2006) modified some of the simplifying assumptions of the original formulation, and we therefore present a brief overview of a fuller version of the model (described in more detail by Berry et al., 2012). Not only is this elaborated model more psychologically plausible than the original version, but it also connects much more directly with signal detection theory. Indeed as far as the model predicts recognition decisions, it is simply SDT.

We assume that old (studied or learned) and new (unstudied and unlearned) items have varying levels of normally distributed memory strength on a single dimension *f*. The mean value of *f* is greater for old (μ_{old}) than for new (μ_{new}) items, and we assume that the variances of these distributions are equal. Thus the difference between the means of the distributions provides an overall measure of memory discriminability.

On presentation of a test item, a sample is drawn from the relevant distribution. Noise (or error) e_r is added to this sample, and the ensuing value is compared against a decision criterion, exactly as in standard SDT. An old item whose strength exceeds the criterion will then correctly be called "old" and be a hit; an old item whose strength falls below the criterion will incorrectly be called "new" and be a miss; a new item whose strength exceeds the criterion will incorrectly be called "old" and be a false alarm; and a new item whose strength falls below the criterion will correctly be called "new" and be a correct rejection. The collection of these different responses will allow d' and hence the separation of the old and new memory strength distributions, as well as the criterion, to be determined.

The same distributions determine responding in the implicit test of memory, making this a single-system model. Specifically, each old and new test item evokes a degree of memory strength of evidence, *f*, drawn from the appropriate underlying old or new distribution. But instead of being compared to a criterion in order to yield a binary decision, this value of *f* is transformed into a different response metric. This response rule can vary from task to task. In many priming tasks, including the principal ones discussed below, the primary measure is response time (RT). Participants respond as rapidly as possible to a new or old test item, and their RT to do so is measured. Priming is then indexed by faster mean RTs for old than for new items. In such circumstances, it is straightforward to map *f* onto RT via some linear response rule such as

$$RT = b - sf + e_p \tag{1}$$

where *s* is the slope and *b* the intercept of the function, and e_p is additional noise that is independent of the noise added to *f* in the construction of the recognition decision.

Within this model, experimental manipulations can be modelled in appropriate ways. For instance, in one condition, full attention may be allocated to items at study whereas in another condition the items may be studied under conditions of divided attention (Berry, Henson, & Shanks, 2006). Within the model, this is naturally reflected by assuming that the mean (μ_{old}) of the *f* distribution is greatest on average for items studied under full attention and is lower for items studied under divided attention (though still greater than the mean for new items). Similarly, some participants in an experiment may have poor memory as a result of brain lesions (amnesia) or advanced age, and these would again be modelled by lower mean values (μ_{old}) for studied items.

The important point to note, though, is that these assumptions about how to model experimental manipulations are completely independent of how memory will be tested. Whether the final test will be an explicit or an implicit one, the manipulation of memory strength is the same. This is the essence of the single-system perspective. It does not say that implicit and explicit memory are the same—such an assertion would be unjustified given that implicit and explicit tests differ in so many ways. However, it does say that memorial influences on implicit and explicit tests are identical and derive from exactly the same source (variations in strength).

Model predictions: Functional dissociations

It is well known that many experimental manipulations and participant variables can affect recognition while having little or no effect on priming (Richardson-Klavehn & Bjork, 1988; Roediger & McDermott, 1993). In normal adults, examples of manipulations that produce this pattern are depth of processing such as making a semantic versus nonsemantic judgement about a word at encoding, or attentional manipulations such as encoding words with or without a concurrent distractor task. A common interpretation of these dissociations is that explicit memory is selectively influenced by the manipulation, whereas implicit memory is not. Often, in cases in which an effect on explicit memory is observed as well as a (similar but smaller) effect on priming, the latter is explained by saying that the priming measure is "contaminated" by explicit memory. Both of these interpretations postulate more than one memory system (or source of memory) to explain the dissociation.

The single-system model can explain this type of dissociation by postulating only one source of memory. As noted, in the model each item in the test phase is associated with a single memory strength value (f) that is sampled from a normal distribution, the mean of which is assumed to be greater for old (studied) than for new (unstudied) items. The value of f for an item is used to generate the recognition judgement it elicits as well as its priming measure. Crucially, this value of f is combined with one randomly sampled noise value for each task. These sources of noise are independent of the memory signal and can, therefore, be conceptualized as nonmemorial influences on task performance.

The functional dissociation patterns described above can be produced by the model if it is assumed that the variance of the noise associated with a priming task (e_p) is usually greater than that of recognition (e_r). This assumption is supported by the typically lower intertrial reliability of priming tasks, compared with recognition (Berry, Henson, & Shanks, 2006; Buchner & Wippich, 2000), and is consistent with the view that the influence of nonmemorial factors is greater in priming tasks than in recognition. From this assumption it follows that manipulations that increase overall memory strength (i.e., increase the difference between μ_{old} and μ_{new}) will be less likely to affect priming than recognition. In sum, such dissociations can arise in the model because the memory signal in priming is overshadowed or diluted by a greater degree of noise.

The presence of noise in the model enables it to explain another finding often taken to support multiple-systems views: Priming and recognition are frequently not correlated (i.e., performance on such tests is stochastically independent). Although the use of stochastic independence as evidence for multiple systems is controversial (Poldrack, 1996), it is not in dispute that very low correlations are often obtained. However, the model can predict a weak correlation between priming and recognition, within the empirical range, because of the independent sources of noise associated with each task. It can seem as if there is a lack of relationship between priming and recognition, even though they are driven by the same memory signal. Berry, Henson, and Shanks (2006) computed this correlation in several studies and found values, at least in some cases, close to 0.0. When fitted to the data (see Berry, Henson, & Shanks, 2006, for details), the model was able to predict correlations very close to those obtained empirically.

Model predictions: Priming in the absence of recognition at the level of a group or condition

The single-system framework described above makes a number of subtle predictions—to which we return later—but also a more straightforward one, namely that priming at the level of a group or condition will never be observed in the true absence of recognition. The reason for this is simple: If recognition were at chance ($d' = 0$), then that would imply that the mean strengths for old (μ_{old}) and new (μ_{new}) items are identical, but then this in turn would mean that the predicted implicit measure such as RT would also be identical. In other words, priming would be absent. Conversely, priming can only occur if μ_{old} is greater than μ_{new}, which in turn implies above-chance recognition discrimination. It is important to emphasize here that we are referring to priming *at the level of a group or condition*. Priming at the level of individual participants or items can have a very different basis, and, as we see later, the model can predict priming in such cases.

It might be thought that this prediction immediately renders the model unviable, for previous studies have often claimed that priming and other implicit memory phenomena can occur in the absence of explicit memory at the level of a group or condition, though these have typically employed tests other than recognition to assess explicit memory. Indeed many illustrations of this are quite famous, such as Claparède's (1911/1995) description of an amnesic patient who could not remember previous meetings with him but nonetheless refused to shake his hand after Claparède had at one of those meetings pricked the patient with a pin hidden in the palm of his hand. We return to priming and recognition in amnesia later. Equally well known, and described in many textbooks, is Kunst-Wilson and Zajonc's (1980) demonstration that the brief presentation of geometrical shapes can induce an increase in liking ratings of those shapes when they are subsequently paired with novel shapes in a forced-choice preference test, despite chance performance when the same items are paired in a forced-choice recognition test. Such demonstrations are invariably controversial, however (Shanks & St. John, 1994). For instance, Newell and Shanks (2007) found that recognition exceeded preference, rather than the converse, in several replications of Kunst-Wilson and Zajonc's study (see also Willems, Dedonder, & Van Der Linden, 2010).

More recent laboratory experiments on priming employing recognition tests of explicit memory have yielded results that are no more convincing. Destrebecqz and Cleeremans (2001) trained participants for many trials on a sequential reaction time task in which a target moved between four horizontal locations according to a fixed 12-element sequence, and participants had to respond to the target's location as rapidly as possible on each trial. In a test of priming, the sequence was changed, and Destrebecqz and Cleeremans found that RTs increased significantly on this block, thus suggesting that participants had learned the sequence and that their sequence knowledge caused responses to be facilitated (primed). In a test of recognition, participants responded to short three-location sequences, some of which were old (from the training sequence) and others new (not from the training sequence). Participants executed each sequence and then made a recognition judgement, and Destrebecqz and Cleeremans reported that at least under some circumstances recognition was at chance. Thus participants seemed to have implicit sequence knowledge such that they could predict the likely location of each successive target on the basis of prior locations—yielding priming—whilst not being able to explicitly recognize the trained sequence.

In several attempts to replicate this pattern, however, we found a contrasting pattern of results (Shanks et al., 2003). When we followed Destrebecqz and Cleeremans's (2001) procedure very closely, we obtained both priming and above-chance recognition, and when we attempted to eliminate recognition (for example, by using a probabilistic rather than a deterministic sequence) we were unable to do so (see also Perruchet & Amorim, 1992). Thus conditions in which priming occurs in the absence of recognition in the SRT task appear highly elusive. A similar picture is obtained in the contextual cueing task (Smyth & Shanks, 2008).

As another example, Merikle and Reingold (1991) presented a pair of words, one above the other, for 500 ms on each study trial and required participants to read aloud the word that was cued with arrows. At test, a single word was presented on each trial against a mottled background mask that degraded the appearance of the word. Participants in the explicit task judged whether the word had been presented in the study phase (old–new recognition judgements), while participants in the implicit task judged whether the contrast between the word and the background was high or low. Trials at test were arranged into blocks consisting of an equal number of old and new words (either cued and new words in their Experiment 1 or uncued and new words in their Experiment 2). The key finding was that when uncued and new words were presented at test, the sensitivity of the implicit task was significantly greater than that of the explicit task, which was at chance. Merikle and Reingold interpreted this result as an "unequivocal demonstration of unconscious memory" (p. 231).

We tested this pattern of results with a striking lack of success in obtaining the dissociation pattern (Berry, Shanks, & Henson, 2006). In one experiment, which followed Merikle and Reingold's (1991) procedure as closely as possible, we obtained a pattern diametrically opposite to theirs: Our participants performed at chance in the contrast priming test but above chance in recognition. In subsequent studies designed to eliminate recognition, we presented words at study for a shorter exposure time and with a stronger manipulation of attention. Whilst we eventually succeeded in eliminating recognition, we found no evidence of priming.

Finally, in some recent experiments we have evaluated priming and recognition with a different method for dividing visual attention at study. Vuilleumier, Schwartz, Duhoux, Dolan, and Driver (2005) and Butler and Klein (2009) found evidence of pure implicit memory using a rapid serial visual presentation (RSVP) procedure at encoding. Both studies found that a priming effect occurred for items that were ignored, but that recognition for these items was not reliably different from chance. In the study phase of Vuilleumier et al.'s experiment, cyan and magenta line drawings of objects were presented simultaneously, superimposed upon one another for 250 ms on each trial. Participants were instructed to attend to either the cyan or the magenta stream of images. At test, they completed a recognition task with old–new judgements, or a fragment identification task in which an object was shown in progressively less fragmented forms until it was correctly identified. The key result was that previously ignored objects were identified at more fragmented levels than previously unseen objects (i.e., there was a priming effect for previously ignored objects), but recognition of these objects was not reliably different from chance. The study by Butler and Klein used a similar encoding procedure, but superimposed words and objects. Each participant completed blocks of RSVP trials in which they attended to either the words or the objects. Using a perceptual identification task, Butler and Klein found a reliable priming effect for words that had been ignored, while recognition memory for these words was not different from chance.

Once again, these effects have proven to be very hard to replicate. Berry et al. (2010) conducted several versions of this experiment with both word and object stimuli, finding either above-chance recognition (and priming) for items in the unattended stream, or chance recognition and priming. No conditions yielded the critical pattern of chance recognition combined with reliable priming. Berry, Henson, and Shanks (2006) reported further experiments of word priming, which yielded a similar conclusion.

Model predictions: Priming in the absence of recognition within items

We have considered the single-system model's prediction that priming cannot occur in the true absence of recognition, but it is crucial to emphasize once again that this prediction relates to groups and conditions, not to individual participants or items selected post hoc in an experimental condition. To appreciate the importance of this point, consider an important analysis of recognition and priming data reported by Stark and McClelland (2000). These authors employed an elegant task for measuring priming and recognition, the *continuous identification with recognition* (CID-R) task. After studying a list of words, objects, or other such items, the test phase of this task takes the following form on each trial. An item, which is either old (from the study phase) or new, gradually clarifies, for example via the steady removal of pixels that are obscuring it, and the participant is instructed to press a key as soon as they can identify the item. Their identification latency (RT) to do this forms the basis of a measure of priming insofar as the typical pattern will be for old items to be identified faster than new ones. The participant then makes a second response (yes–no or a confidence rating) to indicate their judgement about whether the item was presented in the study phase or not. The CID-R task permits the concurrent measurement of recognition and RT, the latter forming the basis of a measure of priming, and therefore it is logical to assume that (from the point of view of the single-system model) both of these responses are based on a single sample from memory.

The analytic novelty in Stark and McClelland's (2000) study is that by using the CID-R task and obtaining such concurrent measures, they were able to measure priming for different item types. In particular, they computed identification RTs for new test items called "new" (correct rejections) and for old items called "new" (misses) and found the pattern RT(miss) < RT(correct rejection). We have obtained the same pattern in several of our own experiments (e.g., Berry, Shanks, & Henson, 2008). The reason the pattern is important is that it represents a priming effect for unrecognized items. Misses and correct rejections are by definition all classified by the participant as new and hence unrecognized. They differ in that misses are objectively old items while correct rejections are new. Hence the pattern described above is indicative of an influence of the objective status of the item (the fact that it was or was not presented on the study list) under conditions in which it is not recognized. On the face of it, this pattern seems a striking illustration that independent sources of memory drive recognition and priming: How could a common memory source yield an effect in identification RTs but not in recognition responses?

Figure 1 holds the answer to this question and allows us to illustrate that when the data are derived from items selected post hoc in an experimental condition, the single-system model counterintuitively can predict priming without recognition. The key insight is that even though misses and correct rejections both fall below the decision criterion, the mean strength of misses is greater than that of correct rejections simply as a result of the mean strength of old items being greater than that of new items. In the single-system model, a single sample, f, from memory is taken for each item, old or new. That sample is combined with nonmemorial noise, e_{p}, in the generation of an identification RT and with uncorrelated noise, e_{r}, in the generation of a recognition judgement. Because the strength of misses will overall tend to be higher than that of correct rejections, a difference in both the magnitude of the recognition strength and the identification RT will be induced, but for many of these items the resulting recognition strength will be too low to exceed the decision criterion. Such items will all be called "new", but those that are in fact old items (misses) will have greater strength on average than those that are in fact new (correct rejections), hence yielding a form of priming without recognition. Figure 2 provides a concrete example of this pattern from an experiment by Berry et al. (2008) and also shows that a similar pattern is obtained for old items—that is, RT(hit) < RT (false alarm). Hits are old items called old and false alarms are new items called old, so these items are not differentiated according to the recognition responses they evoke. Nevertheless, they yield a priming effect. Also shown in Figure 2 are

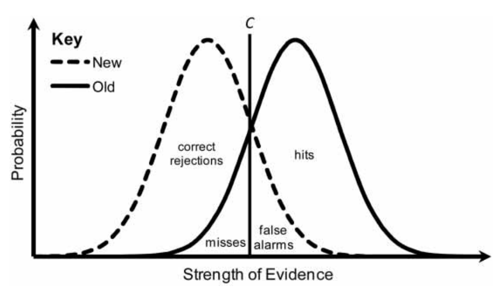

Figure 1. *Signal detection theory (SDT) of old–new recognition judgements. The abscissa represents recognition strength-of-evidence.* C *represents the decision criterion. Items to the right of* C *will be judged "old", and those to the left of C will be judged "new". An old item is classified as a hit if judged old or a miss if judged new; a new item is classified as a false alarm if judged old or a correct rejection if judged new.*

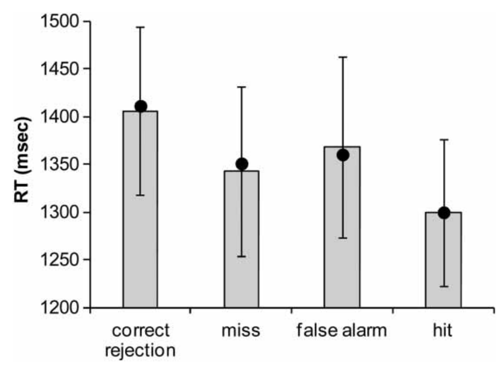

Figure 2. *Identification reaction times (RTs) classified according to recognition outcome in normal participants in the continuous identification with recognition (CID-R) task (from Berry et al., 2008). Priming for items not recognized (indicated by shorter RTs for misses than for correct rejections) was found in the data and was also predicted by the single-system (SS) model (black circles). Error bars denote 95% confidence intervals.*

the predictions of the single-system model (for details see Berry et al., 2008): It reproduces the RT patterns for the four item types very closely and predicts both of the patterns RT(miss) < RT (correct rejection) and RT(hit) < RT(false alarm), and it does so because of the intrinsic differences in mean item strength described above.

Shanks and Perruchet (2002) obtained a similar pattern when 6-point recognition confidence ratings rather than yes/no judgements were obtained in a sequential reaction time experiment. In this study, participants responded as rapidly as possible to a target, which moved between four horizontal locations according to a fixed sequence. At test, participants responded to short six-location sequences, which were either old (from the training sequence) or new (not from the training sequence). Participants executed each sequence and then made a recognition judgement on a scale from 6 ("certain I have seen this sequence before") to 1 ("certain I have not seen this sequence before"). Shanks and Perruchet analysed RTs to old and new test trials as a function of the recognition judgement and found that at every level of recognition, RTs were faster for old sequences. For example, when participants rated the sequence as new with high confidence (rating = 1), the trial is a miss if it is truly an old sequence and is a correct rejection if it is truly a new sequence. The pattern RT (miss) < RT(correct rejection) was obtained as well as equivalent patterns at all other levels of recognition judgement. Importantly, Shanks and Perruchet (2002) showed that the single-system model closely simulated the pattern.

Although the above demonstration refers specifically to the interpretation of priming effects in the absence of recognition when items are selected post hoc, a similar line of reasoning can allow the single-system model to account for such priming effects when participants are selected post hoc from a sample (Shanks, 2005).

A framework for comparing single- and multiple-system models

Thus far, then, we have reviewed a range of findings which are characterized by two properties: First, all of these findings appear superficially to imply the existence of distinct systems driving explicit (recognition) and implicit (priming) memory, and, secondly, in each case we have shown that the data can in fact be simulated by a simple single-system model in which a unitary source of memorial evidence is available but which is combined with independent sources of nonmemorial, task-dependent noise to generate explicit and implicit response measures.

While this support for the single-system approach is striking and counterintuitive, it of course does not directly demonstrate that multiple-systems viewpoints are incorrect. Certainly, in the absence of clear-cut evidence against the single-system model, one might appeal to parsimony as a reason for preferring this approach over more complex multiple-system ones, but it remains the case that the data are just as consistent with multiple-system theories as they are with a single-system one. Indeed, in the absence of further constraints, this must logically always be the case: If a multiple-system theory permits interacting modules contributing to any given task and assumes that all but one of its modules is switched off in a particular situation, it will reduce to a single-system model and hence make indistinguishable predictions.

However, modern model-selection methods allow models to be compared not only in terms of their fit to datasets (which will always be better for a model with more degrees of freedom) but also in terms of their flexibility (Lewandowsky & Farrell, 2011). An overly complex model might be able to explain not only an observed dataset, but also many other potential data patterns, which a simpler model would not be able to fit, were they to be obtained. A model that can only predict patterns, including an empirically observed one, in a small part of the space of possible data sets is clearly preferable to one that can predict patterns in a large part of the space. Selection criteria like the Akaike information criterion (AIC) and Bayesian information criterion (BIC) penalize models for excessive flexibility, as measured by number of free parameters. With this in mind, we (Berry et al., 2012) took the

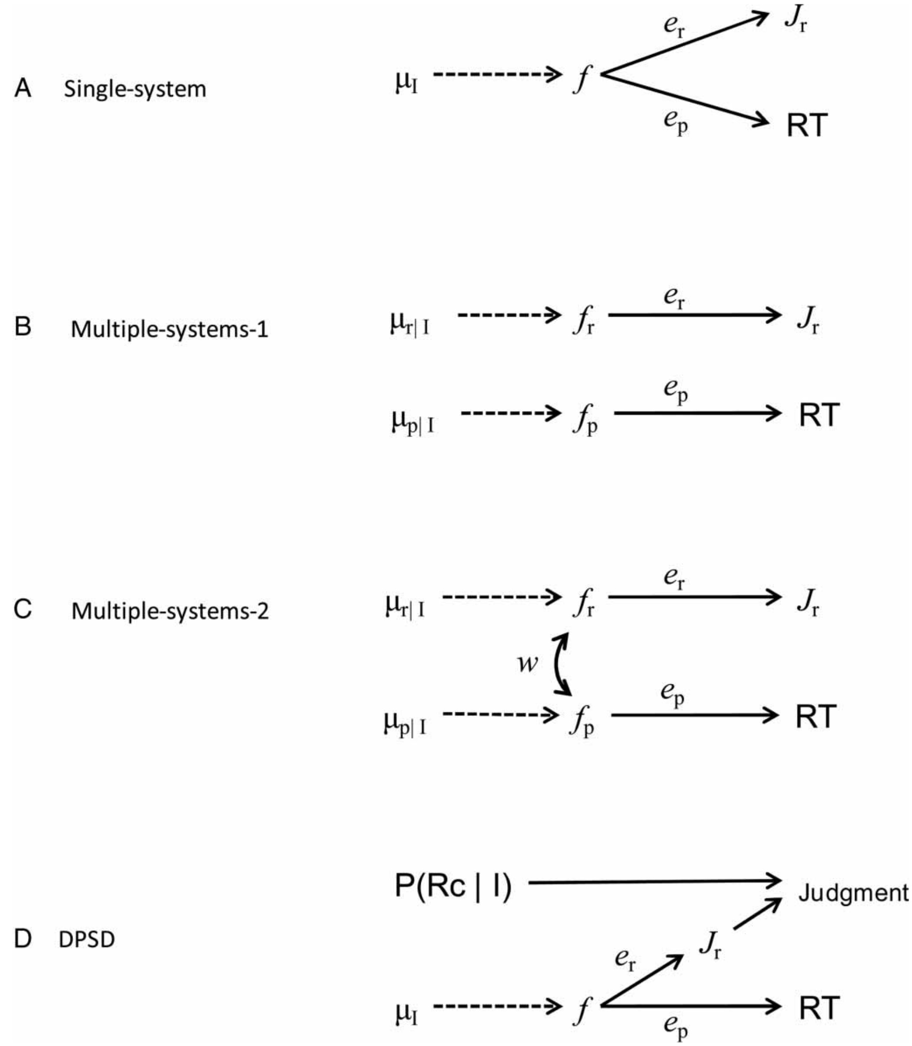

Figure 3. *Four models of recognition and priming. (A) Single-system (SS) model: Each item's value of* f *is sampled (represented by the dotted line) from a distribution with mean μ_I (where the subscript I stands for item type, and I = old, new). The same value of* f *is used to generate* J_r, *the recognition judgement, and the identification reaction time (RT). (B) Multiple-systems-1 (MS1) model: The values* f_r *and* f_p *are sampled from independent distributions of memory strength, and* f_r *and* f_p *are uncorrelated. (C) Multiple-systems-2 (MS2) model: The values* f_r *and* f_p *are sampled from independent distributions of strength, but* f_r *and* f_p *can be correlated (by an amount equal to* w*). (D) Dual-process signal detection (DPSD) model: As in the SS model, one value of* f *is used to calculate an item's* J_r *and RT, but there is an additional recollection process, P(Rc | I), where Rc stands for recollection, which can drive recognition judgements. If an item is not recollected, its recognition judgement is based on* J_r.

single-system model as a starting point for developing a much more general framework within which alternative, multiple-systems assumptions could be framed as readily as a single-system assumption.

Figure 3 illustrates the framework. Panel A depicts the single-system (henceforth SS) model in which *f* is sampled from an underlying distribution for old or new items, as appropriate, and μ_I is the mean of this distribution (*I* stands for item type, old or new). The memory strength signal is combined with error e_p or e_r for priming or recognition, as appropriate. The resulting value determines the identification RT according to Equation 1 and determines the recognition decision via a standard SDT process: That is to say, if the resulting value is greater than the decision criterion, an "old" judgement is made, otherwise the judgement is "new". When the required response is a recognition confidence judgement (e.g., on a 6-point scale), multiple criteria are assumed but the process is fundamentally the same.

Panel B depicts a straightforward modification of the SS model to turn it into a multiple-systems model. Specifically, this multiple-systems-1 (MS1) model assumes that quite distinct and independent memory representations control explicit and implicit memory. One pair of old and new distributions is sampled to generate a recognition response, while a second pair of distributions is sampled to generate the identification RT. These samples (f_r for recognition and f_p for priming) are translated into responses in the same way as in the SS model. The critical difference between the SS and MS1 models, therefore, is in the independence of the memorial signals in the MS1 model, which is free to assume that these are unrelated, as they might be if they depend on distinct brain networks. For example, in fitting a set of CID-R data, the MS1 model can assume that the overlap of the old and new distributions is entirely different between the explicit and implicit systems. By assuming that the old and new distributions for explicit memory are completely overlapping (i.e., $d' = 0$) while those for implicit memory are not, the MS1 model can therefore predict priming at the level of a group or condition in the absence of recognition. It is natural to assume that any model that incorporates distinct signals would also—when realized in the brain—include distinct encoding and retrieval mechanisms for those signals, which is why the MS1 model is appropriately characterized as a multiple-systems model.

In assuming independence between the sources of implicit and explicit memory, the MS1 model instantiates views expressed by several researchers including Endel Tulving (Tulving & Schacter, 1990; Tulving, Schacter, & Stark, 1982). On the basis of early evidence of stochastic and functional independence, Tulving et al. (1982) wrote in regard to the implicit test of fragment completion:

> Whatever it is that is transferred from the episodic study of a word to the subsequent fragment completion task *is not identical or even correlated* [emphasis added] with whatever it is that makes it possible for the subjects to distinguish between words previously encountered in the experiment and words not encountered. The information that subjects use in completing the fragments of primed words is not the same kind of information on which people rely in remembering events from their past. (p. 341)

Whatever the merits of the methodology and interpretation of studies of stochastic and functional independence, there have been no previous attempts either to formalize a model that assumes complete independence of memory sources or to quantitatively and qualitatively contrast this type of model with alternative models (such as the single-system model) that rest on quite different assumptions.

It should be clear that both the SS and MS1 models are special cases of a more general model, depicted in Panel C of Figure 3. In this multiple-systems-2 (MS2) model, independent distributions for explicit and implicit memory are sampled as in the MS1 model, but this model allows for f_r and f_p to be correlated across items. The degree of correlation is represented by the parameter w, which can vary between 0 and 1. Intuitively, the incorporation of a nonzero degree of correlation generates a more plausible model than the MS1 model. For example, some items at study are likely to be intrinsically more memorable than others, and fluctuations of attention are likely to lead to greater encoding of some items than others, such that implicit and explicit memory for these items will be correlated even if separate and noninteracting systems control them. When w is set to zero, the MS2 model reduces to the MS1 model. On the other hand, when $w = 1$ and when the overlap of the strength distributions for the two systems are identical, the MS2 model reduces to the SS model. Hence the MS2 model represents our general framework within which the two other models are special cases. It is worth noting that although our implementations of these models require several additional free parameters (such as the placement of the decision criterion, the mean value μ_{old} of the old item distribution relative to the new item distribution, and the intercept and slope parameters in Equation 1), these parameters are included in all of the models (for full details, see Berry et al., 2012).

It is important to realize that although the general model (MS2) is a highly detailed model, which makes precise assumptions about the basis of implicit and explicit memory responses, and which generates precise numerical predictions, it is one that virtually any advocate of the multiple-systems approach should be comfortable with. After all, it adopts signal detection theory as its account of recognition memory, a theory that has accumulated over 50 years of support and which has withstood many challenges. As far as implicit memory is concerned, the general model assumes little more than that the strength of the implicit memory representation is linearly related to the response measure. While there might be debate about the exact form of the mapping from f onto RT (the linear function may be less suitable than other monotonic functions), this mapping will only have quantitative and not qualitative consequences for the model's predictions. Hence the general framework should seem a natural and fairly uncontentious way of formalizing multiple-systems theory. The only notable exception to this is in regard to those who reject SDT as a theory of recognition memory. There is a substantial body of evidence for, and many supporters of, the proposal that recognition is itself driven by distinct and dissociable signals relating to recollection and familiarity (Yonelinas, 1994, 2002). But it turns out to be straightforward to develop the general framework so as to accommodate this so-called "dual-systems" theory of recognition. We turn to this model later.

Testing the models: Data from memory-intact individuals

Data from CID-R experiments allow the models to be discriminated. In these experiments (Berry et al., 2012), normal participants studied a word list prior to a test stage in which on each trial the test item, an old or new word, gradually clarified on the screen. Over a period of 7,500 ms, the word was repeatedly flashed and followed by a mask, with the duration of the word getting longer in each flash and that of the mask getting shorter, creating the appearance of the word gradually coming into full view through visual noise. Participants pressed a key when they had identified the word (and they then typed it to ensure they had indeed identified it correctly) prior to making a recognition judgement on that word. Various aspects of the data, such as the magnitude of priming and recognition, as well as more subtle item analyses, and overall fit as measured by the Akaike information criterion, tease the models apart.

We have already considered a number of predictions of the single-system model, such as (a) priming cannot be above chance when recognition is at chance, and (b) the pattern RT(miss) < RT (correct rejection) should be observed in item analyses. Additional predictions, however, can be derived from a contrast of the three models.

A fluency prediction

A common finding in experiments that measure both priming and recognition across items is that items which are identified faster tend also to be called "old" in recognition. This effect is termed a "fluency effect" on the grounds that it seems to suggest that the more easily an item is processed, the more likely it is to evoke a feeling of familiarity (Jacoby & Dallas, 1981; Mandler, 1980). Indeed, experimental manipulations have been employed in order to artificially demonstrate such a link (Kinder, Shanks, Cock, & Tunney, 2003; Whittlesea, Jacoby, & Girard, 1990). For example, Kinder et al. (2003) presented participants with items to study prior to a CID-R test in which items gradually clarified. The novel manipulation in this study was that the rate of clarification was experimentally manipulated: Some items came into view more rapidly and others less so. Kinder et al. found that items were more likely to be endorsed as "old" when they clarified more rapidly. Although this pattern was found to depend on some subtle experimental factors (most particularly that it only occurred when the test comprised only new items, and hence all "old" responses were false alarms), it clearly shows that a link exists between fluency of processing and recognition judgements.

The fluency effect can be described formally by the pattern p("old"|fast RT) > p("old"|slow RT) where fast and slow RT are determined by, for instance, a median split of the participant's RTs in a given experimental condition. It is more convenient, however, to conceptualize the effect in a different way—that is, by the patterns RT(hit) < RT(miss) and RT(false alarm) < RT(correct rejection). The former pattern indicates that when participants call old items "old" (hit) rather than "new" (miss), their RTs are faster, and likewise when they call new items "old" (false alarm) rather than "new" (correct rejection).

Critically, the models differ in their predictions of such fluency effects. The SS model predicts robust fluency effects because an old item called "old" will on average have a higher value of f than one called "new". Even though f is combined with random noise, e_r, to generate the recognition judgement, this noise on average has a value of zero. For an item to be a hit rather than a miss, therefore, it must on average have a higher value of f. But this same value of f also determines (via Equation 1) the identification RT for that item, which will accordingly tend to be faster for hits than for misses. The same logic applies to new items (false alarms and correct rejections).

The MS1 model, however, is unable to predict such fluency effects. The reason for this is easy to see. If we take two items of the same type (old/new), such as two old items, then on this model they must be predicted to elicit, on average, equal identification RTs even if they elicit different recognition responses. Although, like the SS model, an old item called "old" will on average have a higher value of f_r than one called "new", this value is uncorrelated with the value of f_p that is independently sampled for that probe item and which forms the basis of its identification RT (and the same applies for new items). Indeed, the expected value of f_p for a hit will simply be the mean value of the implicit memory strength distribution for old items, which is also the expected value of f_p for a miss. The more general MS2 model is able to predict either pattern, depending on the value of the correlation parameter w.

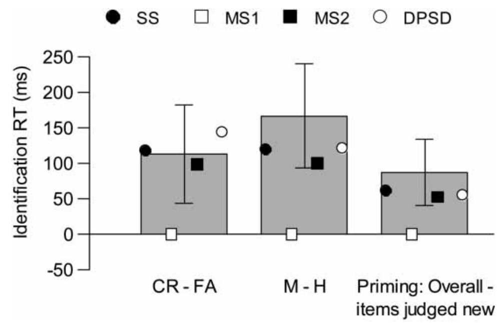

Figure 4. *Data and model results concerning fluency. Correct rejection – false alarm (CR – FA) refers to the fluency effect within new items, miss – hit (M – H) refers to the fluency effect within old items, and "priming: overall – items judged new" refers to the difference in the overall priming effect and the priming effect for items judged new. Bars denote data, and symbols indicate the expected result from each model. Error bars denote 95% confidence interval of the difference in means. SS = single-system model; MS1 = multiple-systems-1 model; MS2 = multiple-systems-2 model; DPSD = dual-process signal detection model; RT = reaction time.*

Figure 4 illustrates data from one of the CID-R experiments conducted by Berry et al. (2012) to test this prediction. The leftmost bar shows the magnitude of the RT difference between false alarms and correct rejections (new items) and indicates a very strong pattern consistent with the fluency effect RT(false alarm) < RT(correct rejection). The middle bar shows the magnitude of the RT difference between hits and misses (old items), revealing the corresponding pattern RT(hit) < RT(miss). Model simulations are indicated by symbols and confirm that the MS1 model predicts neither of these effects while the SS model's predictions are within the observed confidence intervals in both cases. Unsurprisingly, the MS2 model can also predict the pattern.

A priming prediction

Recall that the pattern RT(miss) < RT(correct rejection) is a priming effect for items judged "new". Although all of the models can predict this pattern, they differ in regard to their expectations about the relative magnitude of this effect. How big will this effect be in comparison with the total priming effect—that is, the difference in RT for all old items compared to all new items? The SS model makes a novel prediction—namely, that the priming effect for items judged new will be smaller than the overall priming effect. The reason for this is easy to see in Figure 1. The mean strength for misses is greater than the mean for correct rejections, but this difference is smaller than that between the mean strength of old and new items overall.

In contrast, the MS1 model predicts that the priming effect for items judged new will be identical to the overall priming effect. The reason for this is as follows. In the MS1 model, as explained above, RT(false alarm) = RT(correct rejection), and these RTs must equal RT(new items). Similarly, it requires RT(hit) = RT(miss), and these must equal RT(old items). It necessarily follows that RT(correct rejection) − RT(miss) = RT(new) − RT(old). That is, the MS1 model predicts that the magnitude of priming for items judged new will be equal to the normal priming effect. The more general MS2 model is able to predict either pattern, depending on parameter values.

The rightmost bar of Figure 4 presents relevant data from one of several tests of this prediction by Berry et al. (2012). The overall priming effect in this dataset was about 80 ms greater than the priming effect for items judged new, and once again the SS and MS2 models, but not the MS1 model, are consistent with the results.

Fitting the models

The model predictions illustrated in Figure 4 were based on a search of the parameter space for each model using maximum likelihood estimation techniques. Full details, as well as discussion of how systematic and predictable the parameter estimates are across different simulations, are provided by Berry et al. (2012). For each model, an AIC value was determined. Across three experiments, the SS model emerged as the preferred model. This is a remarkable outcome: In fitting about 17,000 datapoints (pairs of RT and recognition judgements), a model that assumes a single underlying memory representation for both explicit and implicit memory yields a closer fit to the data, considering its flexibility, than either of the multiple-system models. Put differently, the addition of a second memory system, which could, in principle, have given the MS models far greater scope to explain dissociations between implicit and explicit memory, failed to increase the fit sufficiently to offset the cost of additional flexibility. When the models were fitted to individual participants rather than to the group as a whole, the SS model was again the best fitting model for the majority of participants, providing some reassurance that the group-level outcome is not a consequence of bias emerging from averaging across participants.

Analysis of the best fitting parameters within the models is instructive. Recall that the parameter w reflects the degree of covariation between the values of f sampled from explicit and implicit memory. This w parameter is fixed to 1 in the SS model and to 0 in the MS1 model, but is free to vary in the more general MS2 model. Not only did the MS2 model achieve a worse AIC value than the SS model, but its best fits to the data were invariably obtained with a surprisingly high value of w. Across data pooled from several experiments, this value was 0.93, suggesting that the MS2 model performed best when it was, in effect, mimicking the SS model.

A somewhat different way of interpreting these findings is as follows. Selection of the model with the lowest AIC value achieves the optimum trade-off between fit and flexibility. Fit is how close the predicted and observed datapoints are. Flexibility is less straightforward to measure, but can be readily conceptualized in relation to "overfitting" (Gigerenzer & Brighton, 2009). Suppose we randomly split a dataset into two equal samples, which we will call the "fitting" and "validation" samples. If a model is highly flexible, then it is likely to achieve a very close fit to the fitting sample, when its parameters are free to vary, but will do so by using its flexibility to fit what is in reality noise in the data. A consequence of this is that because noise in the fitting sample will be uncorrelated with noise in the validation sample, the model is likely to achieve a poor fit to the validation sample when its parameters are fixed to the values derived from the fitting sample. In contrast, a less flexible model with fewer degrees of freedom will be able to capture the signal in the fitting sample to some greater or lesser extent, but will be less likely to inappropriately fit the noise and in consequence will do a better job of fitting the validation sample when its parameters are fixed. The AIC selects the model that achieves the best fit in such a cross-validation procedure (Lewandowsky & Farrell, 2011).

This can clearly be seen in Figure 5, which presents an analysis of the data from one of the CID-R experiments conducted by Berry et al. (2012, Experiment 1, cued condition)). Each datapoint depicts an individual participant and shows the observed recognition (left column) and priming (right column) against the values predicted by the SS (top panels), MS1 (middle panels), and MS2 (bottom panels) models. The data for each participant were split into two samples at random, the models were applied to these samples and their parameters adjusted to achieve the closest fit, and the fit to the validation sample with these parameter values now fixed was determined. Although the MS2 model fits the data from the fitting sample better than the SS model (not shown), it performs noticeably worse when forced to make parameter-free predictions for the validation sample, as shown by the wider scatter of the points from the diagonal.

Whenever one model is found to fit some dataset better than another, by assessment of AIC or by another measure, the question arises whether this comes about simply because in some way or other the deck is stacked in favour of the winning model. With regard to the competition described above, perhaps it is the case, for example, that all of the models are fundamentally wrong and that the SS model is only preferred by AIC because it is a simple model. Put differently, perhaps the SS model would be selected by AIC even when the true model generating the data is a different model? Of course, we cannot know with certainty what the true model is, so this is a difficult hypothesis to test. However, a reasonable test of the hypothesis can be performed by using the models themselves to generate data. Suppose we generate a large set of artificial data from the MS2 model, setting its parameters to the best fitting values obtained from the fit described above so as to ensure that the generated data resemble true (i.e., participant) data as closely as possible, and then fit all three models to this dataset. If something inherent to the competition and the nature of the data biases the AIC comparison in favour of the SS model, then we would expect to see it incorrectly selected as the true model when it is required to fit data truly generated by the MS2 model. On the other hand, if the AIC comparison is unbiased, then this "model recovery" exercise should identify the MS2 model when the MS2 model truly generated the data, the SS model when the SS model truly generated the data, and so on.

In an extensive model recovery exercise based on data from several experiments, Berry et al. (2012) found that the AIC comparison did enable the true model to be recovered in the vast majority of cases. It does not seem that anything in the fitting method or in the formulation of the models unfairly stacks the deck in favour of the single-system model.

Testing the models: Data from memory-impaired individuals

It is remarkable that both qualitative and quantitative aspects of the data from the experiments described above were so well captured by a model that assumes a single underlying memory resource. Several predictions could have led to the model being falsified—its predictions that priming will not be above chance when recognition is at chance, that the pattern RT(miss) < RT(correct rejection) (priming for items judged new) will be observed in item analyses, that fluency effects will occur within old and new items, and that priming for items judged new will be weaker than the overall priming effect.

Nevertheless, the single-system model's greatest challenge is to provide a convincing account of the selective pattern of memory impairment observed

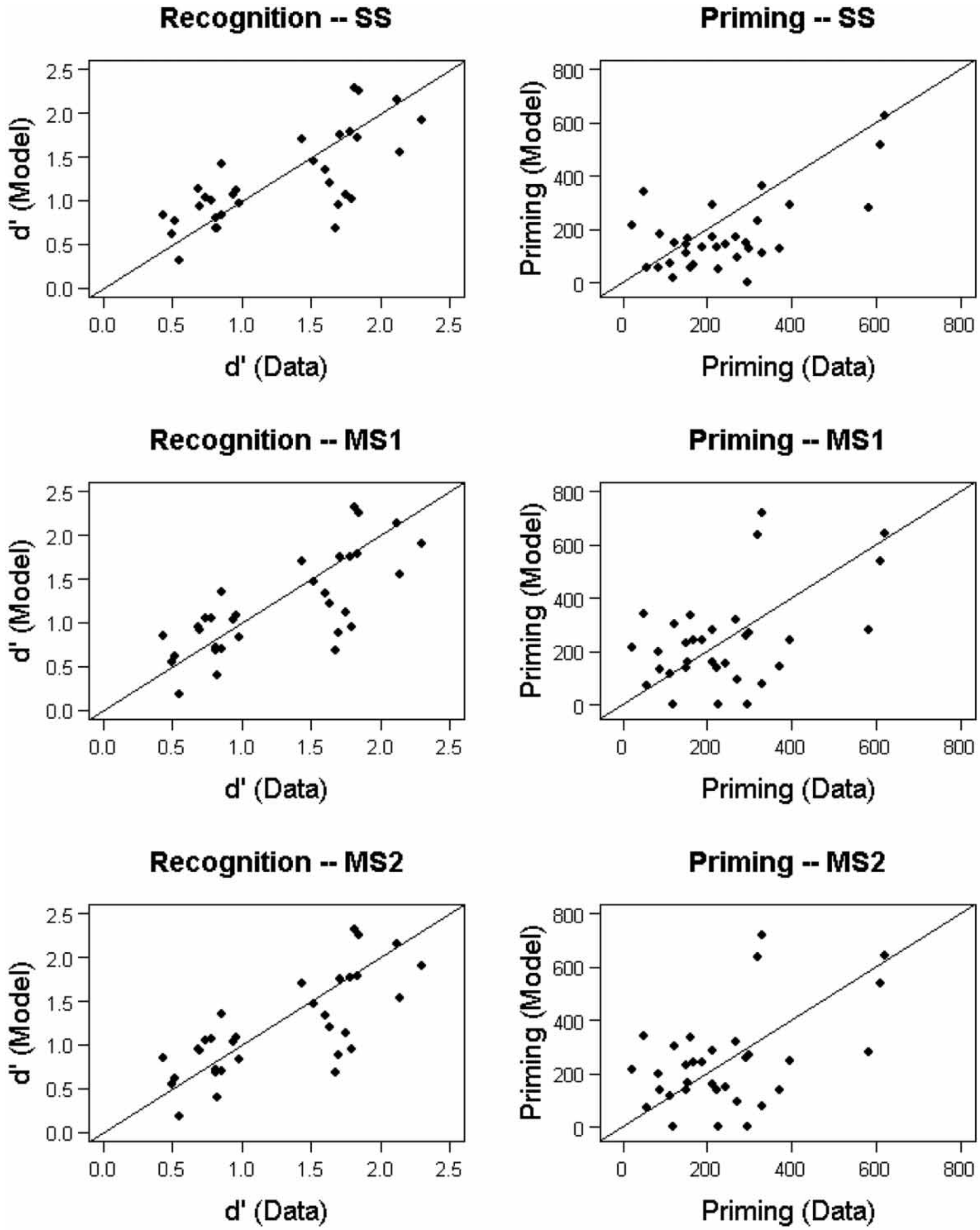

Figure 5. *Results of a cross-validation analysis of the data from the cued condition of Experiment 1 in Berry et al. (2012). The abscissa represents participants' recognition scores* (d′, *left column) and priming (ms, right column), and the ordinate represents model predictions for the SS (top row), MS1 (middle row), and MS2 (bottom row) models. The model predictions were derived via cross-validation in which each model was first fitted to half the data selected at random, with its parameters being optimized to achieve this fit, and then the model with these parameter values fixed was used to generate predictions for the other half of the data. Each point represents an individual participant.*

in individuals with, in particular, the classic amnesic syndrome (similar patterns are often reported in normal ageing). Specifically, amnesia has been found repeatedly to lead to substantial decrements in explicit memory combined with normal or near-normal implicit memory. Unless it can accommodate and shed light on this pattern, the single-system model cannot be taken as revealing anything fundamental about the organization of memory processes in the brain.

An important illustration of the challenge facing the SS model is revealed in data reported by Conroy, Hopkins, and Squire (2005, Experiment 2). These data are of particular relevance because they were obtained using the CID-R task and are therefore amenable to similar model-based analyses to those described above. Conroy et al.'s participants read a list of words in the study phase, and then, at test, old and new words were presented using the CID-R procedure. In this procedure, each word gradually clarified from a mask of pixels over a period of 11 s. Participants pressed a button to halt the clarification (their identification RT was recorded), and then they made a verbal identification of the word. An old–new recognition judgement was made after each item was identified.

Conroy et al. (2005) tested eight control participants (CON group) and three individuals with focal damage to the hippocampus (HIP group) and found that while recognition was impaired in the HIP relative to the CON group, priming and overall fluency effects did not differ. The data are shown in Figure 6 and highlight priming of about 600 ms in both groups (bottom panel, bars marked "overall"). This clear functional dissociation has of course been obtained in numerous other studies using methods other than the CID-R task and has been repeatedly cited as the strongest single piece of evidence for the existence of separate memory systems in humans. Can the SS model capture this pattern?

We fitted the SS, MS1, and MS2 models to the raw data from this study and observed several notable results. First and most importantly, the SS model had no particular difficulty reproducing the dissociation between recognition and priming. As shown in the top panel of Figure 6, the model predicted a large reduction in recognition between the CON and HIP groups but only a small group effect on priming, and the predicted values in both cases were close to the means actually obtained. How does the model manage to generate this dissociation? In the model, the overlap of the old and new item distributions is assumed to be greater for the hippocampal than for the control participants. This leads inevitably to a reduction in recognition d'. Recall, however, that the value of f sampled from the relevant old or new item distribution in the model is combined with a source of noise in the derivation of the identification RT (Equation 1). If this noise is sufficiently large, it effectively dilutes the impact of the reduction in the overlap of the old and new distributions, leading to a weak effect of the latter manipulation on priming. It is true that the model does predict an effect of hippocampal damage on priming, but the effect can be sufficiently small to be undetectable in any realistic experiment constrained by small numbers of items and participants. Consistent with this prediction, it has been argued that when carefully assessed, impairments in priming are evident in amnesia (e.g., Ostergaard, 1999; Ostergaard & Jernigan, 1996). But the key point is that varying a single parameter can lead to a dissociation between two measures of memory, thus invalidating the claim that dissociations require multiple systems.

Figure 6 reveals some other interesting patterns. As seen previously, control subjects showed priming for items judged new: the pattern RT(miss) < RT(correct rejection). The hippocampal individuals also showed this pattern, and in both cases this is a violation of the MS1 model: As shown in the bottom panel of the figure, that model predicts that the magnitude of priming overall will equal the magnitude of priming for items judged new. The figure also reveals that there was little convincing evidence in the HIP group of priming in the absence of recognition: Although recognition was lowered relative to controls and was not reliably greater than zero (note that the confidence interval in Figure 6 overlaps zero), all three participants had values of d'

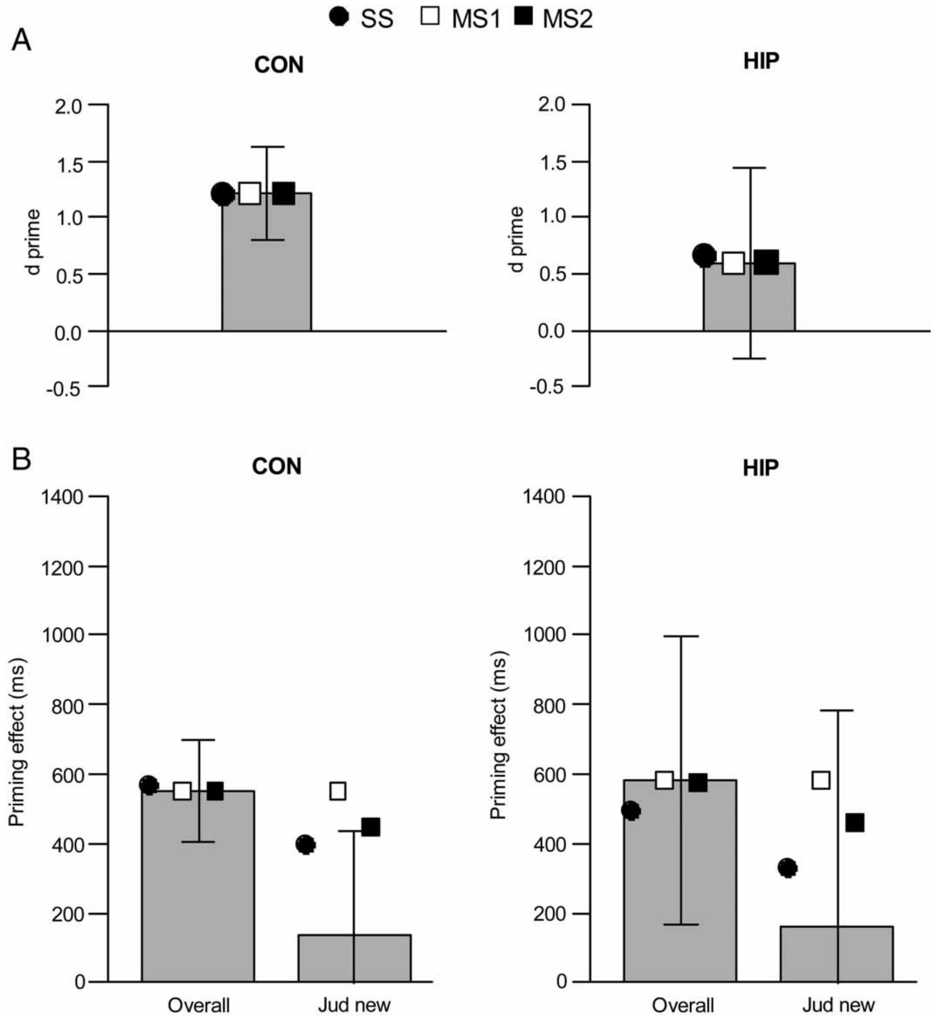

Figure 6. *Recognition performance (d′; Panel A) and overall priming versus priming for items judged new in Conroy et al. (2005), Experiment 2 (Panel B). Bars indicate experimental data. The error bars indicate 95% confidence intervals of the group mean. Symbols indicate the expected result from each model. SS = single-system model; MS1 = multiple-systems-1 model; MS2 = multiple-systems-2 model; CON = control group; HIP = focal hippocampal lesion group. Jud new = judged new.*

substantially greater than zero. A further pattern (not shown in the figure) was that fluency effects occurred for both groups, in particular for old items, RT(hit) < RT(miss). Again the MS1 model does not predict this effect, for the reasons discussed previously. In addition to this qualitative profile, the SS model was preferred to both other models (MS1 and MS2) by AIC for both the control and hippocampal groups.

This ability of the single-system model to fit data from individuals with amnesia is even more remarkable than its ability to fit data from memory-intact individuals. Dissociations between priming and recognition have been the touchstone of multiple-systems theories, and yet the results described above suggest that this pattern is better explained on the basis of a single underlying memory representation that is transformed into priming and recognition behaviour via processes that introduce additional nonmemorial noise. The added flexibility of models that include a second memory system leads either to qualitative mispredictions (in the case of the MS1 model) or to an increase in fit, which is insufficiently large to compensate for the added flexibility.

Recently we have explored the relationship between recognition and priming in another population that manifests memory impairment relative to healthy young controls—namely, older individuals. Although many previous studies (see Fleischman, 2007) have suggested that priming can be intact across the lifespan, we (Ward, Shanks, & Berry, 2012) have found that when priming is measured in a large sample (so as to ensure high statistical power) of individuals aged approximately 70 years, small but real decrements in perceptual priming are detectable, alongside the expected substantial decrements in recognition memory. Although it remains to be seen how well the different models fit these data, this pattern is qualitatively consistent with the predictions of the SS model and inconsistent with the MS1 model.

It is worth briefly mentioning CID-R data reported by Conroy et al. (2005) from two additional individuals with more extensive damage to the medial temporal lobes (MTL). The two patients were G.P. and E.P., whose performance across a range of memory assessments has been extensively studied. E.P. is particularly interesting as his explicit memory is more severely attenuated than for virtually any other reported individual. He poses a particular challenge to the SS model because he shows relatively normal priming but has repeatedly performed at chance in recognition tests. Therefore if any single participant is going to falsify the single-system theory, it should be E.P. When fitting a limited set of data from an individual participant, however, it is rare to be able to draw firm conclusions, and, as described more fully by Berry et al. (2012), this proved to be the case for G.P. and E.P. According to AIC, G.P.'s performance was best fit by the SS model whereas E.P.'s performance favoured the MS2 model. However, the MS2 model failed to capture some important qualitative aspects of E.P.'s behaviour. In fitting his data, the model assumed that μ_{old} and μ_{new} were identical for recognition memory—in other words, it assumed that he had absolutely no explicit memory and that the old and new distributions in the explicit system were completely overlapping. This assumption seems reasonable given that his recognition performance was indeed at chance. However, under such circumstances (and for the reasons discussed previously) the model is forced to predict that the magnitude of overall priming and of priming for items judged new should be identical, and this was not the case for E.P. In the data, the difference between these priming magnitudes was of the order of 200 ms, a numerically large effect that only the SS model predicts. It is thus difficult to draw firm conclusions regarding E.P.'s memory impairment—some aspects of his performance favour the MS2 model whereas others favour the SS model. Future studies of single cases, whether they have extreme memory impairments like E.P. or not, will need to ensure that larger datasets are collected as this is a prerequisite for discriminating between the models.

One final point to mention in relation to these findings concerns the possibility that they arise because of the concurrent nature of the measurement method in the CID-R task. Whenever explicit and implicit memory are measured in tandem, it is of course possible for them to influence or "contaminate" each other. For example, knowing that a recognition response will be required at the end of each trial might alter the participant's cognitive processing in the preceding identification part of the trial. Conversely, the nature of the identification process (such as whether it is fast or slow) might alter the subsequent recognition decision. Does the evidence we have described for the single-system view arise simply because the task in effect is forcing the two measures to converge in ways that they would not if measured independently?

Although answering this concern is complex, we believe that interactions between identification and recognition in the CID-R task are in fact remarkably weak. Bear in mind that Conroy et al. (2005) found precisely the same sort of dissociation between priming and recognition in amnesia that is typically found when they are measured separately. Moreover, Ward, Shanks, and Berry (2012) reported that there is no detectable impact on the derived measure of priming from informing participants prior to each CID-R test trial whether the upcoming stimulus is an old or new item. One might imagine that such an instruction would strongly encourage participants to employ explicit memory to help them identify old items—and that this would in turn yield faster responses for such items and hence greater priming—yet no evidence of this was obtained.

Testing the models: Neuroimaging evidence

One response to the behavioural, computational, and neuropsychological (i.e., lesion) findings described above is to turn to evidence from neuroimaging studies. And indeed, consistent with the multiple-systems view that implicit and explicit memory systems are neurally distinct (e.g., Gabrieli, 1998), priming and recognition are, in most cases, associated with different patterns of brain activity. By using functional magnetic resonance imaging (fMRI), for example, retrieval from explicit memory is frequently associated with haemodynamic response increases in prefrontal, parietal, and medial temporal regions (Fletcher & Henson, 2001; Kirwan, Wixted, & Squire, 2008; Kuhl, Rissman, & Wagner, 2012). In contrast, priming is commonly associated with haemodynamic response decreases in occipital, temporal, and prefrontal regions (Henson, 2003). This reduction in the haemodynamic response—a phenomenon referred to as repetition suppression —is thought to reflect increased processing efficiency, as also indexed by behavioural measures of priming. Event related potential (ERP) studies (e.g., Rugg & Curran, 2007) also provide some evidence that priming- and recognition-related activity at retrieval are associated with distinct time-courses and topographies (but see Paller, Voss, & Boehm, 2007). These neural differences also extend to the encoding phase: Subsequent priming and explicit memory are associated with distinct patterns of haemodynamic responses (Schott et al., 2006) and distinct electrophysiological responses (Schott, Richardson-Klavehn, Heinze, & Düzel, 2002) at encoding.

These types of findings might be considered problematic for single-system views. However, only a few of these imaging studies have directly contrasted the neural correlates of implicit and explicit memory within the same paradigm (i.e., matching the experimental conditions). Of those that have, some compared the neural correlates associated with the contrast of misses versus correct rejections during a recognition memory test, hypothesized to reflect implicit memory, with those associated with the contrast of hits versus misses, hypothesized to reflect explicit memory (Henson, Hornberger, & Rugg, 2005; Rugg et al., 1998). As discussed previously, however, miss responses are not necessarily a pure manifestation of implicit memory. Others have compared stimulus repetition effects across explicit or implicit memory tasks (e.g., Donaldson, Petersen, & Buckner, 2001). The most compelling studies have compared implicit and explicit memory tasks that differ only in the instruction given to participants (e.g., within the word-stem completion paradigm) and which measured priming and recognition on a trial-by-trial basis within each task (Schott et al., 2005; Schott et al., 2006).

However, even these studies may not be conclusive (see Dew & Cabeza, 2011, for a thorough review). Consider a recent experiment by Nosofsky, Little, and James (2012). These researchers contrasted perceptual categorization, widely argued to be an example of implicit or nondeclarative learning, and recognition. While fMRI confirmed that different brain systems were engaged by the two types of test, Nosofsky et al. noted that this pattern could reflect a single system operating in the two situations with different parameter settings. For example, participants might adopt a different criterion for a categorization compared to a recognition decision. By deliberately encouraging participants to adopt different parameter settings, Nosofsky et al. were able to demonstrate that brain activity varied with these settings and not with the task itself. Strikingly, while repetition suppression was found in the categorization task, and activity increases were found in a baseline recognition test, suppression was also found in a version of the recognition test in which participants were induced to adopt a lax decision criterion. Thus the contrast between activity increases in explicit tests and activity decreases in implicit tests was due not to the explicit/implicit contrast but to an uncontrolled difference in parameter settings.

Finally, it is worth mentioning that some have found commonalities in the neural correlates of the encoding processes leading to priming and recognition (Turk-Browne, Yi, & Chun, 2006). Future research will continue to illuminate the commonalities and potential differences in the neural processes underlying priming and recognition, but at present it would appear premature to take existing neuroimaging evidence as proving a compelling case for multiple systems.

Recollection, familiarity, and priming

The models we have discussed so far have assumed that classic signal detection theory provides an adequate account of explicit recognition memory. Although the models differ in the connection between the explicit and implicit systems, they all assume that recognition memory judgements are based on drawing a sample from the relevant normally distributed old or new strength representations and comparing this against a decision criterion. There are, however, many reasons to believe that such an account is at best a simplification and at worst incomplete.

Numerous studies have provided evidence that a second process, recollection, can contribute to recognition decisions. These "dual-process" accounts agree that the SDT view provides an accurate model of decisions based on unidimensional memory strength (that is, familiarity), but propose that this is only part of the story and that both recollection and familiarity can yield "old" recognition responses. Whereas SDT-based responses are accompanied by nothing more than a subjective sense of familiarity, recollection-based ones are evoked when the test item cues recollection of the study episode. In Yonelinas's (1994, 2002) model, for example, recognition responses are assumed to arise from a binary recollection process or from a familiarity-driven one when recollection fails.

Much recent work in recognition memory has sought to evaluate the evidence for this second process over and above the familiarity-driven SDT one. We do not review this extensive literature here, which has included both behavioural (e.g., Yonelinas & Parks, 2007) and neural (e.g., Vann et al., 2009) studies. Our particular interest is in exploring what predictions might be derived from the dual-systems model of recognition if it was extended to also make predictions about priming.

We have already noted that a possible connection between familiarity and priming has often been proposed (e.g., Jacoby & Dallas, 1981). Thus an obvious possibility is that the familiarity process within the dual-process model is the basis of priming. Hence two processes (familiarity and recollection) contribute to recognition memory, while one of those (familiarity) also determines priming. Put differently, this model starts from the SS model and supplements it with a recollection process for some recognition decisions. This model, which we call the "dual-process signal detection" (DPSD) model, is a multiple-systems model in that it incorporates an independent process that contributes to recognition but not to priming. However, because the familiarity process is common to both (as in the SS model), close correspondence between priming and recognition can also be expected. Although other ways of extending dual-process theory to priming can certainly be imagined, this is a simple initial way of doing so. How does this model fare when applied to CID-R data?

Berry et al. (2012) reported a number of results from fitting this model to their data, but here we describe just one of their findings (from Experiment 3). In this experiment, the CID-R task was modified such that after identifying each test item, with RT again being measured and forming the basis of an assessment of priming, participants made a slightly different type of recognition decision. Specifically, a remember/know task was employed. In this type of task, participants indicate whether they believe the item is old or new and, if old, whether they simply "know" that it was on the study list or instead "remember" seeing it. The instructions emphasized that recognition can bring back to mind something from the study trial (e.g., a thought), and in such cases a "remember" response is appropriate, whereas a "know" response should be used when nothing is brought back to mind. Under these conditions, the DPSD model makes a counterintuitive and testable prediction.

In the model (see Figure 3, Panel D), recollection is assumed to be a probabilistic response that occurs on some trials but not others. These trials are marked by the participant using the "remember" (R) response description. On all other trials, where the participant might call a test item "new" (N) or "know" (K), responses derive from the familiarity process. The model straightforwardly predicts that identification RTs will be faster for K than for N trials. Consider the situation where a test item is in fact old (i.e., a studied item). If the participant scores a hit and makes a K response, then on average that must be because the strength *f* of the item is higher than for those trials where they score a miss and call the item new. Since the familiarity process—just like in the SS model—determines identification RTs, it follows that RTs will be faster on average for K than for N trials (regardless of whether the item is in fact old or new). But what about R responses? Recognition decisions on these trials are not based on a high value of *f* but on the completely independent recollection process. Thus on average the strength of an item that evokes an R response will be simply the mean for items of that type: μ_{old} or μ_{new} depending on whether the item is old or new. This value will then, of course, determine the identification RT for that item. Hence it follows that whereas RTs on K trials will tend to be fast, those on R trials will not. Items evoke R responses not because they are highly familiar (which would lead to fast RTs) but because they are recollected, a process that is independent of familiarity. Berry et al. (2012) confirmed this prediction in formal applications of the DPSD1 model.

What happened in the experiment? The results were very clear in showing that RTs were faster on R than on K trials, not the other way round. Not only is this result incompatible with the DPSD model, but it also falls very easily out of the SS model (as well as the MS1 and MS2 models). Instead of assuming independent sources for "know" and "remember" responses, the SS model simply assumes that these gauge responses made at different response criteria. Whereas a "know" response is made when familiarity exceeds an intermediate threshold, a "remember" response is made when it exceeds a higher threshold. This follows numerous studies that have applied SDT to the remember/know paradigm (Dunn, 2004; Wixted, 2007). Thus extending the CID-R task to permit the collection of remember/know judgements, far from providing a further challenge to the SS model, in fact yields data that provide additional support for it.

Although the addition of a separate recollection process may not be required, it is undoubtedly the case that the SS model makes at least one unrealistic assumption, namely that the variances of the old and new strength distributions are equal. A range of findings from recognition memory experiments suggests that these variances are typically unequal. Berry et al. (2012) provided some evidence that the major differential predictions of the SS, MS1, and MS2 models are unaffected by setting the variance of old item strength greater than that of new item strength.

The causal relationship between fluency, recognition, and priming

In this section we return to a key issue touched upon earlier. In light of the extensive support we have obtained for the SS model, what does it tell us about the causal relationship between three key memory processes, fluency, recognition, and priming? Recall that a view on this question that posits a linkage between them has been frequently expressed in the past. Jacoby and Dallas (1981) speculated that fluency might be a cause of both recognition and priming. Fluency—referring to the subjective ease of processing an item and measured by RT—plainly causes priming if old items, in consequence of their prior exposure, are in fact processed more fluently on average than new ones. How could fluency cause recognition? A common idea is that the individual might attribute the experience of processing fluency to repetition and in effect "infer" that fluently processed items must have been studied (Johnston, Dark, & Jacoby, 1985). Thus fluency is assigned the key role in this theory, providing the basis both of priming (through the enhanced fluency of old items) and of recognition (via unconscious attribution of fluency to familiarity).

Past tests of this view, however, have tended to cast doubt on the linkage between fluency and recognition (see Wagner & Gabrieli, 1998). Although correlations between RT and recognition have been reported (Johnston et al., 1985), as well as influences on recognition from manipulations of fluency (Kinder et al., 2003; Whittlesea et al., 1990), these effects have not been sufficiently strong to support a causal link. For example, Poldrack and Logan (1997) found that variability in RTs was far too large to explain the levels of recognition discrimination they observed in their experiment. Conroy et al. (2005), while not disputing the existence of a connection between fluency and recognition, also concluded that fluency effects are far too small to explain observed levels of recognition and therefore assumed that recognition has an independent basis (i.e., declarative memory) unrelated to fluency. On this view, priming and fluency are both manifestations of nondeclarative memory, dissociable from declarative memory. To illustrate, Conroy et al. asked what level of recognition would be achieved in the best case scenario where each participant judged all items identified faster than their median RT as "old" and all items identified slower than the median RT as "new". For their control group, for instance, this calculation yielded a d' of 0.59, considerably below the empirically observed level (1.31).

The SS model suggests a very different possibility: Fluency, recognition, and priming are independent effects of a common underlying cause (f). This parsimonious account does not give fluency a causal role, makes no reference to attributional process by which fluent processing might induce recognition, and does not require the involvement of a separate system in recognition memory. But how can it be that fluency and recognition have a single, common, memorial basis, yet can be so weakly related? Strikingly, Berry et al. (2008) showed that the SS model predicts a value of $d' = 1.31$ for recognition performance by Conroy et al.'s (2005) control group described above (identical to the observed value), while at the same time predicting a value of $d' = 0.51$ for the level of recognition that would be expected if all items identified faster than the median were called "old", and all items identified slower than the median were called "new". This counterintuitive pattern arises because, in the model, fluency is not the basis of recognition. Instead, both are dependent on an underlying f distribution, which is combined with independent noise to generate the recognition and RT measures. The dependency between fluency and recognition is weak in the model because the noise added in the generation of RTs and hence fluency dilutes its correlation with recognition. By contrast, the amount of noise added to f to generate a recognition decision is relatively lower, and so the level of recognition accuracy can be high. Two noisy measures of an underlying variable will always be more weakly associated with each other than either is with the variable itself.

In sum, a model in which fluent processing (i.e., fast identification RTs) and recognition judgements arise from a single memory source provides a different—and, we argue, more compelling—perspective on the relationship between fluency, recognition, and priming.

The future for research on implicit and explicit memory

The work reviewed here represents the early stages of an effort to use computational models to inform our thinking about the different ways in which memories can manifest themselves. We have reported a number of results that provide a surprising degree of support for the idea that explicit and implicit memory might be driven by a single underlying memory representation, coded along a strength dimension (f). A model based on this idea explains large sets of recognition and priming data better than multiple-systems versions. When modern model-selection procedures such as the Akaike information criterion are used to compare models, the added flexibility of multiple-systems models turns out to be a greater cost than any benefit from improvement in fit. Moreover, a multiple-system model embodying Tulving's (Tulving & Schacter, 1990; Tulving et al., 1982) independence view makes a number of incorrect qualitative predictions, such as that priming overall and priming for items judged new will be equal in magnitude and that there will be no fluency effects within old and new items.

Particularly striking is the fact that the single-system model seems to provide a good account of the existing CID-R data from individuals with amnesia. The model accounts for the selective impairment in recognition compared to priming in such individuals by reference to a general reduction in memory fidelity in amnesia combined with the influence of independent sources of non-memorial noise in the translation of the common memory representation into behaviour: Priming is assumed to be a generally "noisier" way of measuring memory than recognition (Buchner & Wippich, 2000), and hence the reduction in memory fidelity becomes more diluted in priming than in recognition.

The MS2 model acknowledges the potential for correlated strength in memory signals, and an important question is whether the high observed correlation (effectively 1.0 according to the preferred SS model) derives from a single representation that drives both tests (the single-system model) or from two independent systems that are correlated because of the singular nature of encoding (the MS2 model with w close to 1.0). It may be that there truly are two anatomically and cognitively separable systems, but that their outputs correlate highly because of interitem variations in item properties, context, attention, neural state, and so on. Even though this model fares less well than the SS model in terms of model-selection criteria, it is of course not directly falsified by any of the results we have described here. Future work will need to consider this possibility, but it should be obvious that addressing it will require more subtle approaches than traditional dissociation methodology.

Whatever the eventual conclusions about the single-system approach, we believe that the use of computational models is an invaluable additional tool for helping to answer key questions about the fundamental nature of memory. Too often in experimental psychology and cognitive neuroscience, theoretical ideas are couched in quite vague terms, which render them hard to test. The value of our general framework (the MS2 model) and the models nested within it (the SS and MS1 models) is that theoretical ideas can be made concrete while all other processes are held constant, and the precise qualitative and quantitative implications of these assumptions can be assessed. The findings reported here also make it abundantly clear that as soon as a model acquires even a modest degree of complexity, it becomes a considerable challenge to forecast what its predictions will be about a specific experimental situation or manipulation.

In addition to further application to CID-R data from normal individuals, where else can the framework be applied? It will be important, plainly, to evaluate how robust the present conclusions are across different ways of testing recognition and priming, and indeed across different types of explicit and implicit memory tests, and using different materials such as pictures of objects (Ward, Shanks, & Berry, 2012). We have alluded to the importance of collecting larger datasets from individual participants (e.g., amnesics) so as to increase the likelihood of being able to discriminate the models. We ourselves are collecting data from older individuals and applying the models to these datasets. It is well known that explicit memory tends to deteriorate with age while implicit memory can remain constant or near-constant. This pattern, similar to that observed in amnesia, therefore provides a strong additional challenge to single-system models. Other work in our laboratory is employing 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 judgement. The different models make different predictions about the relationship between the identification RTs and the recognition judgement. For example, because the SS model assumes that greater values of *f* will lead to faster identification RTs and also to a greater likelihood of an old judgement, it predicts that the item judged old on a 2AFC trial will also tend to have the shorter identification RT. In the MS1 model, after an item's identification RT has been calculated, another value of *f* is sampled to determine recognition. It hence 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. Another important extension is to adapt the general framework to deal with source memory as well as item memory.

Of considerable interest is the potential use of the modelling framework described here to interpret neuroimaging data (e.g., fMRI). Imagine that a set of CID-R data is acquired whilst neural activation is measured at test. By fitting the SS model to the behavioural data, an estimate can be made of the value of *f* sampled on each test trial. One testable prediction that is consistent with the SS model is that there might be a brain region whose activity correlates with *f* and which therefore fulfils the role of the common memory source driving both priming and recognition. Future work will profitably explore this and numerous other implications of the application of computational models to the study of implicit and explicit memory.

Original manuscript received 29 March 2012
Accepted revision received 1 May 2012
First published online 18 July 2012

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