A retrieved context model of serial recall and free recall

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Abstract

A full characterization of memory must include how participants use exogenous and endogenous cues to guide retrieval. In free recall, in which endogenous cues play a large role, retrieved context theories have emerged as a leading explanation of data on the dynamics of memory search (Lohnas & Healey, 2021). More recently, Logan and colleagues have advanced a retrieved context model to explain data on serial recall and motor production (Logan, 2018, 2021; Logan & Cox, 2021, 2023). Comparisons of recall transitions have further highlighted similarities among these tasks (e.g., Bhatarah, Ward, & Tan, 2008; Golomb, Peelle, Addis, Kahana, & Wingfield, 2008). Here I evaluate retrieved context theory's ability to simultaneously account for data from these classic recall procedures. I show how a serial version of the context maintenance and retrieval model (termed sCMR) can account for dissociations between serial position curves and temporal clustering effects. I also show how sCMR can account for grouping effects in serial recall, extending the assumptions of grouping from free recall (Lohnas, Healey, & Davachi, 2023). The sCMR model provides a common theoretical framework to harmonize the disparate phenomena studied using these classic memory procedures, but also reveals the distinctions between serial and free recall through their relative dependence on different model-based mechanisms.

Keywords: episodic memory; free recall; modeling; retrieved context; serial recall

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1 Introduction

It is well-established that memory performance varies with the type of retrieval cues provided at test (e.g., Greene, 1989; Tulving, 1985; Tulving & Pearlstone, 1966). However, in more open-ended recall tasks, it remains debated how participants use internally-generated cues to retrieve information from memory. In recent decades, dozens of studies have attempted to resolve this debate with analyses in two classic recall paradigms: free recall and serial recall. In both tasks, participants study a sequence of individually presented items. In free recall, participants attempt to recall the items in the order they come to mind whereas in serial recall participants attempt to recall the items in their presentation order. Each task gives rise to a characteristic serial position effect, with free recall exhibiting marked advantages in recall of recently studied items (the recency effect) and a smaller benefit for early list items (the primacy effect). Serial recall exhibits both effects as well, but has a much larger primacy effect than free recall and a small recency effect, often affecting only the last one or two items.

Based on these and other dissociations, distinct classes of theories have emerged to explain data from these two paradigms. Recent theories of free recall have emphasized the importance of contextual coding of memories as well as their semantic organization (Howard & Kahana, 2002a; Lohnas, Polyn, & Kahana, 2015; Polyn, Norman, & Kahana, 2009; Sederberg, Howard, & Kahana, 2008). In contrast, theories of serial recall have emphasized positional coding, chunking and the importance of tagging the beginning of the list to facilitate recall initiation (Brown, Preece, & Hulme, 2000; Burgess & Hitch, 2006; Farrell, 2012; Henson, Norris, Page, & Baddeley, 1996; Ladd & Woodworth, 1911; Lewandowsky & Farrell, 2008; Page & Norris, 1998). Although the development of these parallel theories proceeded for several decades, recent evidence suggests that the tasks exhibit some striking similarities, particularly in the manner in which participants transition among items (Bhatarah, Ward, & Tan, 2006; Bhatarah et al., 2008; Bhatarah, Ward, & Tan, 2009; Golomb et al., 2008; Grenfell-Essam & Ward, 2012; Grenfell-Essam, Ward, & Tan, 2017; Spurgeon, Ward, & Matthews, 2014; Ward, Tan, & Grenfell-Essam, 2010). These findings pave the way for a theoretical harmonization of the two procedures.

As one notable recent example, Farrell developed a chunking model to explain data from both free and serial recall, emphasizing that participants endogenously group each list into smaller groups (Farrell, 2012; Spurgeon, Ward, Matthews, & Farrell, 2015). According to this model, recall begins by cuing the context of a group, and then the model attempts to recall items from that group in order using within-group positional codes. In brief, recall of a group begins with the item associated with position 1 within that group, then the item associated with position 2, and so forth. This approach is similar to other serial recall models which use explicit positional codes to cue retrieval, but across all serial positions rather than within a group (e.g., Brown et al., 2000; Burgess & Hitch, 1999; Henson, 1998).

The model of Farrell (2012) generalizes the use of groups and positional codes to both serial and free recall, and mainly differs between paradigms with using the final group cue to initialize immediate free recall but not serial recall. This model can account for recall initialization, recall transitions, recall accuracy, and recall errors across a variety of standard recall manipulations.

The current set of studies present an alternative model approach, showing how retrieved context theory can account for several major phenomena across the two paradigms. According to this theory, each studied item is associated with a temporal context state, and temporal context changes slowly with each studied item. Temporal context also serves as the retrieval cue during recall. The present model builds upon recent studies by Logan which show how principles of retrieved context theory offer a parsimonious account of several key features of data obtained in serial recall tasks (Logan, 2018, 2021; Logan & Cox, 2021, 2023, see also Osth & Hurlstone, 2023). Logan's Context Retrieval and Updating (CRU) model extends principles of retrieved context theory from free recall (Howard & Kahana, 2002a; Polyn et al., 2009; Sederberg et al., 2008) such as the context maintenance and retrieval (CMR) model. Yet a unified retrieved context model across serial recall and free recall remains undeveloped.

Importantly, although CRU makes accurate predictions in serial recall and CMR makes accurate predictions in free recall, these predictions have thus far been conducted more flexibly, with different models and some differing assumptions between paradigms. It may be that a model constricted to generally the same assumptions and parameters across tasks would be unable to account for findings from both tasks. In addition, to account for findings from serial recall, whole report and copy typing, CRU uses retrieval cues differently than retrieved context models of free recall. Thus, a more unified model approach helps to address the similarities and differences across tasks, especially with respect to the use of temporal context representations which have found to be more critical in free recall than serial recall.

1.1 Summary of Simulations

Here I evaluate predictions of the context maintenance and retrieval model generalized to serial recall (sCMR) in its ability to account for several key findings emerging from analyses of free and serial recall. In Simulation 1 I consider how sCMR can account for recall simultaneously in free recall and serial recall. I examine classic findings of recall probability and recall transitions in both paradigms, using a study in which the same set of participants performed one session of each recall task. To foreshadow the results, sCMR makes accurate predictions for most participants, and the distributions of model parameters across participants provide further insights into model mechanisms which vary across tasks.

In Simulation 2 I evaluate sCMR's ability to capture recall transitions which have been argued as evidence against core assumptions included in retrieved context models (Farrell, Hurlstone, & Lewandowsky, 2013; Henson, 1996; Osth & Dennis, 2015a). Considerable prior research on free recall has highlighted the critical role that previously recalled items play in cuing subsequent responses (see Lohnas, in press, for a review). These studies have demonstrated that participants tend to transition between items studies in neighboring serial positions (henceforth, the *contiguity effect*; Healey, Long, & Kahana, 2019; Kahana, 1996), and these transitions have a forward bias. Serial recall exhibits a similar pattern: following an omission, participants tend to make transitions to the prior or subsequent item, known as fill-in and in-fill errors, respectively (Farrell et al., 2013; Henson, 1996; Logan, 2021; Osth & Dennis, 2015a; Page & Norris, 1998; Solway, Murdock, & Kahana, 2012). The nature of these transitions has recently emerged as a touchstone, distinguishing predictions of several models.

Positional code models predict that fill-in is more common than in-fill (Farrell, 2012; Henson, 1998; Henson et al., 1996; Page & Norris, 1998). When such model is attempting to recall the nth item, broadly speaking the model assumes that early list items benefit from greater strength, so if the correct (nth) item is unavailable for recall, then the next most likely item to be recalled will be from an earlier list position (e.g., $n-1$). By contrast, retrieved context models more naturally predict in-fill. These models assume that recall of an item also updates context with information from that item. The updated context state promotes recall of items whose associated contexts include the just-recalled item, but items studied prior to the just-recalled item do not have that item in their context. Thus, items studied after the just-recalled item are more likely to be recalled next. For decades the fill-in effect has assumed to be evidence against models without positional codes such as retrieved context models.

However, Logan and Cox (2023) showed that CRU can predict the fill-in effect by assuming that recalling an error evokes retrieval of a start-of-list context. This promotes recall of items studied earlier in the list, including items studied before the just-recalled item. They noted however that this fit served as a qualitative proof of concept for retrieved context models and requires further characterization. Simulation 2 aims to use retrieved context models with more parsimonious principles from free recall, which generally do not use list context, to account for the fill-in effect.

Simulation 3 evaluates sCMR predictions of segmenting or chunking longer lists of serial recall into shorter groups. The presence of grouping has been a longstanding interest in serial recall (e.g., Farrell & Lewandowsky, 2004; Henson, 1999; Madigan, 1980; Maybery, Parmentier, & Jones, 2002; Ryan, 1969; Wickelgren, 1967). Recently there has been increasing interest at the intersection of segmenting continuous experience into meaningful events and the implications for episodic memory (for recent reviews, see Clewett, DuBrow, & Davachi, 2019; Radvansky & Zacks, 2017). In particular, grouping is posited to support within-group associations at the cost of across-group associations (e.g., Farrell, 2012; Heusser, Ezzyat, Shiff, & Davachi, 2018; Lohnas et al., 2023; Radvansky & Copeland, 2006; Swallow, Zacks, & Abrams, 2009; Zwaan, 1996). Here I will assess whether principles from CMR, which can account for grouping in free recall (Lohnas et al., 2023; Polyn et al., 2009), can generalize to grouping effects in serial recall. This account uses a single temporal context representation for the entire list, in contrast to requiring a hierarchical or positional structure (e.g., Farrell, 2012). More broadly as well, the success of this set of simulations provides a quantitative application of assessing the role of temporal context representations in serial recall and free recall.

2 Overview of sCMR: Context maintenance and retrieval model of episodic recall

This section reviews principles of the retrieved context model framework, most generally applied to free recall, and the minimal changes required to simulate serial recall. Retrieved context models in other paradigms also preserve these principles including final free recall (Howard, Youker, & Venkatadass, 2008), item recognition (Healey & Kahana, 2016; Rouhani, Norman, Niv, & Bornstein, 2020) and cued recall (Howard, Jing, Rao, Provyn, & Datey, 2009; Zhou, Singh, Tandoc, & Schapiro, 2023, see also Osth & Fox, 2019). Keeping the changes as minimal as possible serves to demonstrate the generalization of this class of models, and also reveals the critical differences in model mechanisms across paradigms.

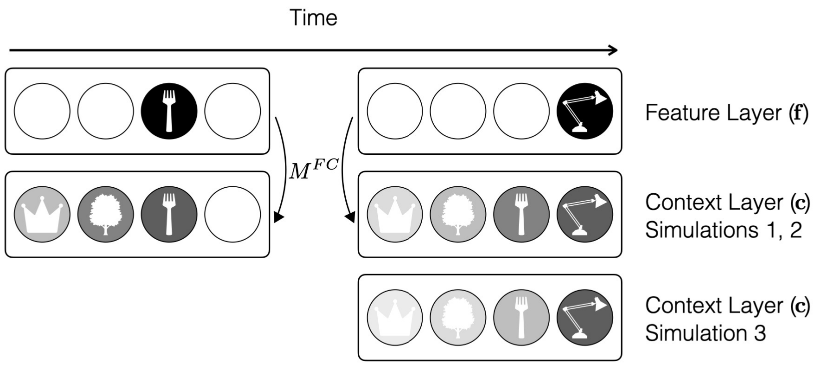

Fig. 1 Encoding for the serial recall version of the context maintenance and retrieval model (sCMR). Each rounded rectangle represents a layer, actualized as a vector. Each circle within the rectangle represents an element of the vector. The background color of the elements, from black to white, correspond to values ranging from one to zero, respectively. Left: FORK was presented to the model most recently. Thus in the feature layer, **f**, the element corresponding to the word FORK is set to one, and all other elements are zero. This feature layer updates the context layer, **c**, through the association matrix $\mathbf{M}^{FC}$. In the context layer, the element associated with FORK has the greatest strength, indicated by the darkest shading of this element. However, previously presented words (CROWN, TREE) also have nonzero strengths for their elements. As context updates, it downweighs prior context states, such that the context elements are a recency-weighted sum of previously presented items (i.e., the darkness of the elements is monotonically increasing with recently presented items). Right: The word LAMP is next presented to the model after FORK. Similar to the presentation of FORK, in **f** the feature element for the currently studied item is set to one and all other elements are zero. Also similar to the presentation of FORK, the context layer **c** is a recency-weighted sum of previously studied items. In Simulation 3 only, an additional temporal disruption item is presented between FORK and LAMP to indicate the start of a new group with LAMP. As a result, the first three items are weighed more weakly in context (i.e., have lighter shading) than in Simulations 1 and 2. See text for further details

2.1 Principles of the context maintenance and retrieval model

Figure 1 shows the basic structure of the model, which includes representations of items, contexts, and associations between them. Items are represented by the distribution of activation across elements (nodes) of a feature vector (layer), $\mathbf{f}$. Each item is represented with a localist representation, using a vector of unit length with a single non-zero element. Each item has an associated context layer, represented by the distribution of activation across elements of a context vector $\mathbf{c}$. These two vectors influence each other via associative matrices $\mathbf{M}^{FC}$ and $\mathbf{M}^{CF}$. The superscripts of these matrices indicate the direction of associations, e.g., $\mathbf{M}^{FC}$ stores the strengths of associations from items to contexts. Each of these matrices is a weighted sum of a pre-experimental component and an experimental component. The pre-experimental component is fixed based on memories formed before the simulated experiment, and the experimental component is updated during the simulated experiment. Model parameters γ_{FC}, γ_{CF} scale the relative amount of experimental and pre-experimental contributions to the respective matrices $\mathbf{M}^{FC}, \mathbf{M}^{CF}$.

Fig.1 shows the state of $\mathbf{f}$ and $\mathbf{c}$ after studying the third and fourth items in a sample list (FORK, LAMP). The associated item element is set to one in $\mathbf{f}$, represented by the dark shading of that element only. The item then creates an input to context, $\mathbf{c}^{\mathbf{IN}}$ via the item-to-context association matrix $\mathbf{M}^{FC}$. For an item i, this input updates context according to the equation:

$$\mathbf{c}_i = \rho_i \mathbf{c}_{i-1} + \beta \mathbf{c}_i^{\mathbf{IN}}. \tag{1}$$

As each item updates context with Equation 1, context becomes a recency-weighted sum of presented items. The context states in Fig.1 also reflect this property, with the increasingly dark shading for increasingly recent items. The model parameter β controls how much each studied item updates context, such that larger values of β cause context states to change more with each context input. During encoding, context updates with the free parameter β_{enc} for each studied item.

Each presented item is also associated with the previous state of context using a Hebbian learning rule, which updates the experimental components of each association matrix:

$$(\Delta \mathbf{M}_{exp}^{CF})^\top = \Delta \mathbf{M}_{exp}^{FC} = \mathbf{c}_{i-1} \mathbf{f}_i^\top \tag{2}$$

In this way, sCMR associates an item with the temporal context in which it occurs. The associations in $\mathbf{M}^{CF}$ are further scaled by a strength parameter which decreases with serial position, consistent with the notion that early list items benefit from increased encoding efficiency (Lohnas, Davachi, & Kahana, 2020; Serruya, Sederberg, & Kahana, 2014; Tulving & Rosenbaum, 2006). Specifically, the item in serial position i updates $\mathbf{M}_{exp}^{CF}$ according to:

$$\phi_s e^{-\phi_d (i-1)} + 1, \tag{3}$$

where ϕ_s scales the extra weight and ϕ_d scales the rate at which this advantage decays with serial position i.

In free recall, the $\mathbf{M}^{CF}$ matrix also encodes pre-experimental semantic associations among items, based on the hypothesis that similar items appear often in the same temporal contexts during one's lifetime (Rao & Howard, 2008). The model parameter s

scales the relative contribution of semantic versus experimental (episodic) associations to $\mathbf{M}^{CF}$.

Once all items in a list have been presented, the recall period begins but how recall proceeds depends on the task. In free recall, the current state of context is used to cue recall of the first item. This context state assigns an activation for each item according to its associative strength to the current state of context:

$$\mathbf{a} = \mathbf{M}^{CF}\mathbf{c}_i. \tag{4}$$

where $\mathbf{a}$ is a vector with each element corresponding the activation of a studied item associated with the current context $\mathbf{c}_i$. These activations are used as input to a Luce choice decision rule (Luce, 1963). By this rule, the probability that each item is recalled is related to its activation strength:

$$P(retrieve, i) = \frac{\mathbf{a}_i^{\tau}}{\sum_k^l \mathbf{a}_k^{\tau}} \tag{5}$$

where τ is a model parameter. Greater values of τ more greatly increase larger values and decrease smaller values, thus increasing recall probability for items with greater activations, or associations to the current context.

At each output position, the model may recall an item or may stop attempting recall for the list. The probability of stopping increases with output position j according to:

$$P(stop, j) = \theta_s e^{j\theta_r} \tag{6}$$

Thus, altogether, the probability of retrieving item i at output position j is

$$P(i, j) = P(retrieve, i)(1 - P(stop, j)). \tag{7}$$

If the stop response is selected, then the recall period ends for the current list. The model's memory is reset and then presentation of the next list begins. If an item is recalled, it updates context using Equation 1 with the free parameter β_{rec}. This updated context then leads to a new set of activations $\mathbf{a}$, and the model attempts to recall another item. However, once an item is recalled, it cannot be recalled during the current study period. Although other retrieved context models invoke more realistic mechanisms for response suppression and response times (e.g., Lohnas et al., 2015; Sederberg et al., 2008), the simplifying assumption of sCMR keeps the focus on the model's predictions of correct recalls and order errors rather than on incorrect repetitions or response suppression.

2.2 Model modifications to simulate serial recall

The model architecture and parameter values were identical across simulations of free recall and serial recall, with two exceptions described below.

2.2.1 Recall Initiation

In serial recall, participants are instructed to initiate recall with the first presented list item, and recall accuracy for this first item is relatively high. In many models of serial recall, it is assumed that participants can access the first item or its associated cue with high accuracy, due to greater attention, distinctiveness and/or novelty experienced at the start of the list (e.g., Anderson & Matessa, 1997; Brown et al., 2000; Burgess & Hitch, 1992; Farrell, 2012; Henson, 1998; Lewandowsky & Farrell, 2008; Lewandowsky & Murdock, 1989; Page & Norris, 1998).

Rather than attempt to simulate an additional attentional or retrieval process, sCMR initiates recall based on the empirical results from the data it is simulating. For Simulations 1 and 2, these probabilities were based on the normalized distribution of probability of first recall.[1] For Simulation 3, in which only the serial position curve was available, the probability of recalling an item at the remaining serial positions was set to a uniform value across the other serial positions such that overall recall probability of initiating with a correct list item summed to one. Following recall of the first item in serial recall, retrieval of the recalled item's context, as well as recall of subsequent items and recall termination, were identical to free recall.

2.2.2 Parameters controlling pre-experimental to experimental item-context associations.

The distinguishing difference between serial recall and free recall, the requirement to recall items in their studied order, led to two differences in model parameters between serial recall and free recall. First, whereas in free recall a just-recalled item tends to cue recall of subsequently presented items, in serial recall an item should cue only the immediately subsequent item. Thus, the parameter controlling this cuing based on experimentally formed associations (γ_{FC}) varied between free recall and serial recall. Second, whereas in free recall participants tend to successively recall items with shared semantic information (e.g., Cofer, Bruce, & Reicher, 1966; Healey et al., 2019; Howard & Kahana, 2002b; Pollio, Richards, & Lucas, 1969; Polyn et al., 2009), in serial recall such semantic information does not benefit recalling items in serial order. Thus, the serial recall variant assumes that semantic associations do not contribute to memory retrieval processes (i.e., the parameter weighing the relative contribution of semantic to episodic associations, s, is set to zero).

2.3 Parameter-fitting technique

A genetic algorithm determined each best-fitting parameter set. This algorithm search minimized the sum of squared errors between sCMR predictions and experimental data, including all data plotted in the main text, except recall probability of the first item in serial recall because the variance of this datapoint did not rely on model parameters. In addition, to capture the qualitative pattern of the fill-in effect for Simulation 2, the search also included the difference in the conditional response probabilities following the first order at $lag = +1$ and $lag =$ -1.

[1] Currently sCMR can only recall items studied in the list, but if a participant begins with an error then the probabilities across all valid serial positions will not sum to one. Thus, in the probability of first recall functions provided to sCMR, recall of all serial positions aside from the first item were normalized so that the values at all serial positions summed to one. Recall of the first item, the most likely possibility, was consistent with the value in the behavioral data and the normalization was applied to remaining serial positions. This also prevented sCMR from (the rare empirical occurrence of) recalling an intrusion or not recalling an item at all in the first serial position.

The algorithm first randomly selected a set of 10000 values for each parameter, drawn from uniform distributions, for an initial generation of 10000 parameter sets. Next, 20 generations of 1000 parameter sets were calculated, where the top 20% of all parameter sets from the previous generation were used as parents for the next generation, with a mutation rate of 10% of each parameter range. From these 20000 parameter sets, the 100 parameter sets with the smallest sum of squared errors were rerun for ten sets of the experimental data. From these 100 parameter sets, the parameter set with the smallest fitness value was deemed the best-fit parameter set.

As described in more detail below, for Simulation 1 the algorithm determined a parameter set for each participant, and for the other simulations the algorithm determined a single parameter to capture the mean performance across participants. Because in Simulation 1 each the dataset forming the basis of the search was from a single participant, all simulations except the final 100 were rerun for three sets of the data. For Simulations 1 and 2, each parameter set was evaluated once with the dataset.

3 Simulation 1: Shared temporal dynamics between serial recall and free recall

This first simulation aims to present a retrieved context account of serial recall with minimal changes from free recall. To date retrieved context theory has been tested separately in free recall or in serial recall, but both tasks have not been examined using a single, constrained model framework. This leaves open the possibility that retrieved context models may require more fundamental changes to mechanisms or parameters between tasks. Such a possibility would preclude a parsimonious theory of episodic memory within the retrieved context framework, and would challenge how retrieve context models can account for the demonstrated consistencies between serial and free recall, even when the recall task is postcued (e.g., Bhatarah et al., 2008; Grenfell-Essam & Ward, 2012; Ward et al., 2010). If the model can account for findings from both tasks successfully, this would serve as more than a sum of its parts. The model would not only explain findings from each task, but also elucidate the minimal set of model mechanisms which change between tasks.

3.1 Method

I assess whether sCMR, which embeds the CMR retrieved context model of free recall, can predict the salient features of serial recall using a dataset of younger adults from Golomb et al. (2008), available from http://memory.psych.upenn.edu/Data_Archive#2008. In this study, each participant performed one session of free recall and one session of serial recall. Aside from the instruction of recall order, all other aspects of the study were identical between sessions.[2] In brief, in both sessions lists consisted of 10 words were presented visually on a computer screen for 1 s, and participants said the words aloud as they were presented. Across lists, words were drawn randomly without

[2]From the original study of 36 participants, I excluded five participants who performed free recall in their serial recall session—beginning recall with the first item for less than 25% of trials—and excluded one participant who performed serial recall in the free recall session, as that participant initiated recall with the first two list items for over 50% of trials. This more conservative criterion was meant to ensure that a failure of sCMR to capture serial or free recall data was not simply due to qualitatively atypical recall patterns.

replacement and lists were presented in blocks with varying interstimulus intervals of 800 ms, 1200 ms and 2400 ms. After the final list item, viewing three asterisks and hearing a tone indicated that participants had up to 60 s for verbal recall. However, participants could end the recall period sooner with a keypress.

A genetic algorithm determined a set of best-fit parameters each participant (see previous section). Nine parameters varied with the algorithm but remained constant between the two recall tasks. Two additional free parameters varied between tasks. Both of these variable parameters control the relative influence of pre-experimental to experimental item-context associations (s; γ_{FC}; see Table 1). The γ_{FC} parameter varied freely within a predetermined range for each recall task. The s parameter also varied freely for free recall simulations, but was set to zero for serial recall simulations (see *Model modifications to simulate serial recall*). For the free recall simulations, semantic similarity values were determined using Latent Semantic Analysis (Landauer & Dumais, 1997).

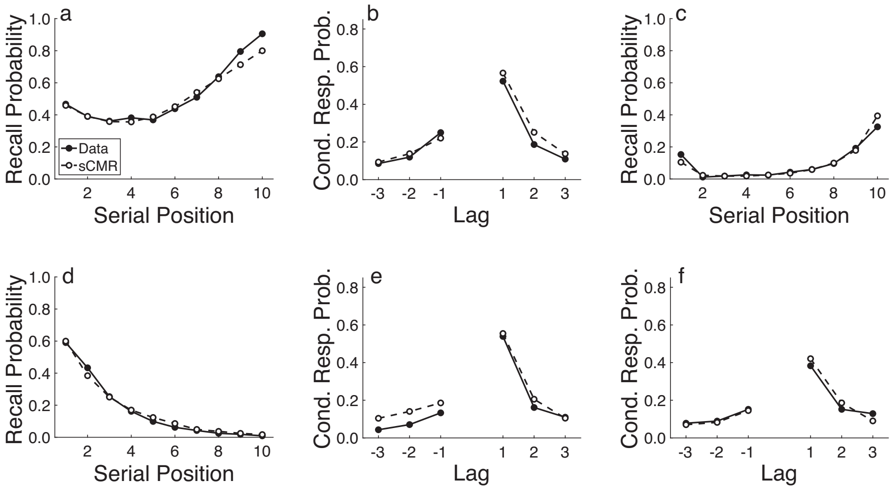

Fig. 2 sCMR predictions and experimental data of primacy, recency and contiguity in free and serial recall. sCMR predicts accurately the plotted recall analyses. Top Row: Free Recall. Bottom Row: Serial Recall. **a,d** Serial position curves. **b,e** Conditional response probability as a function of lag. **c** Probability of first recall. **f** Conditional response probability as a function of lag following the first order error. Data are from Golomb et al. (2008)

3.2 Results

3.2.1 Free recall

By starting with sCMR predictions of critical free recall phenomena, this provides an intuition of retrieved context models in their primary paradigm while ensuring that a simultaneous fit to serial recall does impair model predictions. Fig. 2 presents sCMR predictions and empirical data averaged across participants (the appendix provides individual participant fits). Fig. 2c shows that sCMR predicts participants' tendency to initiate recall with the most recently presented items. In sCMR, the end-of-list context used to cue recall of the first item is a recency-weighted sum of presented items, and thus more recently presented items dominate the retrieval cue (see Fig. 1). The stronger representation of recency items in the context cue also leads to sCMR's prediction that recency items are more likely to be recalled across output positions (Fig. 2a). In free recall, the tendency to recall early list items, or the primacy effect, mainly reflects the increased context-item associations of early list items.

sCMR also predicts the temporal contiguity effect, a salient feature of free recall (Healey et al., 2019; Kahana, 1996). This is shown in Fig. 2b, which plots the probability of recalling an item from serial position i+lag immediately following recall of item i, conditional on the availability of item i+lag as a valid recall (lag-CRP; Kahana, 1996). sCMR naturally predicts the temporal contiguity effect because recall of an item leads to retrieval of its context, and this retrieved context is incorporated into the context used to cue recall of the next item. This updated cue promotes recall of items with shared temporal contexts of the just-recalled item. sCMR predicts the asymmetry effect, or the increased probability of forward over backward transitions (Kahana, 1996), because an item's pre-experimental context is incorporated into temporal context only after the item is presented. Consequently, a presented item has a more similar contextual representation to items presented after its own presentation. Taken together, sCMR accounts for classic recall dynamics in free recall.

3.2.2 Serial recall

Because sCMR assumes high accuracy for recalling the first list item, this promotes recall of items with similar temporal contexts also presented at the beginning of the list, and thus discourages recall of recency items. Along with the primacy gradient, these mechanisms allow for sCMR to account for the primacy effect in the serial position curve (Fig. 2d). When recall begins with an early list item, this promotes recall of items with similar temporal contexts, thus encouraging recall of other early list items and discouraging recall of recency items. As recall continues and context updates from early list items, context serves as a weaker cue for recency items. This contributes to reduced recall accuracy across output positions. Further contribution to this finding, with each output position it is increasingly likely that the model will recall an incorrect item due to the noisiness of the retrieval process. This noise is independent across output positions but increasing the number of noisy recalls increases the probability that at least one recall will be incorrect. As a final contributing factor to reduced recency in serial recall, the probability that the model stops recall increases with output position (see Equation 6).

In the experimental data, the serial recall instruction leads to greater asymmetry in the lag-CRP than in free recall (Fig. 2e), which primarily reflects a reduction in $lag = -1$ transitions from free recall to serial recall reduced asymmetry (Ward et al., 2010, $M = 0.250$ versus $M = 0.133, SEM = 0.0200, t(29) = 5.83, p < .0001$). In sCMR, differences between tasks reflect the difference in parameters controlling the relative strength of pre-experimental to experimental item-to-context associations including γ_{FC}. This strength contributes to the role of temporal context in retrieval cues. When an item is recalled, its temporal context contributes to the next retrieval cue, and stronger experimental item-to-context associations cause more of an item's recent temporal context to contribute to the recall cue. This in turn promotes recall of other items represented more strongly in the just-recalled item's temporal context. However, in serial recall, it is not as beneficial to have items studied *before* the just-recalled item in the retrieval cue, because subsequent recalls should be from items studied *after* the just-recalled item. In contrast, in free recall, items studied before the just-recalled item can be correct recalls. Thus, the intuition is that sCMR downweighs the item-to-context associations in serial recall. Examining the distribution of γ_{FC} values across participants, the mean is numerically but not statistically lower for serial recall than free recall (γ_{FC} vs γ_{FC}^{fr}, respectively, in Table 1; $p > .3$). However, across participants there is a significant correlation between the reductions in $lag\ = -1$ transitions and γ_{FC} values ($r = .81, p < .0001$). This suggests that the γ_{FC} parameter contributes to the change in temporal transitions across tasks even if the reduction in the parameter value is less reliable than the reduction in $lag\ = -1$ transitions.

Differences in the s parameter also contribute to changes to temporal transitions in serial recall. In serial recall s was set to zero, but in free recall the distribution of s values was set on an open interval containing zero, thus leading to significantly positive values ($M = 1.31, SEM = 0.136, t(29) = 9.64, p < .0001$). Whereas the shared temporal context between studied items promotes successive recall of temporal neighbors, the shared semantic context between items can help to support recall of items with stronger semantic associations at all lags. Thus, an increase in s should increase reliance on semantic associations generally in conflict with temporal associations and the temporal contiguity effect. In each recall paradigm, I quantified each participant's temporal contiguity effect with a temporal clustering score (Polyn et al., 2009). Across participants, the reduction in temporal clustering scores from serial recall to free recall correlated with their best-fit s parameters in free recall ($r = .63, p = .0002$), thus indicating the contribution of the s parameter to reducing the use of temporal associations.

The lag-CRP in Fig. 2 plots transitions to all items, and in serial recall correct $lag = +1$ transitions dominate this function. The debate among theories of recall has centered around errors in recall transitions when the transition is an error and thus not $lag = +1$. Because items following an error may be clouded by the original error, recently the convention is to calculate the lag-CRP from the first error on a list to another list item (Osth & Dennis, 2015a; Solway et al., 2012). Fig. 2f plots this function, assuming that the preceding recalls are correct items and both the error and the following recall are neither repeats nor intrusions. In this study, participants exhibited an in-fill effect, with transitions more likely to $lag = +1$ than to $lag = -1$ ($M = 0.383$ versus $0.152, SEM = 0.0445, t(29) = 5.20, p < .0001$). sCMR captures this effect for the same reason that it captures the forward asymmetry in the lag-CRP, because recall of an error still retrieves its context. Thus, items studied after the recalled error contain that item within their own context. This overlap in context states promotes recall of items studied after the error item.

Taken together, sCMR can account for benchmark analyses of serial position effects and transitions in serial recall in the present dataset. However, the in-fill effect is not always present in experimental data. Rather, sometimes participants demonstrate the fill-in effect, recalling the items prior to a recall error (Farrell et al., 2013; Henson, 1996; Logan, 2021; Osth & Dennis, 2015a). This effect has posed a challenge for retrieved context models such as sCMR, which traditionally in free recall predict a strong forward asymmetry. In the next simulation, we examine sCMR predictions of the fill-in effect.

4 Simulation 2: A retrieved context account of the fill-in effect

A special type of recall error has served as a defining distinction between serial recall theories. Specifically, when a participant mistakenly recalls an item too early (e.g., recalls item $i + 1$ at output position i), theories are divided whether the participant next fills in with an earlier item such as i or in-fills with a later item such as $i + 2$. Adding fuel to the theoretical debate, some serial recall studies exhibit the in-fill effect (e.g., Dougherty, Halpern, & Kahana, 2023; Golomb et al., 2008; Solway et al., 2012) and some studies exhibit the fill-in effect (e.g., Farrell et al., 2013; Henson, 1996; Osth & Dennis, 2015a). Thus, although sCMR naturally explains the in-fill effect in Simulation 1, the purpose of Simulation 2 is to establish that sCMR can also predict greater recall in the backward direction following a recall error.

4.1 Method

I simulated sCMR using the list structure from a study presented in Osth and Dennis (2015a) using data available from https://osf.io/8zycm/. In this study, 100 participants performed serial recall of 62 lists each with six words. Each word was presented for 1 s followed by a blank interstimulus interval for 250 ms on a computer screen. Participants then viewed a prompt to type the studied words one at a time in order, and had 20 s to do so. I chose to simulate the condition in which words were randomly selected without replacement across lists both because this design more closely parallels classic free recall studies and because sCMR's memory resets between lists. In this condition, if participants knew that an item occurred at a specific position but could not remember the item, they could not provide a "pass" response but rather recalled the next word from the list. Again, this condition more closely matches free recall, in which task instructions usually do not require participants to specify if they know other items were studied in the list but cannot remember what they were. Further, because sCMR does not have a mechanism to enable a pass response this avoids having the present simulation obfuscate whether the model's failure reflected incorrect assumptions of a pass mechanism or of retrieved context theory. It is worth noting that for this condition, Osth and Dennis (2015a) deemed that there was "neither a fill-in nor an in-fill effect" because the numerical advantage for transitions of $lag = -1$ over $lag = +1$ failed to reach significance. However, given that sCMR is fit to the mean values of this analysis without incorporating the variance, these numbers nonetheless provide a meaningful standard for sCMR to capture an effect other than the in-fill effect while simultaneously predicting recall probability and transitions across all output positions.

I used the same genetic algorithm procedure to determine the best-fit parameters as in Simulation 1. However, the algorithm only determined serial recall parameters, and thus this model had nine parameters. Further, because the aim was to capture the numerical advantage of backward over forward transitions, the algorithm determined a single set of best-fit parameters for the average data.

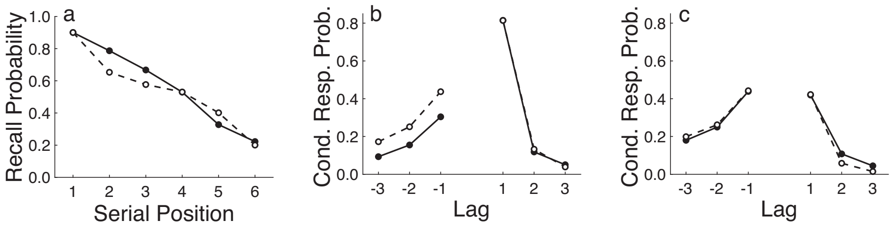

Fig. 3 sCMR predictions and experimental data of primacy, recency and the fill-in effect. sCMR provides an accurate account of the plotted serial recall analyses. **a** Serial position curves. **b** Conditional response probability as a function of lag. **c** Conditional response probability as a function of lag following the first order error. Data are from Osth and Dennis (2015)

4.2 Results

To lead with the critical result of this simulation, sCMR predicts the fill-in effect successfully, shown in here Fig. 3c as greater conditional response probability of backward transitions than forward transitions following the first order error. In sCMR, both the fill-in effect and the in-fill effect reflect the temporal contiguity effect. As explained the in the previous section, sCMR naturally accounts for the contiguity effect because the just-recalled item reinstates its associated temporal context from study and this updated context cues recall of items studied nearby in the list. One notable difference is that with a shorter list-length, at the start of the recall period context remains closer to the context state from the start of the list. That is, for a given context drift rate, context drifts further from the start-of-list context with more items in a list. As a result, in this shorter list of only six items, following a recall error the context cue has stronger representations of early list items. The additional strength attributed to these items promotes their recall and thus overcomes the forward asymmetry effect in the lag-CRP.

It is also worth noting that the model parameter controlling the drift rate at encoding (β_{enc}) was determined separately for each participant in Simulation 1 and for the average data in Simulation 2 (see Table 1). If the drift rate differed between simulations, then the prediction of the fill-in effect might reflect a difference in drift rates rather than in list-lengths. However, β_{enc} does not differ between the distribution of values across participants in Simulation 1 and the value for Simulation 2 ($p > .3$). The influence of list-length on the presence of the fill-in effect is also consistent with some prior findings (Farrell et al., 2013).

Despite the backward asymmetry following a recall error, across all transitions sCMR still predicts that forward transitions are more likely (Fig. 3b). This reflects both sCMR's assumptions leading to the forward asymmetry effect and the inclusion of transitions from correct recalls. When the model has already recalled items studied earlier in the list, these items no longer compete for recall and cannot be recalled again.

sCMR accounts for the probability of recall by serial position (Fig. 3a) with recall more likely for early list items. As in Simulation 1, across output positions the reduced recall advantage for later serial positions, increased probability of recall termination and accumulation of errors lead to low recall of recency items. Thus, despite the similar serial position effects and correct transitions as in Simulation 1, in Simulation 2 sCMR can account for greater probability of filling in over infilling.

5 Simulation 3: Temporal Grouping Effects

In this simulation I examine the influence of imposing a grouping structure which encourages participants to group the longer sequence of the entire list into smaller subsequences or groups. Under such conditions, participants organize their recalls based on the temporal grouping structure. Notably they exhibit more errors when transitioning across groups, and exhibit primacy and recency effects within each group, mirroring the primacy and recency effect across the entire list (DuBrow & Davachi, 2016; Farrell & Lewandowsky, 2004; Henson, 1996, 1999; Hitch, Burgess, Towse, & Culpin, 1996; Madigan, 1980; Ryan, 1969). These results, often taken as evidence against retrieved context theory, serve as a critical finding for sCMR to explain. Indeed, recently Logan and Cox (2023); Osth and Hurlstone (2023) presented simulations of the CRU model, which shares retrieved context assumptions of sCMR, yet CRU failed to predict a recency effect across the list and in the final group.

Here I examine recall grouping effects with studies using the common serial recall manipulation of having longer interstimulus intervals between groups (Farrell & Lewandowsky, 2004; Henson, 1996, 1999; Hitch et al., 1996; Madigan, 1980; Ryan, 1969). In such experiments, participants study nine lists of items, either as a single group or as three groups of three items. When there is a temporal pause in the list, sCMR assumes that this induces a shift in temporal context, updating context according to Equation 1 with an additional free parameter (β_{group}). Otherwise, the model parameters remain constant between the grouped lists and ungrouped lists. This assumption not only constrains the model between list types, but also assesses whether retrieved context model assumptions of grouping in free recall generalize to serial recall. For lists in which a shared encoding task defines each group, the free recall variant upon which sCMR builds, CMR, assumes that a new group induces a shift in temporal context (Lohnas et al., 2023; Polyn et al., 2009).

5.1 Method

I used the same genetic algorithm approach from Simulation 2 to fit sCMR to the serial position curves from Figure 4 of Farrell (2012). The serial position curves present results averaged across several experiments in which participants studied lists of nine items as either three groups of three items, indicated by a longer temporal pause between groups, or as a single group (Henson, 1996; Hitch et al., 1996). Figure 4 from Farrell (2012) also presents model predictions of grouping in serial recall, and

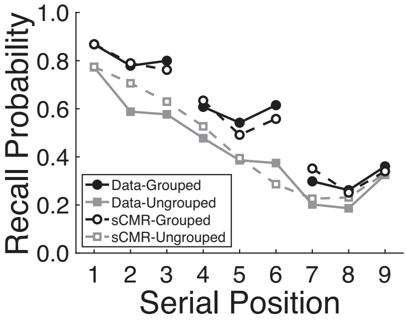

Fig. 4 sCMR predictions of probability of recall as a function of serial position in grouped and ungrouped lists. In grouped lists, groups of three items were separated by a longer temporal pause before items 4 and 7, whereas ungrouped lists had consistent timing between all items. Serial position curves are extracted from Figure 4 of Farrell (2012), which was averaged across datasets using lists of digits from Henson (1996) and Hitch et al. (1996). sCMR accounts for the primary features of these serial position curves; see text for details

thus serves as a good comparison for sCMR. Aside from setting the parameter β_{group} to 0 in the ungrouped lists and letting this parameter vary in the grouped lists, all other parameters remained constant between the grouped and ungrouped lists. For this mixture of experiments, I simulated an artificial data set of 50 "participants", each of whom had 50 grouped lists and 50 ungrouped lists.

5.2 Results

Fig. 4 shows that sCMR can account for the serial position curves with and without grouping. In the latter case, sCMR can account for the primacy and recency effects in a similar way to Simulation 1. Early list items benefit from the reinstatement of context from the first list item, and the additional associative strengths of primacy items to temporal context. The serial position curves in the plotted datasets (averaged from Henson, 1996; Hitch et al., 1996) exhibit a greater recency effect than in Simulation 1, but sCMR can account for this recency effect using the same mechanisms as in free recall.

The serial position curves between the ungrouped, control lists and the grouped lists differ at nearly all serial positions. If sCMR correctly recalls the first item then when compared to an ungrouped list, in a grouped list the items studied after a pause are associated more weakly to the item's reinstated context because the pause shifts temporal context further away from the context at the start of the list (see Fig. 1). As a result, the second and third items in the first group benefit from less competition from later list items, and these items boast greater recall probability in grouped than ungrouped lists.

Turning to recall of the fourth item in the list, recall of this item is more reduced from the preceding item in grouped than ungrouped lists. sCMR predicts this finding because recall of an item immediately prior to the pause will cue the next item more weakly than in an ungrouped list without a pause. This may also explain why items at the end of each group benefit from greater recall. In the ungrouped list, the greatest competition (i.e., next most likely recall) comes from the item studied after it, but in grouped lists that next item (from the next group) is represented more weakly in context of the item which precedes it (in the current group). Thus, this across-group item serves as a weaker competitor during recall, and thus increases the recall probability of end-of-group items. The reduction in competition from neighboring items in grouped lists may also explain why the model predicts accurately that recall is greater at each serial position in the grouped list compared to the ungrouped list.

It is also noteworthy that sCMR captures the list-level recency effect in both list types, especially because sCMR predicted the lack of a recency effect in the serial position curves from the other two serial recall simulations. Although sCMR predicts a recency effect in both ungrouped and grouped lists, the best-fit parameters across both list types nonetheless need to account for accurate recall in grouped lists. As described in the previous paragraph, items studied in a different group from the just-recalled item are represented more weakly in the context cue due to the shift in context between groups. This helps to explain why the best-fit free parameter for the amount of context retrieval for each recalled item, β_{rec}, is higher for this simulation than Simulations 1 or 2 (see Table 1); sCMR retrieves a larger range of temporal context states to ensure that the weakly represented item is still recalled next. This greater context retrieval benefits the recency effect as well. When recency items are recalled correctly, this increases the retrieval of context states which serve as a stronger cue for the final list item. This retrieval is also greater when more recency items are recalled correctly and thus retrieve their contexts. In the present simulation, when compared to serial recall of a similar long list as in Simulation 1 (Figure 2), accuracy is generally higher for the few items preceding the final list item. Thus, this higher accuracy also helps to ensure that these recency items support recall of the final list item. Taken together, sCMR captures the notable aspects of recall for grouped and ungrouped lists consistent with its free recall analog (Lohnas et al., 2023; Polyn et al., 2009).

Parameter	Simulation 1	Simulation 2	Simulation 3
β_{enc}	0.581 (0.030)	0.577	0.124
β_{rec}	0.790 (0.037)	0.581	0.922
ϕ_s	2.500 (0.248)	2.086	3.420
ϕ_d	1.195 (0.096)	0.134	0.526
θ_s	0.035 (0.004)	0.005	0.050
θ_r	0.358 (0.037)	0.772	0.018
τ_i	4.259 (0.407)	11.389	9.466
γ_{CF}	0.852 (0.021)	0.671	0.535
γ_{FC}	0.255 (0.026)	0.520	0.921
γ_{FC}^{fr}	0.304 (0.045)	-	-
s	1.310 (0.136)	-	-
β_{group}	-	-	0.826

Table 1 Best-fit parameters of the sCMR model. The values reported for Simulation 1 include the mean (and SEM) across the 30 individual participant fits. The values for Simulations 2 and 3 are the single parameter set used to fit the data averaged across participants. For details of the use and meaning of each parameter, see *Overview of sCMR: Context maintenance and retrieval model of episodic recall.*

6 Discussion

Theories of episodic memory aim to characterize how memories are represented as well as the mechanisms supporting successful encoding and retrieval. Much of the computational modeling work emerging from these theories has developed separately in free recall and in serial recall. Retrieved context models have had much success in accounting for recall dynamics in free recall (Howard & Kahana, 2002a; Lohnas & Healey, 2021; Lohnas et al., 2015; Polyn et al., 2009; Sederberg et al., 2008) and principles of these models have emerged as an important alternate account in serial recall (Logan, 2018, 2021; Logan & Cox, 2021, 2023; Osth & Hurlstone, 2023). Combined with recent empirical investigation (e.g., Bhatarah et al., 2008; Farrell et al., 2013; Osth & Dennis, 2015a, 2015b; Solway et al., 2012), these lines of work underscore the parallels between, and the importance of assessing a generalized retrieve context model across, recall paradigms. Here I examined three sets of simulations of sCMR, a generalized retrieved context model of free and serial recall. sCMR can account for several key findings using its core assumptions that each item is associated with a slowly changing temporal context state, temporal context is the recall cue, and recall of an item evokes retrieval of its associated context from study.

Simulation 1 compares model predictions for participants who performed one session each of free recall and serial recall. sCMR makes accurate predictions of each participant's recall patterns with changes to only two (out of 11) parameters, along with a difference in recall initiation, between recall sessions. sCMR accounts for the primacy effect in both tasks due to the stronger context-item strengths of early list items. sCMR accounts for a weaker recency effect in serial recall than free recall because the retrieved context of correctly recalled early list items drifts further from recency items, and with increasing output position recall errors and stopping are more likely. sCMR accounts for the temporal contiguity effect in both recall tasks because the temporal context of the just-recalled item most strongly contributes to the recall cue for the next item. Finally, sCMR accounts for reduced backward transitions in serial recall due to the two model parameters which varied between tasks; both of these parameters influence the contribution of experimental episodic associations to the recall cue. Thus sCMR uses the same core principles, mechanisms and representations for both recall paradigms but assumes that participants rely less on distant or backward associations in a task requiring recall in serial order.

sCMR dissociates between recall paradigms based on the contribution of forward episodic associations to the retrieval cue. Specifically, semantic context-to-item associations and backward episodic item-to-context associations contributed more strongly to the recall cue in free recall than in serial recall. This follows the intuition that using these two types of context information would be detrimental in serial recall, in which recall of an item should ideally cue the next studied item rather than a prior item or a semantic associate. Although sCMR updates the experimental item-context associations after studying an item, the relative weight of these experimental associations (versus pre-experimental associations) to the recall cue could be determined at the start of the recall period. In the present simulations, participants had a consistent recall task for an entire session or study and thus the parameter controlling the weights of experimental and pre-experimental associations were kept constant ($\gamma_{FC}, \gamma_{CF}, s$).

However, if the type of recall test were postcued then the model could adjust the association weights following the recall instructions.

In Simulation 1, sCMR makes predictions consistent with the experimental data of Golomb et al. (2008), in which participants were more likely to make transitions in the forward direction in both free recall and serial recall. Yet in some serial recall studies participants are more likely to fill in, or recall the preceding item, following a recall error of skipping an item. Simulation 2 thus examined sCMR's ability to explain this finding. Because retrieved context models more naturally predict a forward asymmetry in free recall, the fill-in effect has been taken as evidence against models such as sCMR (Farrell et al., 2013; Henson, 1996; Logan, 2021; Osth & Dennis, 2015a). However, sCMR can account for the fill-in effect as well. Like the in-fill effect, sCMR predicts that the next recalled item, even if followed by the first order error, is more likely to share temporal context with the current context state. Further, Simulation 2 had a shorter list-length and thus fewer intervening items between an item's initial presentation and when it is later recalled. As a result, sCMR predicts that following an error temporal context more strongly represents neighboring early list items, producing the fill-in effect. Remarkably, some positional models use a similar mechanism, accounting for the fill-in effect based on stronger representations of early list items (e.g., Henson, 1998). Further attesting that sCMR can account for this effect more naturally, with the same parameter set the model also made accurate predictions of the serial position curve and lag-CRP across output positions. sCMR's account of this effect, based on list-length, is also consistent with past studies suggesting that the fill-in effect is more likely with shorter list-length (Farrell et al., 2013, but see Dougherty et al., 2023; Osth & Dennis, 2015a).

In Simulation 3, sCMR accounts for serial position curves of grouped and ungrouped lists with the same assumption as retrieved context models in free recall (Lohnas et al., 2023; Polyn et al., 2009), that a new group induces a disruption to temporal context. These disruption items lead to greater transitions between correct items in the same group but reduced transitions across groups, as well as primacy and recency effects within groups. Thus sCMR did not need to assume different parameter values across grouped and ungrouped lists, nor did the model need to assume additional hierarchical representations. This parallels the assumption for CMR2, a retrieved context model variant in which memories accumulate over multiple lists in a session: the model does not assume a separate list context, but a temporal disruption item was presented in between each study-recall cycle (Healey & Kahana, 2016; Lohnas et al., 2015; Pazdera & Kahana, 2023). This assumption also has some support from the event segmentation literature, as reviewed in the next section.

6.1 Grouping and segmentation in retrieved context models

To date, retrieved context models have had success in accounting for grouping structures in free recall with experimental manipulations of grouping (Lohnas et al., 2023; Polyn et al., 2009). Without this grouping structure, the model does not assume that a longer list is divided into groups. However, there is empirical evidence that participants may acquire consistent grouping structures in recall tasks (e.g., Kahana & Jacobs, 2000; Madigan, 1980; Romani, Katkov, & Tsodyks, 2016; Ryan, 1969; Wickelgren, 1967). On a theoretical level, Farrell's (2012) model makes more accurate predictions in serial recall and free recall when assuming that participants automatically form groups from longer lists. For instance, the model can account for the nonmonotonicites in the serial position curve of the ungrouped lists from Fig. 4 when assuming that participants form groups in those lists.

As another potential approach to examine grouping, and indeed part of the motivation for Farrell's model, comes from the event segmentation literature. Albeit gauged in different terminology than groups, this literature focuses on how people segment their continuous stream of experience into meaningful events (Radvansky & Zacks, 2014; Zacks, Speer, Swallow, Braver, & Reynolds, 2007). This literature also provides further foundation for sCMR's assumption that a new group leads to a disruption to temporal context, even in situations where the new group (or event) is not a temporal pause. For instance, participants perceive two items (of matched temporal distance) as occurring further apart in time when they are from different events than when they are in the same event (Clewett, Gasser, & Davachi, 2020; DuBrow & Davachi, 2013; Ezzyat & Davachi, 2014; Faber & Gennari, 2017; Lositsky et al., 2016). Further, brain regions implicated in temporal information exhibit salient changes at event boundaries (e.g., Baldassano et al., 2017; Ezzyat & Davachi, 2014; Heusser, Poppel, Ezzyat, & Davachi, 2016; Lohnas et al., 2023; Lositsky et al., 2016).

Event segmentation studies have also established that changes to memory performance and neural activity are similar between experimentally imposed events and endogenous updating of event or group information (for a recent review see Clewett et al., 2019). In lists of items, boundaries may reflect salient changes to sensory content or context (e.g., Clewett et al., 2020; DuBrow & Davachi, 2016; Heusser et al., 2018; Lohnas et al., 2023; Pu, Kong, Ranganath, & Melloni, 2022). However, in serial recall studies which commonly use lists of unrelated words or digits, other factors may inform when participants begin a new group within a longer list. Indeed, much of the serial recall literature examining within-list groups rely on experimental manipulations (for a review, see Farrell, 2012). Thus theoretical and empirical advances in serial recall studies could benefit from the largely untapped approaches from event segmentation studies to examine endogenous grouping, such as having participants to indicate when they form a new group during presentation (e.g., Bailey, Kurby, Sargent, & Zacks, 2017; Boggia & Ristic, 2015; Magliano, Radvansky, Forsythe, & Copeland, 2014; Newtson, 1973, 1976), or using brain activity to infer when a participant forms a new group (e.g., Baldassano et al., 2017; Schapiro, Turk-Browne, Norman, & Botvinick, 2016).

In addition to experiment manipulations, future recall studies may also benefit from theoretical advancements including models aimed to explain when a participants will form a new event (e.g., Elman & McRae, 2019; Franklin, Norman, Ranganath, Zacks, & Gershman, 2020; Reynolds, Zacks, & Braver, 2007). As one of the most relevant computational models to the present work, the Structured Event Memory makes quantitative predictions of episodic memory and event structure based on predictability and similarity across events (Franklin et al., 2020). SEM also makes accurate predictions of free recall and serial recall as a function of whether items were studied in the same or different events.

Several computational models have been developed to explain the impact of event segmentation on episodic memory. Some of these models, like sCMR, assume that temporal context changes slowly over time, and each item is associated to this slowly changing temporal context representation (Horner, Bisby, Wang, Bogus, & Burgess, 2016; Pu et al., 2022). Whereas the model of Horner et al. (2016) assumes that a new event evokes a sharp drift in temporal context, the model of Pu et al. (2022) assumes that an event boundary resets temporal context, and this reset includes reinstatement of temporal context from the beginning of the list. Both of these models simulate memory for temporal order judgments of item pairs, and Pu et al. (2022) presented simulations suggesting that their model could better account for differences such as the length and position of the events in which the items occurred. Notably, this model predicts a memory advantage for items studied earlier in an event, which also appears to be present in the serial position curves of the grouped data presented here. To date these models cannot make predictions in recall tasks, but integrating their principles and testing their novel predictions with the sCMR framework provides another avenue to generalize retrieved context models to effects of episodic memory. We next review other computational models which serve to generalize episodic memory across recall paradigms.

6.2 Comparison to other models integrating serial and free recall

The present set of simulation studies aims to provide a model of recall dynamics generalized across memory paradigms, and several other models share this goal. sCMR is most similar to the CRU model, as both models rely on principles of retrieved context theory to define and associate context to studied items (Logan, 2018, 2021; Logan & Cox, 2021, 2023; Osth & Hurlstone, 2023). Thus, both models assume that each studied item is associated with a slowly changing context representation, and in serial recall context serves as the retrieval cue. Both models also have had success in accounting for effects of serial position, recall transitions and grouping. However, CRU has two noteworthy differences from sCMR, thus underscoring the importance of a unified retrieved context model of serial recall and free recall.

First, in CRU the context retrieval cue updates with item information rather than studied context information. This assumption would be more challenging to bridge with retrieved contexts models of free recall, or with several notable empirical findings in free recall which are more consistent specifically with retrieval of context information over item information (e.g., Lohnas & Kahana, 2014; Siegel & Kahana, 2014; Talmi, Lohnas, & Daw, 2019). Further, the assumption of retrieved context, rather than retrieved item information, may contribute to sCMR's ability to account for the recall advantage for the final item in Simulation 3. By contrast, CRU generally underpredicts the recency effect including in grouped lists (Logan, 2021; Logan & Cox, 2023; Osth & Hurlstone, 2023). In sCMR, successful context retrieval of the preceding items (e.g., retrieving contexts of the items in serial positions 7 and 8) accumulate to serve as a strong compound cue for the next item (e.g., item 9), because these context states are represented most strongly in the context for the next item. In CRU, item information seems to not be enough to support this recency effect.

As a second difference between sCMR and CRU, in CRU recalling an error in serial recall evokes retrieval of the context state from the start of the list. Whereas CRU simulates tasks requiring memory for serial order, retrieved context models of free recall assume that each retrieved item—error or not—evokes retrieval of its context. Thus, in contrast to CRU, sCMR does not retrieve context any differently following an order error in serial recall. However, because in shorter lists the context state will be closer to context from the start of the list after an order error, CRU and sCMR have a similar conceptual mechanism to support the fill-in effect: the context retrieval cue is more similar to items from the start of the list, thus supporting their recall over recently presented items.

sCMR also shares conceptual similarities with several models which represent item strength or distinctiveness. For instance, the Adaptive Character of Thought-Rational (ACT-R) model (Anderson, Bothell, Lebiere, & Matessa, 1998; Anderson & Matessa, 1997) also makes accurate predictions of free recall and serial recall. ACT-R assumes that as each item is presented it enters a short-term memory buffer, and that memory strengths of presented items decay over time. In serial recall, the ACT-R model assumes that participants start at the beginning of the list and then recall proceeds in a forward direction. ACT-R predicts that recall probability is higher in earlier list positions because the model is more likely to make an error with each subsequent output position. In free recall, ACT-R begins recall with items in the short-term memory buffer, and thus predicts a recency effect. These buffer items have the strongest memory strength because less time has passed since their presentations. Thus sCMR, like ACT-R, captures the recency effect because recently presented items have greater memory strengths but in serial recall errors increase with output position. After initializing recall with buffer items, ACT-R uses a set of strongly activated items to cue recall of other items. This is similar to sCMR's recall cue with temporal context; both types of recall cues represent recently encountered items more strongly to promote the temporal contiguity effect. ACT-R can also account for grouping effects with a similar approach to the Farrell (2012) model, representing groups hierarchically and then cuing items within each group. ACT-R can also account for recall latencies, but the present version of sCMR has not been developed to do so.

Although this version of the ACT-R model has not explicitly addressed transition dynamics in recall tasks, its assumptions would likely lead to reasonable predictions of lag-CRPs. Specifically, using salient items in memory to cue recall during free recall and shared information among neighboring items could produce a contiguity effect. The assumption to attempt to proceed forward in the list during serial recall could lead to a pronounced asymmetry effect. This difference in recall strategies between the two tasks – whether to attempt to use the next item to move forward or whether to use a set of recalled items to cue recall of the next item – is similar to how sCMR captures the difference between serial and free recall. In sCMR, changes to the γ_{FC} parameter influence the strength of the next-presented item versus other studied items in the recall cue. Further, in sCMR free recall simulations, the greater value of the semantic parameter s reflects that a just-recalled item supports recall of its semantic associates, and in free recall ACT-R can also assume a role for semantic information (c.f. Anderson & Bower, 1972).

The Scale-Independent Memory, Perception, and Learning (SIMPLE) model (Brown, Neath, & Chater, 2007) assumes that each item's memory representation is based on a logarithmic function of how recently the item was presented, and items with more distinctive representations boast greater recall probability. The logarithmic function leads to more distinct temporal representations of recency items, leading to the prediction of a recency effect in free recall. In serial recall, recency is reduced because more time has passed from the start of the recall period until the items should be recalled, not unlike the reduced recency in sCMR due to context drifting further away from these items. SIMPLE accounts for the primacy effect in both tasks because items presented earlier in the list benefit from edge effects, as they have less temporal crowding from subsequently presented items. Thus, the SIMPLE account provides a less ad-hoc solution for the advantage of primacy items than sCMR. Although the model can account for transposition gradients in serial recall, to date the model only produces recall probabilities for each presented item rather than recall dynamics. Also like sCMR, SIMPLE can account for the serial position effects between grouped and ungrouped lists of items by assuming that the start of each group is more temporally isolated from the prior item (Brown et al., 2007; Liu & Caplan, 2020).

The Laminar Integrated Storage of Temporal Patterns for Associative Retrieval, Sequencing and Execution (LIST PARSE) model (Grossberg & Pearson, 2008) represents item strengths in memory with neural activity. As each item is presented, it enters a short-term memory buffer with total neural network activity consistent across the number of items in the buffer. Item strength (i.e., neural activity) generally decays over time and thus recency items will benefit from less decay between their presentation and the start of the recall period, but less so in serial recall with more recalled items occurring between a recency item's presentation and its recall attempt. LIST PARSE predicts the primacy effect because items studied earlier in the list, before the buffer is full, benefit from greater neural activity and subsequently recall probability. LIST PARSE also predicts that temporal pauses alter the integration and thus the activity of items in working memory. As a result, items in different groups are represented more distinctly and treated more like mini-lists with primacy and recency effects. Shared information between items also leads to predictions of transpositions errors, although currently the LIST PARSE model only makes predictions concerning recall probabilities.

Whereas sCMR often shares similar implications with respect to mechanistic and reprentational differences across recall paradigms and grouping, sCMR helps to provides insight into the role of temporal context as a potential contribution to changes in the strengths of memories, both in relation to the retrieval cue and to one another.

The Farrell (2012) model also elucidates how item representations facilitate item-by-item recall. In this model, each presented item is associated with a list context, a group context, and an item context. The Farrell (2012) model accounts for the primacy effect by assuming that there is a heightened probability for participants to initiate recall with the first list item, not unlike sCMR's assumption for initiating serial recall. Similar to the ACT-R model, in free recall the model is more likely to initiate recall with the last group, leading the model to predict a greater recency effect in free recall. Once the first item is recalled, its group context is reinstated which promotes recall of other items in that same group. The Farrell (2012) model always attempts to recall the item presented after the just-recalled item, which leads to accurate predictions of the temporal contiguity and asymmetry effects in both recall tasks.

Based on other modeling work, sCMR helps to shed light on shared representations, associations, and processes between recall tasks, with some shared principles to other models. We next review other model mechanisms and assumptions which may serve future advancements to sCMR.

6.3 Future model developments

In serial recall sCMR makes the simplifying assumption to initiate recall with the first list item on most trials. This assumption is similar conceptually to the assumption that, with high accuracy, recall begins with reinstatement of a cue from the beginning of the list (e.g., Anderson & Matessa, 1997; Brown et al., 2000; Burgess & Hitch, 1992; Farrell, 2012; Lehman & Malmberg, 2013; Lewandowsky & Murdock, 1989; Osth & Farrell, 2019). This also sidesteps adjudicating between model failures of recall initiation versus model failures of retrieved context assumptions. However, sCMR may benefit from the assumption of other retrieved context models which assume an additional item is encoded at the start of each list and can be reinstated at the start of the recall period (Healey & Wahlheim, 2023; Sederberg, Gershman, Polyn, & Norman, 2011). Recently, Healey and Wahlheim (2023) showed that their model with this post-encoding pre-production reinstatement (PEPPR) mechanism accounts for patterns of free recall better than a variant which worked 'backwards' to get to the beginning of the list or a prior list. However future work remains to determine how serial recall evokes endogenous cues for accurate recall initiation. Yet given that recall initiation differs between serial recall and free recall, the simplistic initiation in serial recall should not take away from conclusions of the model's generalization across recall paradigms.

Several serial recall effects have been taken as qualitative evidence against retrieved context models such as sCMR. Simulations 2 and 3 show that sCMR can account for two of these effects but sCMR still faces challenges from other effects. However, these effects require developing a variant of sCMR which predicts learning across lists instead of resetting memory between lists. As one example, sCMR model might also overpredict the recall advantage of keeping the relative order of list presentation consistent across lists while varying the positions (Ebenholtz, 1963; Kahana, Mollison, & Addis, 2010; Keppel, 1964; Winnick & Dornbush, 1963). As a more critical example, items recalled (mistakenly) from prior lists are more likely to be recalled in the same serial and/or output position as their original lists. It is challenging to explain how sCMR might account for this finding without the addition of positional information across lists. In a similar way, sCMR does not have a mechanism to predict increased positional confusions in grouped lists. Specifically a recall error in a grouped list for the n^{th} item from group g is more likely from the n^{th} item of other groups (e.g., $g-1$,$g+1$), suggestive of positional codes within each group (e.g., Henson, 1999; Hitch et al., 1996; Ryan, 1969). However, retrieved context models such as sCMR and CRU predict that serial recall errors are generally from items with similar temporal context states. Thus CRU predicts that recall errors in grouped lists are other items studied near item n, as in ungrouped lists (Logan & Cox, 2023; Osth & Hurlstone, 2023).

Although CRU can only overcome this shortcoming when incorporating positional codes (Logan & Cox, 2023), this remains a challenge for sCMR.

Nonetheless, these potential challenges do not need to make the sCMR framework obsolete. Rather, participants may rely on associative information in free recall and serial recall, and additionally may rely on positional information in serial recall. However, the boundary conditions of using positional information remain to be characterized, especially in light of the current results. Further, Logan and Cox (2021, 2023) propose several mechanisms by which a retrieved context framework could incorporate positional coding when needed, while still maintaining associative information to support temporal contiguity effects. Future work remains to assess how temporal context works with or against positional information, but the current results reveal the importance of using model simulations for querying which effects retrieved context models can predict. Thus, the present work provides a piece to the puzzle by demonstrating that sCMR can account for findings from free serial and serial recall with minimal and informative changes between paradigms, including findings which have been taken as evidence against retrieved context theories.

7 Conclusion

Episodic memory is generally assumed to reflect a common underlying set of cognitive representations and mechanisms. Yet memory performance varies with the memory task, partially due to differences in the presence and use of retrieval cues (e.g., Greene, 1989; Tulving, 1985; Tulving & Pearlstone, 1966). This has led to different theories for different memory paradigms, and in particular leaves more open questions for paradigms in which participants must generate their own internal cues. The present work aims bridge the gap between two paradigms which require such internal cues, free recall and serial recall. sCMR, building on the retrieved context model framework in free recall, provides a quantitative framework and explanation for memory representations and retrieval mechanisms with minimal changes between paradigms. The results serve as more than a sum of their parts, providing a parsimonious account of these recall tasks while also highlighting the variability within and across episodic memory paradigms.

8 Author Contributions

L.J.L. made all author contributions.

9 Declarations Section

9.1 Ethics Approval and Consent to Participate

Not Applicable

9.2 Conflict of Interests

The author declares to have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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No funding was obtained for this study.

9.4 Data Availability

Computer code used to generate the present simulations is available at the Open Science Foundation repository: https://osf.io/qsr7p/. This code relies on analysis software available from https://github.com/vucml/EMBAM, as well as datasets available from http://memory.psych.upenn.edu/Data_Archive#2008 (Simulation 1) and https://osf.io/8zycm/ (Simulation 2).

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Appendix: Simulation 1 by participant

sCMR was fit to each participant individually, with a single set of parameters for each participant (see the *Method* subsection for *Simulation 1*). Whereas Fig. 2 provides the average experimental data and average sCMR fits across participants, the individual model fits for each participant are provided below.

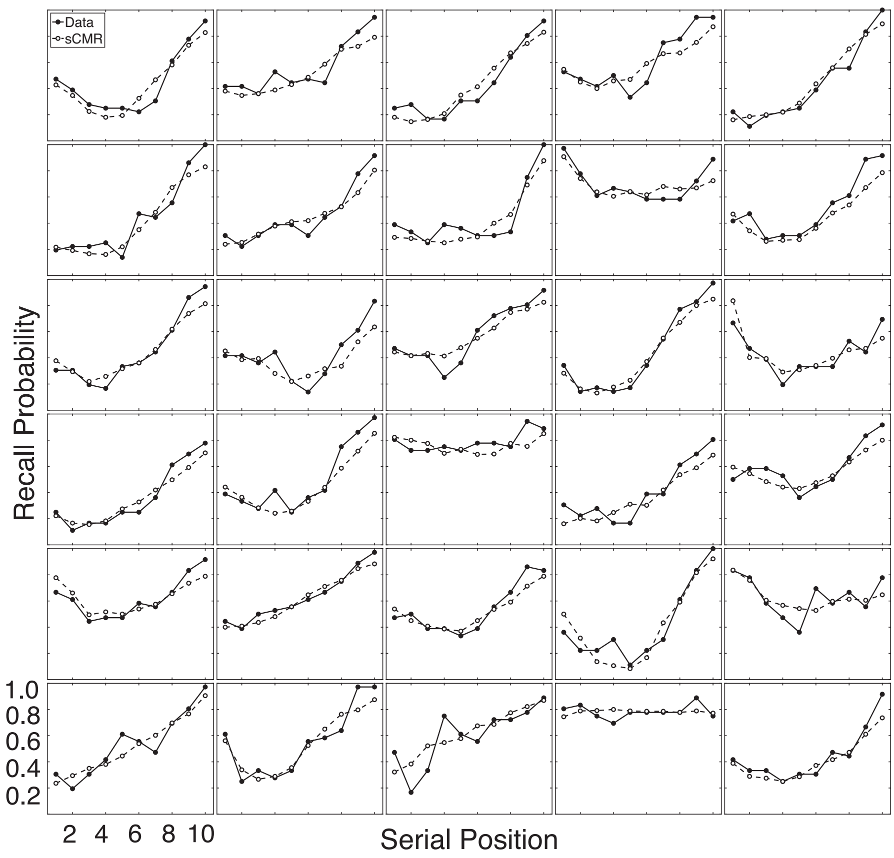

Fig. 5 sCMR predictions and experimental data of serial position curves by participant in free recall. Ascending participant numbers go from left to right in each row, and then down each column. Data are from Golomb et al. (2008)

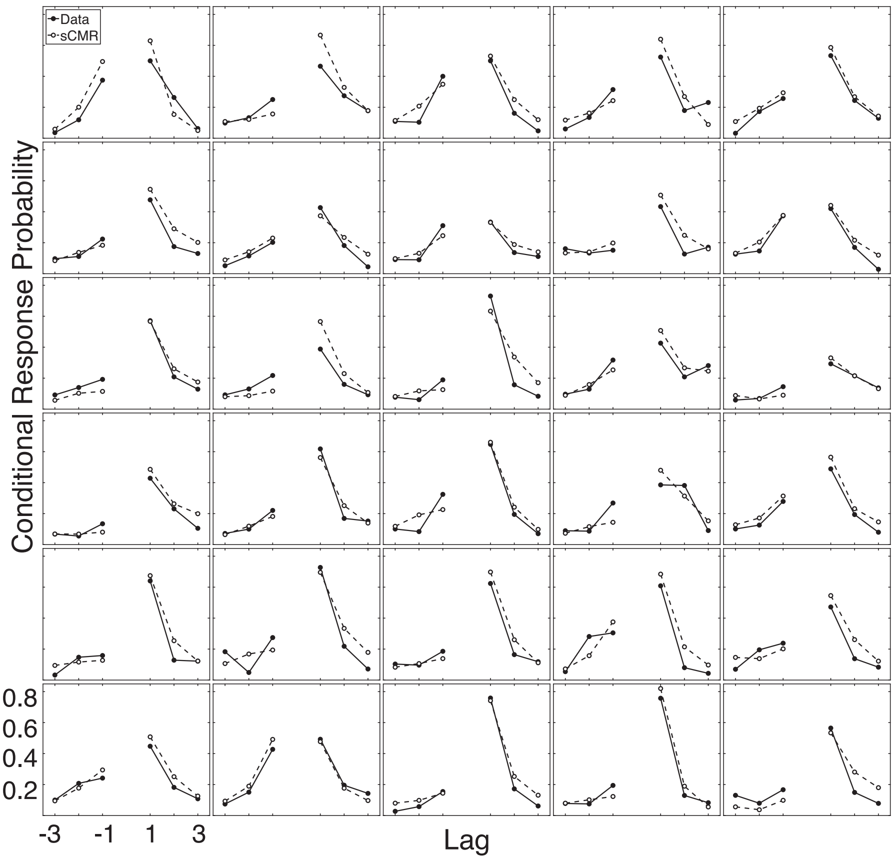

Fig. 6 sCMR predictions and experimental data of conditional response probability as a function of lag across all valid output positions in free recall. Ascending participant numbers go from left to right in each row, and then down each column. Data are from Golomb et al. (2008)

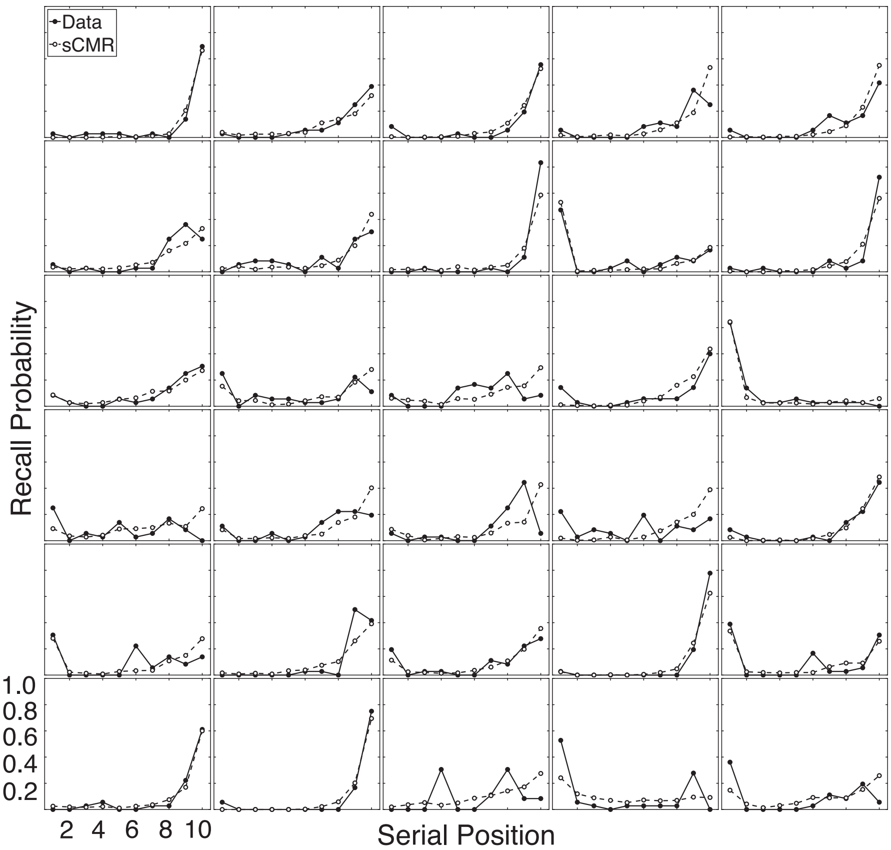

Fig. 7 sCMR predictions and experimental data of probability of first recall by participant in free recall. Ascending participant numbers go from left to right in each row, and then down each column. Data are from Golomb et al. (2008)

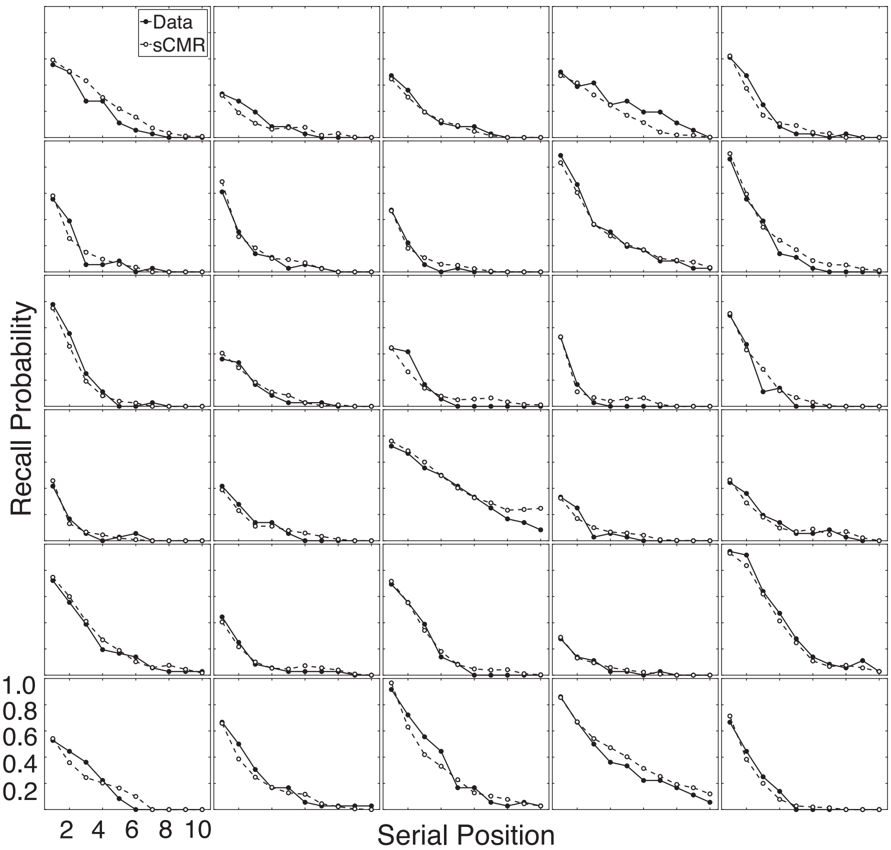

Fig. 8 sCMR predictions and experimental data of serial position curves by participant in serial recall. Ascending participant numbers go from left to right in each row, and then down each column. Data are from Golomb et al. (2008)

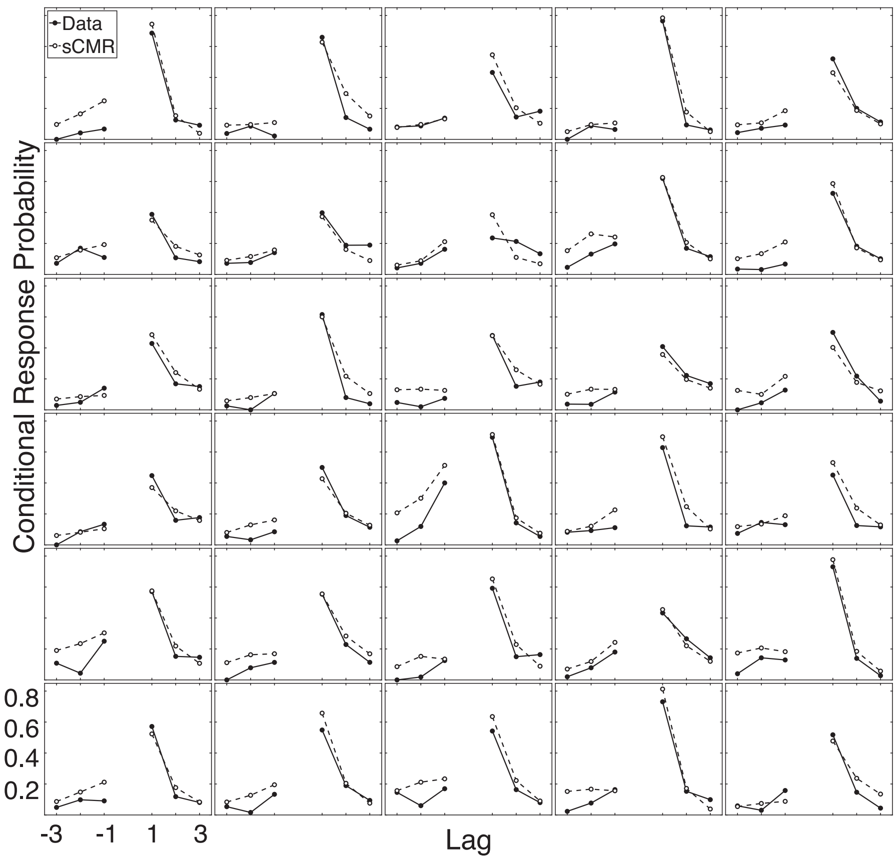

Fig. 9 sCMR predictions and experimental data of conditional response probability as a function of lag across all valid output positions in serial recall. Ascending participant numbers go from left to right in each row, and then down each column. Data are from Golomb et al. (2008)

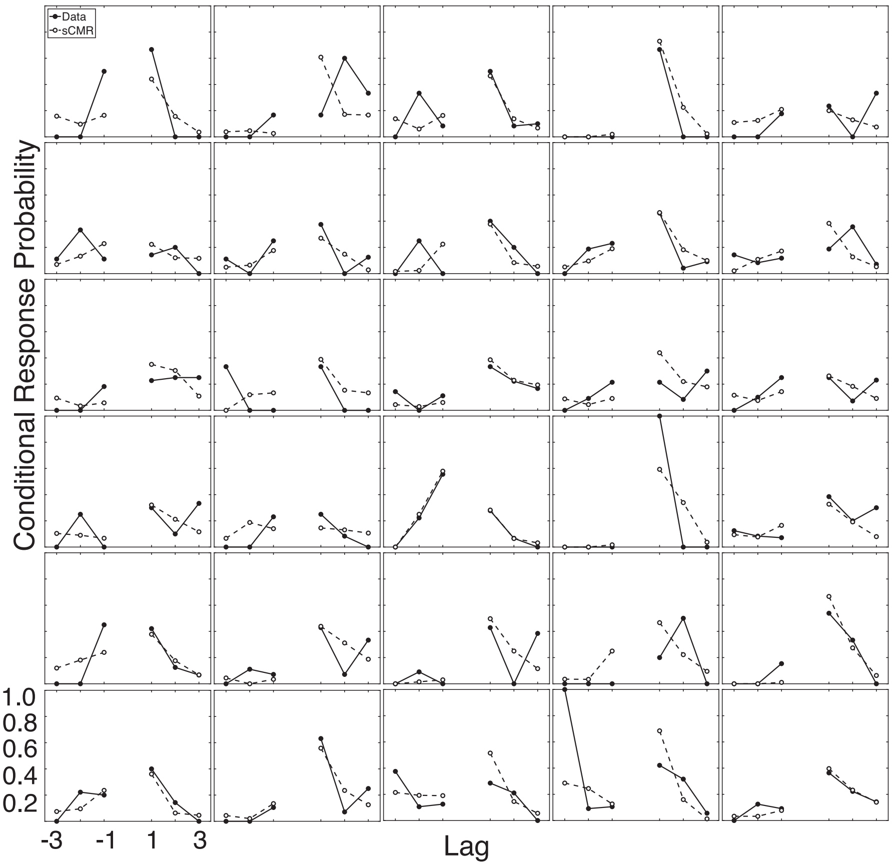

Fig. 10 sCMR predictions and experimental data of conditional response probability as a function of lag following the first order error in serial recall. Ascending participant numbers go from left to right in each row, and then down each column. Note the change in y-axis to accommodate two participants with a conditional response probability value of one. Data are from Golomb et al. (2008)