

Empirical and theoretical limits on lag recency in free recall

SIMON FARRELL

University of Bristol, Bristol, England
and University of Western Australia, Perth, Western Australia

AND

STEPHAN LEWANDOWSKY

University of Western Australia, Perth, Western Australia

One widely accepted empirical regularity in free recall holds that when people successively transition from report of one list item to another, they prefer transitions across short lags (e.g., by reporting items from adjacent serial positions) to transitions involving large lags. This regularity has provided crucial support for the temporal context model (TCM), a model of the evolution of temporal context in episodic memory (Howard & Kahana, 2002a). We report a reanalysis of 14 data sets that shows that, contrary to the presumed preference for short lags, people often produce transitions with larger lags during recall. We show that these data cannot be accommodated by the TCM. We furthermore show that existing applications of the model have, for mathematical convenience, introduced assumptions that have circumvented its core principle of context evolution. When we instantiated the TCM as it was actually described, with a gradually evolving context, we found that its behavior qualitatively departed from that of the version currently implemented, but that the model was still unable to capture the nature of transitions in free recall. We conclude that the TCM requires further modification and development before it can explain the data that constitute its main source of support. Supplementary materials relevant to this article can be downloaded from the Psychonomic Society's Norms, Stimuli, and Data Archive, www.psychonomic.org/archive.

The free recall task has been prominent in theoretical approaches to episodic memory (e.g., Brown, Neath, & Chater, 2007; Laming, 1999; Raaijmakers & Shiffrin, 1981; Tan & Ward, 2000; for an early review, see Murdock, 1974). Particularly intense debate has surrounded the origin and nature of the *recency effect*, which refers to the greatly enhanced recall of items from the last few list positions (see, e.g., Postman & Phillips, 1965). Recency has been variously ascribed to a limited-capacity short-term buffer (Glanzer & Cunitz, 1966; Postman & Phillips, 1965) or to the temporal distinctiveness of terminal items (e.g., Brown et al., 2007; Glenberg & Swanson, 1986; Neath, 1993).

Another type of recency emerges from examination of lag-conditional response probabilities (*lag-CRPs*), which conditionalize recall probability on the lag $j-i$ between the serial positions i and j of two successive recalls. This analysis of recall contingencies has revealed two consistent behaviors (Howard & Kahana, 1999; Kahana, 1996;

Kahana, Howard, Zaromb, & Wingfield, 2002): First, a recalled item tends to be followed by items nearby in the list, such that the lag-CRP function declines with increasing lag; this is referred to as *lag recency*.¹ To date, all reported lag-CRP functions have exhibited this regularity, with small-lag transitions always being more likely than those involving greater lags. Second, lag-CRP functions are asymmetric, so that a transition of a given positive lag is more likely to occur than a transition with a negative lag of the same magnitude. The proximity and asymmetry of transitions in the lag-CRP function are obtained even when researchers have accounted for the constraint that fewer opportunities occur for transitions of greater distance (Howard & Kahana, 1999).

The proximity and asymmetry of transitions during free recall constitute two empirical regularities that have guided recent theorizing (e.g., Davelaar, Goshen-Gottstein, Ashkenazi, Haarmann, & Usher, 2005; Howard & Kahana, 1999, 2002a). In particular, the nature of the lag-CRP functions in free recall, as well as the nature of recency over various time scales, has been central to the development of the temporal context model (TCM; Howard, Fotedar, Datey, & Hasselmo, 2005; Howard & Kahana, 2002a). In common with other models of episodic memory (e.g., Brown, Preece, & Hulme, 2000; Dennis & Humphreys, 2001; Glenberg et al., 1980), the TCM assumes a critical role for the association between items and the temporal context in which they occur. At study, items are associated with a continuously changing context signal, and the context signal in turn is used to retrieve items during recall.

A fundamental assumption of the TCM is that context is *retrieved*: At any point in time, the current context signal is assumed to be a composite of the previous state of the context and the context that was retrieved in response to the item presented or recalled (Howard & Kahana, 2002a). This core property of the TCM gives rise to two principal predictions: First, the first item recalled is expected to come from one of the terminal list positions, because the context at the beginning of recall most closely matches the items just presented. Second, all subsequent recalls are expected to involve neighboring list positions, because the retrieved context overlaps most with its list neighbors (Howard & Kahana, 2002a). Although the TCM is not a fully specified model of free recall (Howard & Kahana, 2002a), it is ideally poised to describe the evolution of temporal context in models that have thus far only assumed the presence of such context, without describing how it evolves (e.g., Farrell, 2006; Lewandowsky & Farrell, 2008a, 2008b).

In this article, we reexamine both the data that have propelled development of the TCM and the theory's predictions. To anticipate our conclusions, we show that the existing data analyses have been limited, and the TCM's assumptions inconsistent, thus potentially fostering mis-

S. Farrell, simon.farrell@bristol.ac.uk

conceptions about (1) the nature of free recall and (2) the TCM’s ability to account for people’s behavior. Specifically, we first reanalyze 14 free recall data sets and show that the lag-CRP functions are in fact frequently *nonmonotonic* if lags outside the narrow window considered to date are included. We then show that the TCM, as implemented to date, is unable to handle the widespread nonmonotonicity of lag-CRPs. We next note that all existing applications of the TCM have used two mutually inconsistent context signals to produce the two phenomena of interest—namely, first-recall probabilities (FRPs: the serial position of the first-recalled item) and lag-CRP functions. We present a modified version of the TCM that resolves this inconsistency, and we show that the behavior of this modified version qualitatively departs from that of the extant model. Although this modified model can produce nonmonotonicity in lag-CRPs, it still cannot convincingly handle the existing data. We conclude that the TCM must await additional development before it can advance our understanding of free recall processes.

REANALYSIS OF LAG RECENCY EFFECTS IN FREE RECALL

To date, published lag-CRP functions have been computed over a limited range of lags, typically from -5 to $+5$ (Howard et al., 2005; Howard & Kahana, 2002a, 2002b; Howard, Kahana, & Wingfield, 2006; Kahana, 1996; Kahana & Howard, 2005; Kahana et al., 2002; Klein, Addis, & Kahana, 2005; Sirotin, Kimball, & Kahana, 2005; Zaromb et al., 2006) or, in a few cases, from -6 to $+6$ or more (Howard & Kahana, 1999; Howard, Venkatadass, Norman, & Kahana, 2007; Howard, Youker, & Venkatadass, 2008). Kahana (1996) justified the focus on this restricted range by citing the smaller number of available observations at longer lags. Nonetheless, the

focus on lags ≤ 6 has excluded a large proportion of the data from consideration (up to approximately 30%, on average, of all nonadjacent transitions; see Table 1). Since these excluded data may provide important additional information about transitions in free recall, we reanalyzed five experiments with 14 different conditions that have provided most extant lag-CRP functions: Experiments 1 and 2 of Howard and Kahana (1999); Murdock and Okada (1970); the 6 conditions of Murdock (1962); and lists from Howard et al. (2007) that did not contain repetitions. All possible transition lags were included in the analyses. To underscore the relevance of this reanalysis, Table 1 shows the number of transitions in those 14 data sets broken down by lag (considering only the first two output positions, for reasons noted later). The table shows the number of transitions at lag 1, at lags 2–5, and at “extreme” lags (>5) that have hitherto been excluded. The table also summarizes the prevalence of extreme lags: P_{ext} refers to the proportion of extreme lags out of all nonadjacent transitions, and R_{ext} refers to the ratio of extreme lags to those at intermediate transitions (i.e., 2–5). The proportions of hitherto-excluded data are sufficiently large (P_{ext} is .30 on average for positive lags, and .29 for negative lags) to warrant examination.

All of our analyses (and the data fitting below) proceeded as follows. First, because Kahana (1996) noted that lag-CRP functions are steepest for the first two output positions, we considered only these responses for every participant and trial; this has also ensured consistency between the simulations we present later and the fits presented in Howard and Kahana (2002a).²

Second, because we were interested in the transition from one correct report to the next, trials that included a repetition, an omission, or an extralist intrusion among the first two responses were excluded. Third, all lag-CRP functions were computed using chance-corrected proportions;

Table 1
Backward and Forward Transitions in the 14 Data Sets Broken Down by Lag for the First Two Output Positions

Study	Condition	Backward					Forward				
		Lags			Extreme Lags		Lags			Extreme Lags	
		-1	-2 \Rightarrow -5	<-5	P_{ext}	R_{ext}	1	2 \Rightarrow 5	>5	P_{ext}	R_{ext}
H&K (1999)	Immediate	215	109	21	.16	.19	226	45	14	.24	.31
	Delay	45	81	55	.40	.68	140	90	44	.33	.49
	ISI = 0 sec	71	133	100	.43	.75	97	94	83	.47	.88
	ISI = 2.5 sec	54	117	77	.40	.66	65	62	56	.47	.90
	ISI = 8 sec	64	149	103	.41	.69	101	108	74	.41	.69
	ISI = 16 sec	74	139	87	.38	.63	86	63	25	.28	.40
M&O (1970)		131	128	58	.31	.45	796	211	64	.23	.30
Murdock (1962)	10-2	188	158	38	.19	.24	562	130	37	.22	.28
	15-2	227	148	31	.17	.21	560	141	28	.17	.20
	20-1	135	92	33	.26	.36	612	150	72	.32	.48
	20-2	109	91	25	.22	.27	679	179	28	.14	.16
	30-1	157	92	38	.29	.41	656	98	68	.41	.69
	40-1	140	116	46	.28	.40	648	111	30	.21	.27
HVNK (2007)		2,890	1,131	142	.11	.13	1,640	352	107	.23	.30

Note—H&K (1999), Howard and Kahana (1999); M&O (1970), Murdock and Okada (1970); HVNK (2007), Howard et al. (2007). For the forward transitions, P_{ext} refers to the proportion (Lags > 5)/(Lags > 1) and R_{ext} refers to (Lags > 5)/(Lags 2 \Rightarrow 5); for the backward transitions, P_{ext} and R_{ext} refer to their backward equivalents. Interstimulus interval (ISI) in the H&K (1999) conditions refers to the duration of intralist distractor activity, and the conditions in Murdock (1962) are coded as list length–presentation duration per item (in seconds).

that is, during aggregation across trials and participants, we took into account the set of all possible transitions for each observed actual transition. All lag-CRP plots shown in this article are based on these chance-corrected transition probabilities.³

An illustrative result is shown in Figure 1 (Howard & Kahana, 1999, delayed recall condition; the data are represented by crosses). Although lag-CRPs decline monotonically within the window of ± 5 , the figure also reveals strong evidence for nonmonotonicity at greater lags in some of the panels. Statistical confirmation of nonmonotonicity was obtained by fitting four candidate descriptive functions to all observed lag-CRPs. The four candidates consisted of two monotonic functions (an exponential and a power function) and two nonmonotonic functions (a quadratic and a composite of complementary exponen-

tials). Formally, as a function of the absolute lag l , the exponential function was

$$f(l) = \exp(-al), \tag{1}$$

where a is a free parameter. The power function was given by

$$f(l) = l^{-a}. \tag{2}$$

For the quadratic,

$$f(l) = a + bl + cl^2, \tag{3}$$

with free parameters a , b , and c . Finally, the function involving complementary exponentials incorporated one increasing and one decreasing exponential function across lags—the latter to capture any upturns in transition probabilities at extreme lags—and was defined as

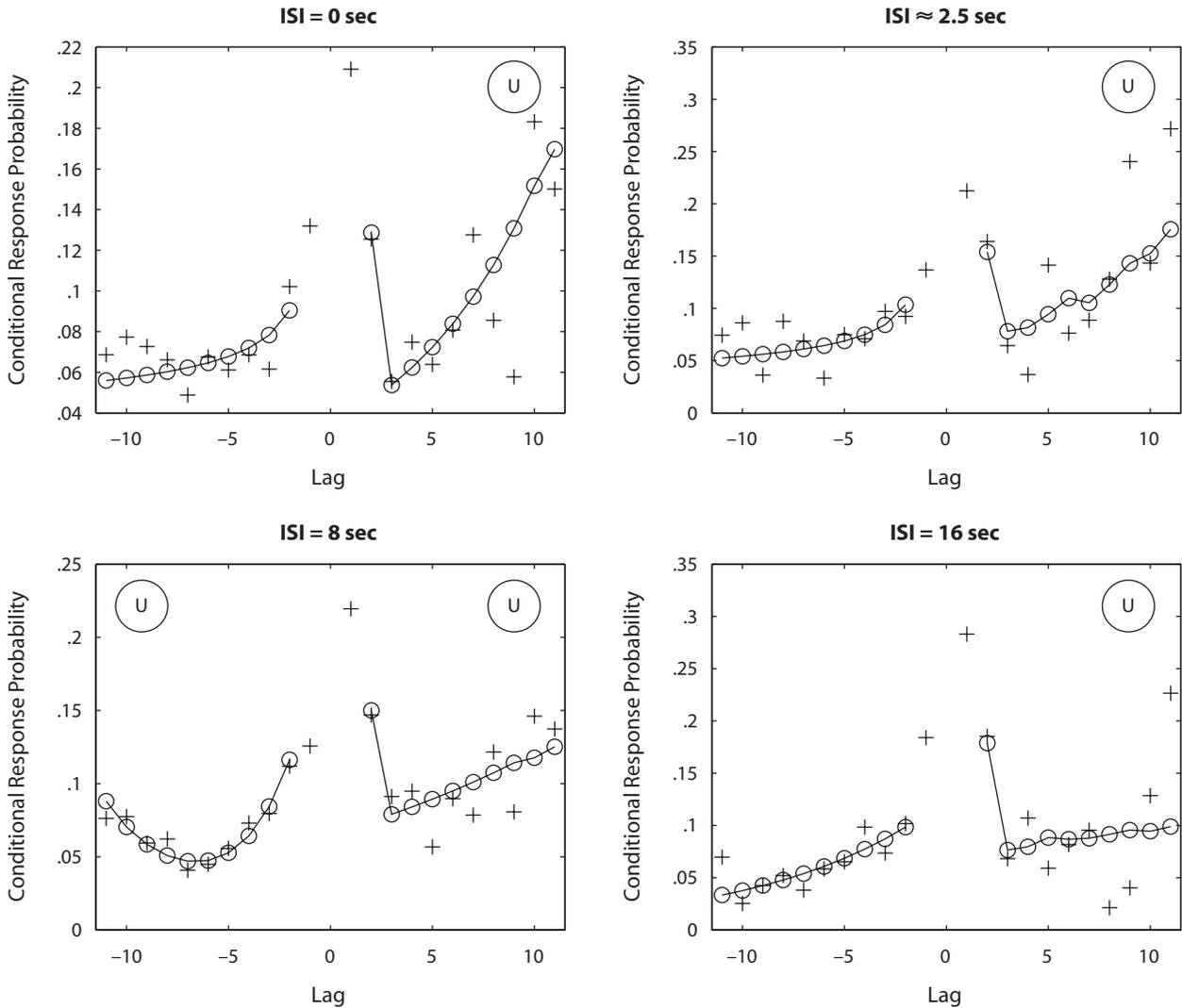


Figure 1. Lag-CRP functions for Experiment 2 of Howard and Kahana (1999), along with predictions of the descriptive model with the highest Akaike weight for forward and backward transitions. The panels correspond to different durations of continuous distraction between items; in all cases, a 16-sec distractor task intervened between the list presentation and delayed recall. Crosses depict the data, whereas the curves show the predictions of the model for transition distances >1 . A circled “U” at the top left or right of a panel indicates that the best-fitting curve is nonmonotonic, for backward and forward transitions, respectively.

$$f(l) = c \exp(-al) + (1 - c) \exp[-b(L - l)], \quad (4)$$

where L is the list length and a , b , and c are free parameters. Note that the argument for the second exponential, $(L - l)$, runs “backward,” thus reversing the exponential decrease with lag into an exponential increase.

Parameters were estimated by fitting each candidate function to each of the empirical lag-CRP functions for the 14 data sets listed in Table 1. Positive and negative lags were fit separately and independently. Because the large discontinuities between lag 1 and the remainder of the lags (which are evident in Figure 1 and were present in all data sets) might have unduly favored the more complex nonmonotonic functions, even if the data were actually monotonic, our fits only considered lags greater than 1.⁴ The solid lines with circles as plotting symbols in Figure 1 represent the best-fitting descriptive model; each circled “U” in a panel indicates that the best descriptive function for a line was nonmonotonic (i.e., either quadratic or the complementary-exponentials function). The figure shows that in five of the eight cases, the best-fitting function was nonmonotonic.

To provide a concise summary of the 14 data sets, the models were compared for each data set using Akaike weights (Burnham & Anderson, 2002; Wagenmakers & Farrell, 2004) obtained from the Akaike information criterion statistic (AIC; Akaike, 1974). The AIC allows comparisons between models of differing complexity, because it trades off goodness of fit and the number of parameters that need to be estimated to achieve that fit. Akaike weights are derived from AIC values but have the additional advantage of being interpretable as conditional probabilities—that is, the probability that a given model is best, given the data and the set of candidates. Table 2 compares the Akaike weights for the candidate functions for all 14 data sets, for negative and positive lags sep-

arately. The best model for each data set is identified by a boldfaced Akaike weight. Figures for the individual experiments are available in the Web-based supplementary materials.

Table 2 suggests a clear conclusion: In many cases, the lag-CRP functions are clearly not monotonic, and across all data sets, the average Akaike weight for the complementary-exponentials function (.58 for backward and .52 for forward transitions) favors a nonmonotonic characterization of the data. To illustrate this overall nonmonotonicity, Figure 2 displays the average lag-CRP functions for the 14 reanalyzed data sets. The plotted points within the ± 5 window (shaded) were formed by averaging the observed transitions at those lags across data sets; the points outside the window were formed by outside-justified alignment. Specifically, the greatest lags shown in the figure (± 9) represent the largest transition possible in the data set with the shortest list length (condition 10–2 of Murdock, 1962); all other data sets were aligned so that their most extreme transition contributed to the average of lag ± 9 , and so on down to ± 6 . A rise in transitions for extreme lags is evident in the figure; in the forward direction, this rise is as large as the drop across intermediate lags (2–5).

Summary

A reanalysis of the free recall data from 644 participants, comprising some 17,500 responses, failed to yield consistent evidence for a monotonic decrease in transition probabilities with increasing lag. We confirmed the observation that immediate transitions (± 1) were uniformly more likely than more remote transitions (Kahana, 1996; Laming, 1999). We also observed the expected monotonic decline across all lags in some of our analyses (see Table 2). However, on balance, when all data were considered together (see Figure 2), there was a clear non-

Table 2
Akaike Weights for Each Descriptive Model and Fit to All Data Sets

Study	Condition	Backward				Forward			
		Exp	Power	Quad	Comp Exp	Exp	Power	Quad	Comp Exp
H&K (1999)	Immediate	.00	.01	.00	.99	.03	.14	.28	.55
	Delay	.12	.48	.17	.23	.17	.53	.12	.18
	ISI = 0 sec	.11	.43	.18	.28	.00	.00	.06	.94
	ISI = 2.5 sec	.12	.37	.25	.25	.01	.01	.12	.86
	ISI = 8 sec	.00	.02	.47	.51	.04	.08	.22	.66
	ISI = 16 sec	.66	.11	.10	.13	.05	.30	.15	.50
M&O (1970)		.00	.01	.00	.99	.00	1.00	.00	.00
Murdock (1962)	10–2	.00	.00	.26	.74	.00	.03	.03	.94
	15–2	.00	.21	.00	.79	.16	.64	.07	.12
	20–1	.00	.01	.00	.99	.00	.00	.11	.89
	20–2	.00	.96	.00	.04	.00	1.00	.00	.00
	30–1	.00	.00	.00	1.00	.00	.00	.33	.67
	40–1	.00	.77	.00	.23	.00	.99	.01	.00
HVNK (2007)		.00	.00	.00	1.00	.00	.00	.08	.92

Note—Exp, exponential; Quad, quadratic; Comp Exp, complementary exponentials; H&K (1999), Howard and Kahana (1999); M&O (1970), Murdock and Okada (1970); HVNK (2007), Howard et al. (2007). Interstimulus interval (ISI) in the H&K (1999) conditions refers to the duration of intralist distractor activity, and the conditions in Murdock (1962) are coded as list length–presentation duration per item (in seconds). Boldface values indicate the largest weight from each set of models, and therefore the best-fitting model. See the text for interpretations.

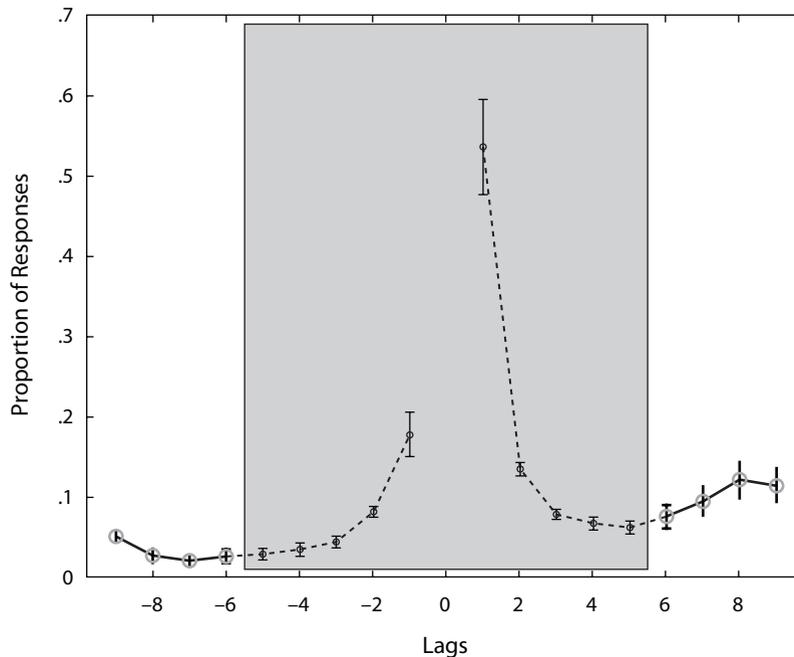


Figure 2. Average observed lag-CRP functions for all 14 data sets. “Extreme lags”—those outside the shaded box—are outside justified; see the text for more explanation. Error bars represent the standard errors across $N = 14$ data sets.

monotonicity of the lag-CRP functions, with an upturn in transition probabilities for lags greater than 5 or 6. These “extreme” lags comprise a significant proportion of all responses (see Table 1), suggesting that their dismissal when summarizing people’s free recall performance is inadvisable. It follows that the monotonic decline of transition probabilities with lag, widely implied in previous work based on a subset of the available data, does not always adequately characterize people’s free recall performance.

This nonmonotonicity can best be understood as the effects of both primacy and recency revealing themselves in the lag-CRP function. For example, the upturn in the forward direction indicates that regardless of the item just recalled, the next item tends to come from the last few list positions. Because our focus here is on the implications of our reanalysis for the TCM, we do not seek to explain what might cause the presence or absence of nonmonotonicity; identification of the relevant variables remains an obvious endeavor for future research. We next quantitatively examined the TCM’s account of these reanalyzed data, and we will show that no consistent set of assumptions can allow the TCM to capture the results.

RECENCY AND LAG RECENCY IN THE TCM

Status and Scope of the TCM

Our critique must begin by analyzing the status of the TCM and its intended scope. This is particularly rele-

vant because in their introductory presentation, Howard and Kahana clearly stated that “TCM is not a free recall model” (2002a, p. 293); instead, the model was presented as a description of limited aspects of free recall—namely, recency (encompassed by FRPs) and associative effects (encompassed by lag-CRPs). Nonetheless, support for the TCM has been adduced by its application to those features of free recall performance since its inception. To date, explorations of the model have addressed its predictions concerning recency over various time scales (Howard, 2004), demonstrated its account of the effects of aging on recency and lag recency (Howard et al., 2006), and extended its scope to spatial navigation (Howard et al., 2005). In all cases, matches between data and predictions have been taken in support of the model. We conclude that, irrespective of what exactly the TCM is a model of, the fact that it is supported by data must imply that it can also be challenged by those same (reanalyzed) data.

Concerning scope, Howard (2004) stated that the “TCM . . . has been used to describe the recency effect and associative effects in immediate, delayed and continuous-distractor free recall experiments” (p. 234). Although this statement implies fairly unequivocally that FRPs and lag-CRP functions *at all retention intervals* are within the purview of the TCM, to date all published lag-CRP applications have been limited to *delayed* recall. In immediate recall, the model has been shown to predict FRPs (see, e.g., Howard & Kahana, 2002a), but modeling of lag-CRP functions has been deemed unsuitable because “in immediate free recall, the CRP is not

stable across output positions . . . , making it a less-than-ideal environment for asking basic questions about contiguity effects” (Howard & Kahana, 2002a, p. 283). We conclude that the TCM was designed to describe recency and contiguity effects at all time scales (see the abstract of Howard & Kahana, 2002a), although lag-CRP functions for immediate recall have thus far been exempted from consideration. This exemption has been justified by properties of the data, rather than by any in-principle inapplicability of the TCM to such data. As a consequence, the TCM’s account of lag-CRPs for immediate recall is undocumented. One purpose of this article is to present a thorough exploration of the behavior of the TCM in immediate recall.

Implementations of the TCM

The core assumption of the TCM, and a source of its attractiveness, is that human memory relies on a continuously evolving temporal context; in contrast to the family of models in which the temporal context drifts randomly (Davelaar et al., 2005; Estes, 1955; Murdock, 1997), the TCM assumes that evolution of the context is driven by the encoding and retrieval of items. In consequence, recent episodes are themselves used to create a context for the encoding of new episodes. This elegant mechanism comes at the cost of some representational and descriptive complexity, which requires careful differentiation between different components of context. To facilitate understanding of our analysis of the TCM, we now introduce some terminology that will be used in the remainder of this article.

When an item is presented for learning at time i , it is assumed to be bidirectionally associated with the present temporal context, which in turn is the weighted sum of two components. The first of these components is the context that prevailed at time $i-1$, called the *carryover context* from here on. The second component is the context that was retrieved by the item presented at time $i-1$. This *retrieved context*, t_{iN} , in turn involves a combination of preexperimental context(s) and contexts associated with the item during the experiment. At test, context is used for cuing retrieval; following recall of an item, the temporal context once again evolves in the same manner as for stimulus presentation.

A crucial implication of this mechanism is that recall at time t is cued by the weighted combination of the carryover context (from time $t-1$) and the retrieved context elicited by the just-recalled item; the relative contributions of those two cue components turn out to be critical in determining the model’s predictions.

Both recency and lag recency follow from these core assumptions about context in the TCM. The recency effect follows from the overlap between the context at the end of list presentation and the one used to initiate recall; if it is assumed that the list-final context carries over into recall, there will naturally be a close match between the recall context and the temporal context associated with items toward the end of the list (see discussion of “nonreinstatable context” in Brown et al., 2000). In consequence, the

first item recalled will almost invariably be from the last few list positions, thus giving rise to steep recency in the FRP function.

Concerning lag recency, the retrieved context component t_{iN} allows the model to predict a decline in lag-CRPs with increasing lags: When item i is recalled and used to evolve the temporal context, it retrieves a context that partially matches the contexts associated with items $i-1$ and $i+1$, with increasingly poorer matches for increasing lag j between item i and item $i\pm j$. As presented here, the TCM necessarily predicts that conditional transition probabilities will fall off monotonically with increasing lag (see, e.g., Equation 31 of Howard, 2004).

Although the evolution of context represents the conceptual core of the model (Howard & Kahana, 2002a, p. 293, summarize the TCM as “a model that prescribes a set of rules for how a distributed episodic representation should change from moment to moment”), in actual fact, contextual evolution has not been instantiated for any of the predictions published to date. For that reason, the forthcoming discussion differentiates between the published implementation of the TCM (henceforth, TCM_{pub}) and a novel implementation, created for the purposes of this article, that incorporates evolving context (TCM_{evo}), which has hitherto only been described rather than implemented.⁵

We first fit TCM_{pub} to the reanalyzed data and, in the process, point out how the instantiation to date has circumvented the evolution of context that forms the conceptual core of the theory. We then present TCM_{evo} and show how its predictions differ from those of the published version, before applying TCM_{evo} to the reanalyzed data.

Standard Implementation: TCM_{pub}

TCM_{pub} was fit to the reanalyzed data using maximum likelihood estimation. Following Howard and Kahana (2002a), and paralleling our reanalysis, we fit only the first two output positions. The first output position determines the FRPs, and the transition between the two output positions determines the lag-CRP. Maximum likelihood parameter estimates were obtained for each participant separately using the simplex algorithm (Nelder & Mead, 1965). Likelihood statistics for all data sets (summed across participants in each case) are given in Table 3. To provide an indication of each model’s performance, the final column in the table provides the critical values of χ^2 (the deviance, $-2\ln L$, approximates a χ^2 distribution). The mean parameter estimates associated with the fits (averaged across participants) are given in Table 4.

Across all data sets, the match between TCM_{pub} and the empirical FRPs varied. Representative fits are shown in Figure 3. The left panel shows the fit to the ISI = 16 condition in Experiment 2 of Howard and Kahana (1999); for these and other data (e.g., Howard & Kahana, 1999; Howard et al., 2007), the model gave a good account of the FRPs. By contrast, for the data of Murdock and Okada (1970) and Murdock (1962), the model overpredicted the recency in the FRPs; this misfit is illustrated in the right panel of Figure 3.

Table 3
Goodness-of-Fit ($-2\ln L$) Values for Two Versions of the Temporal Context Model, for Each Experiment and Condition Fit

Study	Condition	TCM _{pub}	TCM _{evo}	Critical χ^2 Value ($\alpha = .05$)
H&K (1999)	Immediate	3,968.6	3,326.6	1,253.8
	Delay	4,435.2	4,413.0	983.4
	ISI = 0 sec	5,545.5	5,526.5	1,248.6
	ISI = 2.5 sec	3,958.5	3,909.6	934.5
	ISI = 8 sec	5,552.0	5,476.5	1,302.4
	ISI = 16 sec	4,137.6	4,077.6	1,035.3
M&O (1970)		13,520.0	11,772.0	2,787.2
Murdock (1962)	10-2	8,764.1	8,149.9	2,364.5
	15-2	9,731.7	8,303.8	2,400.4
	20-1	10,985.0	9,473.5	2,320.5
	20-2	11,163.0	9,585.1	2,342.0
	30-1	11,478.0	9,274.1	2,348.1
	40-1	11,220.0	9,068.9	2,319.5
HVNK (2007)		35,113.0	28,722.0	12,875.0

Note—H&K (1999), Howard and Kahana (1999); M&O (1970), Murdock and Okada (1970); HVNK (2007), Howard et al. (2007). A smaller value indicates a better fit.

Concerning lag-CRPs, in most cases the model's predictions did not accord with the empirical results. Figure 4 shows representative predictions of TCM_{pub} for the data shown earlier in Figure 1 (recall that all panels involve delayed recall, but with different ISIs, and a continuous distractor task). Across all data sets, TCM_{pub} often underpredicted the occurrence of +1 transitions; in Figure 4, this is illustrated in the bottom right panel for the 16-sec ISI condition. The model also consistently failed to capture the nonmonotonicity in the data, as is evident from all panels of Figure 4. Note, however, that the model's predictions are roughly in accord with its previously published predictions, except that here the predicted lag-CRP functions span a wider range of lags and are more likely to underestimate the occurrence of +1 transitions.

The deviation between the predictions and the data in the FRPs and the lag-CRPs can be attributed to the heavy tails and frequent nonmonotonicity of the empirical lag-CRPs. To handle the large number of extreme transitions, TCM_{pub} produced relatively flat lag-CRP functions, at the expense of underpredicting the ± 1 transitions. The only way in which the model can flatten the predicted lag-CRP functions is by decorrelating the successive list contexts by increasing the contribution of retrieved context. Given the trade-off between the carryover and retrieved contexts, one consequence is the excessive recency in the predicted FRPs.

In summary, as currently instantiated, TCM_{pub} is qualitatively and quantitatively unable to accommodate the data. In particular, the model fails to capture the clear nonmonotonicity in the lag-CRPs. This problem has remained undiscovered to date because analysis and modeling have been restricted to a relatively narrow window of lags.

In addition to noting the model's mispredictions, the manner in which those predictions are obtained also deserves clarification. In all applications to date, Howard, Kahana, and colleagues have made a simplifying assumption

that, though subtle, has had significant implications. Specifically, TCM_{pub} assumes that at the outset of recall, the context cue is identical to the context prevailing at the end of list presentation (Howard & Kahana, 2002a). In consequence, the first item recalled will almost invariably be from the last few list positions, thus giving rise to steep recency in the FRP function. If postlist distractors are present, context is updated after list presentation, and the prerecall context is no longer identical to the context for the last list item, thus generating the reduction in recency with distractor-filled delays.

By contrast, when accounting for the lag-CRP functions in TCM_{pub}, Howard and colleagues have consistently assumed that the carryover context, which lingers

Table 4
Mean Maximum Likelihood Parameter Estimates Obtained in Fitting Each Version of the Temporal Context Model to Each Data Set

Study	Condition	TCM _{pub}		TCM _{evo}	
		β	τ	β	τ
H&K (1999)	Immediate	.44	.30	.34	.20
	Delay	.70	.22	.68	.26
	ISI = 0 sec	.56	.29	.59	.42
	ISI = 2.5 sec	.61	.26	.59	.32
	ISI = 8 sec	.54	.31	.53	.34
	ISI = 16 sec	.36	.31	.42	.32
M&O (1970)		.28	.25	.39	.35
Murdock (1962)	10-2	.34	.29	.27	.23
	15-2	.39	.27	.24	.15
	20-1	.33	.30	.23	.22
	20-2	.32	.28	.16	.13
	30-1	.37	.26	.32	.23
	40-1	.38	.21	.29	.20
HVNK (2007)		.52	.23	.43	.20

Note—H&K (1999), Howard and Kahana (1999); M&O (1970), Murdock and Okada (1970); HVNK (2007), Howard et al. (2007). An explanation of the parameters can be found in the supplementary materials for this article, or in Howard and Kahana (2002a).

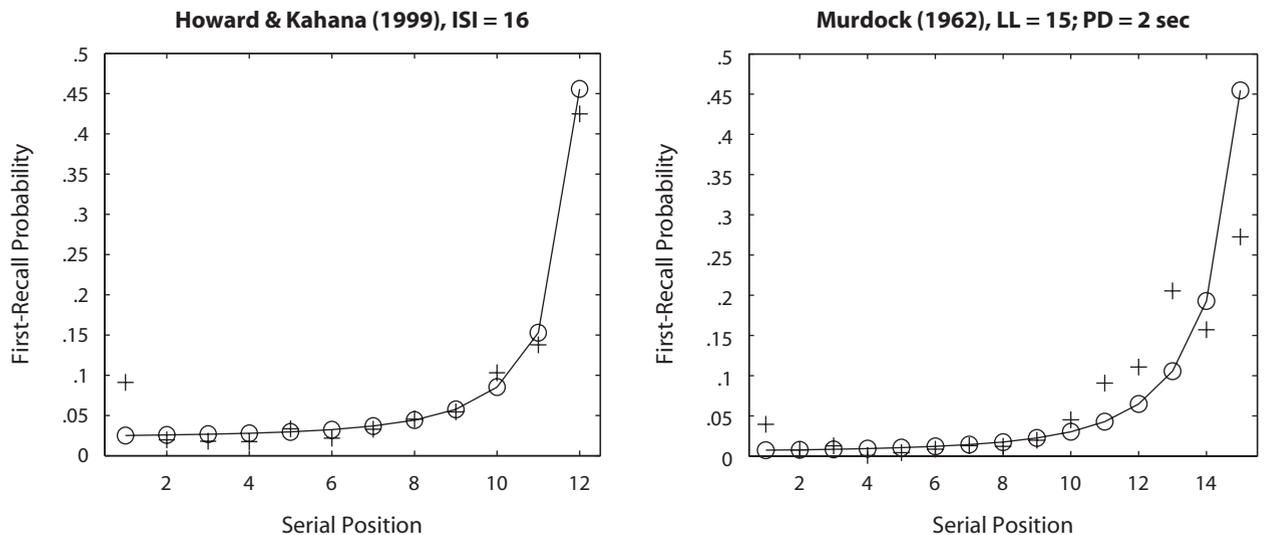


Figure 3. Illustrative fits of TCM_{pub} to FRPs. Left panel: Fit to data from the ISI = 16 condition in Experiment 2 of Howard and Kahana (1999). Right panel: Fit to data from the list length = 15, presentation duration = 2 sec condition of Murdock (1962).

from the previous recall, is *orthogonal to all contextual states from the list* (Howard, 2004; Howard & Kahana, 2002a); this is equivalent to assuming that an infinitely long time has intervened between the list and the recall attempt to be modeled. In consequence, the model necessarily predicts monotonically decreasing lag-CRP functions, because the retrieved context, elicited by the just-recalled item, provides the sole basis on which to discriminate between potential recall candidates; the compound context cue thus preferentially elicits list items proximate to the immediately preceding recall.

It follows that TCM_{pub} 's predictions for FRPs and lag-CRPs, respectively, are obtained under two very different circumstances. When predicting FRPs, the context prevailing at the end of study (or its updated derivative) is used as a cue; when predicting lag-CRPs, the carryover context is not actually carried over between recalls, but is instead assumed to be orthogonal to the temporal contexts associated with all list items. The use of two distinct assumptions about the relevant context cue creates a gap between the stated deep properties of the model and its implementation. On the one hand, an appealing core property of the model is the notion of a context that gradually evolves by combining the carryover context with the retrieved context. On the other hand, in all applications to date, the model's predictions were not derived in this fashion when accounting for the lag-CRP function. Irrespective of the quality of the fits of TCM_{pub} , this disconnection between the description of the model and its actual implementation undermines the use of the model as a conceptual tool.

To date, no published simulation has shown the TCM's predictions if it were permitted to let context evolve from the state at the end of list presentation to a final (possibly orthogonal) state by continuously updating the context with those retrieved for the recalled items. It is possible

that the TCM will behave quite differently when it is computationally implemented as it has been described; accordingly, we next present a modified version of the TCM in which context evolves gradually across list presentation and recall.

Recency and Lag Recency With Evolving Context: TCM_{evo}

Demonstrations of the TCM with continuously evolving context. What happens when the appropriately evolved context is used in place of an orthogonal carryover context to predict lag-CRP functions? Assuming a continuously evolving context throughout list presentation and recall requires some reexpression of the model, because the extant solutions only apply when there are no repetitions of items. These solutions are insufficient here, because once an item has been recalled from a list, it has effectively been repeated. This modification of the model is embodied in a new instantiation introduced here, TCM_{evo} , which is detailed in the Web-based supplementary materials. Briefly, unlike the published version, TCM_{evo} uses the context retrieved by the first-recalled item in conjunction with the proper carryover context to produce the compound cue for the second retrieval.

An initial examination of the model revealed a striking nonmonotonicity of the forward lag-CRP functions in TCM_{evo} . Irrespective of whether recall was immediate or delayed or involved a continuous distractor task, lags greater than 5 attracted nearly as many—or indeed more—transitions than did lag +1. This striking upturn resulted from the use of carryover context in this model, in contrast to TCM_{pub} . In TCM_{pub} , the retrieved context elicited by the first-recalled item is combined with an orthogonal (and, hence, noninformative) carryover context—in consequence, this combined context is dominated by that associated with (and retrieved by)

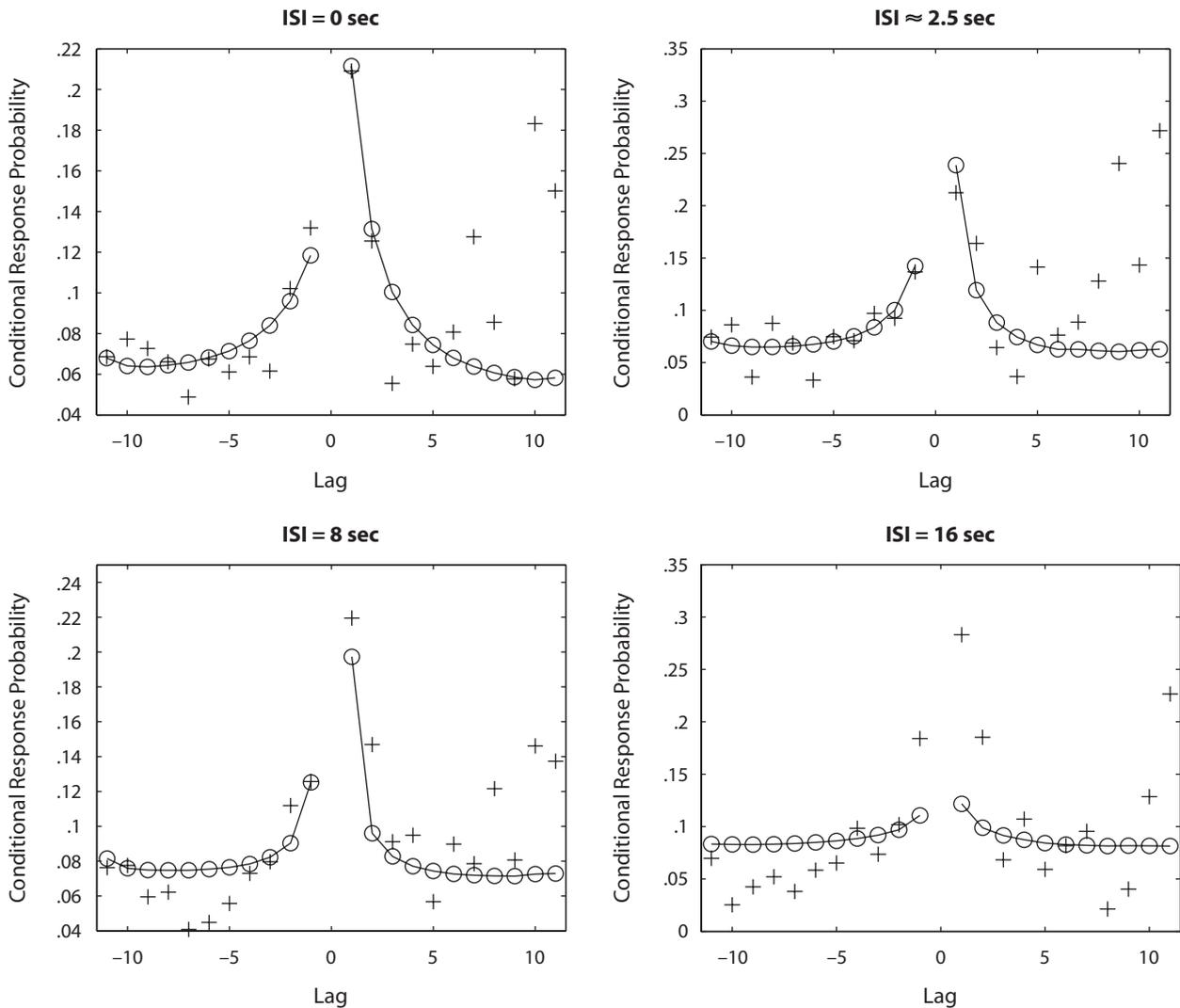


Figure 4. Lag-CRP functions predicted by TCM_{pub} (connected circles; crosses are the data) for the ISI = 0 (top left), 2.5 (top right), 8 (bottom left), and 16 sec (bottom right) conditions in Experiment 2 of Howard and Kahana (1999).

the previously recalled item, which for obvious reasons gives rise to lag recency. In TCM_{evo} , by contrast, the retrieved context is combined with a temporally informative carryover context that—early in recall—necessarily overlaps with the end-of-list context. Hence, cuing with the combined context tends to elicit either a neighboring item (lag recency, driven by the retrieved component) or an item toward the end of the list (recency, driven by the carryover component), thus necessarily giving rise to extreme nonmonotonicity and the U shape of the predicted lag-CRP functions.

This is a noticeable characteristic of TCM_{evo} even for delayed recall: Our initial examinations revealed that even after updating the temporal context with an additional seven items before initiating retrieval (as we assumed for delayed recall, approximating the value in Howard & Kahana, 2002a), the model still shows a strong tendency to make extreme transitions. Both quali-

tatively and quantitatively, this behavior of TCM_{evo} deviates at all time scales from the principle of contiguity that was proposed by Kahana (1996) and Howard and Kahana (1999).

Applying the TCM with continuously evolving context to data. Although the implementation of a continuously evolving context yields predictions that differ considerably from those of the existing published applications of the TCM, the nonmonotonicities observed in our earlier reanalysis of the data are at least in tentative qualitative agreement with TCM_{evo} 's predictions, as just described. We therefore fit TCM_{evo} to the reanalyzed data.

The maximum likelihood statistics for the fits of TCM_{evo} are shown on the right in Table 3, and the corresponding mean parameters are given in Table 4. Representative predictions of TCM_{evo} are shown in Figures 5 and 6. Although TCM_{evo} was able to reproduce the nonmonotonicity of the lag-CRP functions (in some

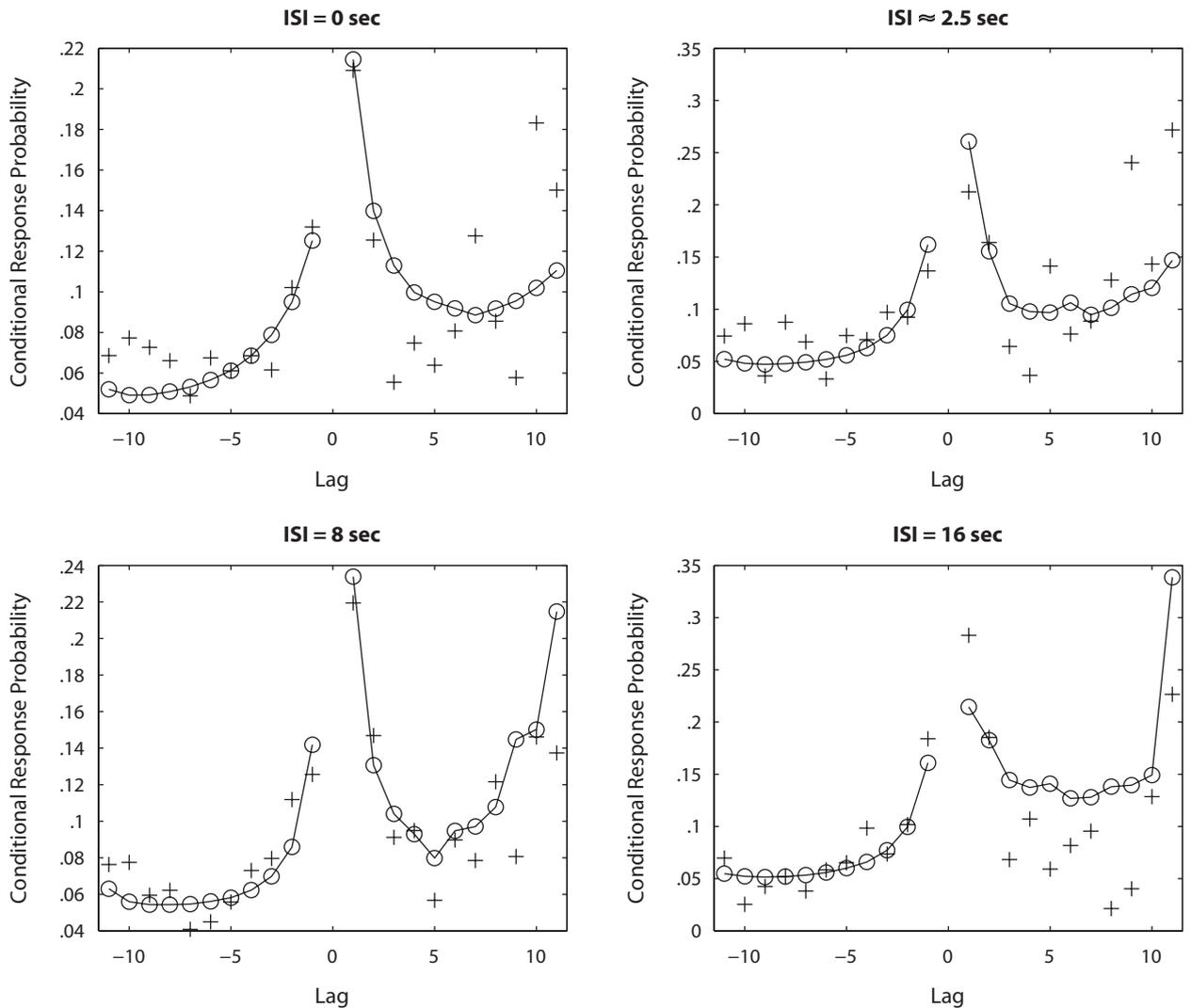


Figure 5. Lag-CRP functions predicted by TCM_{evo} (connected circles; crosses are the data) for the ISI = 0 (top left), 2.5 (top right), 8 (bottom left), and 16 sec (bottom right) conditions in Experiment 2 of Howard and Kahana (1999).

cases, excessively so; see the bottom right panel of Figure 5), this often occurred at the cost of underpredicting the standard lag recency effect (i.e., transitions of small lag, particularly immediate ± 1 transitions; see the bottom right panel of Figure 5 and the right-hand panel of Figure 6).

The simulations showed that when context is assumed to evolve continuously throughout list presentation and recall, TCM_{evo} produces behavior that is somewhat more in accord with the (reanalyzed) pattern in the data. TCM_{evo} correctly (albeit often excessively) predicted nonmonotonicity in the lag-CRP functions, particularly in the forward direction. Accordingly, the quantitative fit of TCM_{evo} was also consistently better, in every instance, than that of TCM_{pub} ; see Table 3.6 On the basis of the disparity between the implementation of TCM_{pub} and the explicit description of the TCM, and the statistical improvement in the model when its implementation is brought in line with

the description by assuming a continuously evolving context, we reject TCM_{pub} and consider it no further. Instead, we will focus on TCM_{evo} in the remaining analyses and discussion.

Recency in TCM_{evo} . We noted at the outset that one reason for the exclusion of lags in excess of ± 5 from all extant analyses has been the presumed scarcity of more extreme transitions. A scarcity of data has presumably also dictated another simplification of analyses to date—namely, the aggregation of lag-CRPs, irrespective of the serial position of the preceding item. This aggregation has been unfortunate: If the lag recency effect truly relates to the conditional dependence between successive recalls, the effect should be present for individual serial positions of the just-recalled item. Some evidence that this is the case was presented by Laming (1999), who showed that the recall of items from the first position and from Positions 14–18 in the experiment of Murdock and

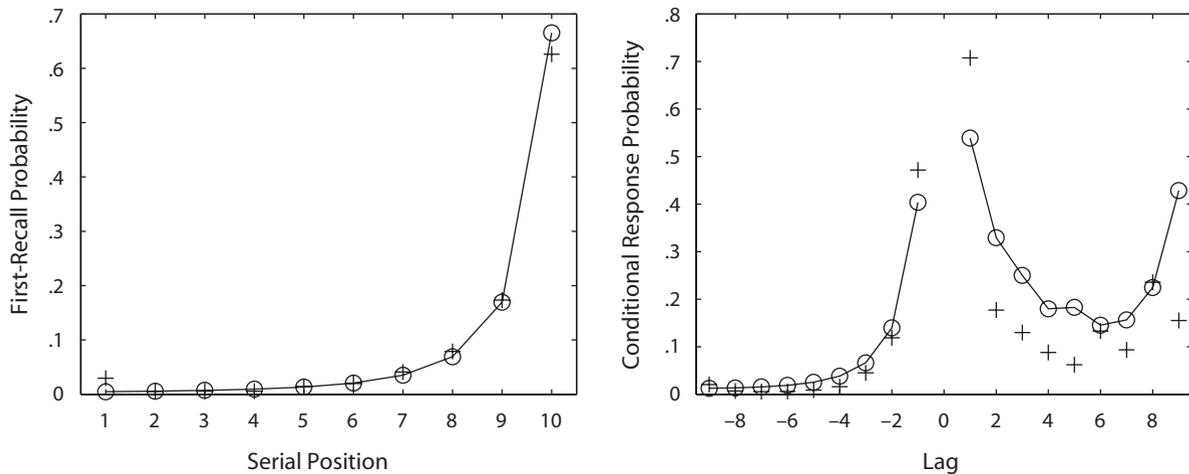


Figure 6. FRP (left panel) and lag-CRP (right panel) functions predicted by TCM_{evo} (connected circles; crosses are the data) for the immediate free recall data of Howard et al. (2007).

Okada (1970) tended to be followed by recall of their respective successor. Although lag-CRP data broken down by serial position may be noisier than the aggregated data, we present a serial-position-based analysis for a data set composed of a very large number of responses. The left column of Figure 7 presents lag-CRP functions for individual serial positions observed in immediate (top) and delayed (bottom) recall. The immediate recall data are from Howard et al.'s (2007) large-scale experiment involving 293 participants, and thus give reasonably smooth lag-CRP functions (the aggregate data are shown in Figure 6). It is clear from this panel that the lag-CRP functions for individual serial positions each possess characteristics similar to those of the aggregate data, showing increased frequencies of local (i.e., ± 1) transitions and a general increase in the frequencies of extreme transitions as compared with intermediate lags. The delayed recall data in the bottom left panel are from Experiment 1 of Howard and Kahana (1999); although the smaller number of responses yields noisier lag-CRP functions, they are consistent with the aggregate data (not shown here).

This consistency in the data contrasts with the lag-CRPs obtained from TCM_{evo} . The top right panel of Figure 7 shows that, for forward transitions in immediate recall, TCM_{evo} does not predict any lag recency effect for individual serial positions. Instead, the predictions are characterized solely by recency: Regardless of which item has just been recalled, one of the last few list items is likely to be recalled next. The model's predictions are therefore in opposition to the regularity in the data: Instead of predicting a large decrease and a small upturn with increasing forward transitions, the model predicts a large monotonic increase. This is not the case for delayed recall, in which the model correctly predicts a conventional monotonically decreasing lag recency effect at each serial position, along with a slight nonmonotonicity for extreme transitions.

It should be noted that these predictions of TCM_{evo} were derived under the best-fitting parameters from the immediately preceding simulations. One objection might be that if the model were fit to the individual curves in Figure 7, rather than the aggregate curves, it would display behavior more in line with the empirical results. As detailed in the supplementary materials, TCM_{evo} was fit by calculating, for each response, the likelihood of that response given its serial position, its output position, and the serial position of any prior recalls on that trial. It follows that the fits reported here are the best possible fits that TCM_{evo} could give to the data as they are analyzed in Figure 7, and that this behavior was obtained under realistic parameter values.

How is TCM_{evo} able to qualitatively produce a conventional lag recency effect across small lags for the aggregate analysis of immediate recall (see Figure 6), whereas the direction of this effect is mostly reversed for all constituent serial positions? The answer is that the predicted conventional lag recency in Figure 6 is an artifact of aggregating across serial positions. There are two factors that contribute to this artifact. First, the top right panel of Figure 7 shows that the predicted probability of the maximum possible transition differs across serial positions and that the extent of recency (as measured by the conditional recall of the last list item) roughly traces out the shape of the aggregate lag-CRP in Figure 6. That is, the most frequent transition at each serial position is from that position to the end of the list; because the distance of that transition decreases with serial position, aggregating across serial positions contributes to an artifactual monotonic decrease of the lag-CRP function. The second contribution to this artifact results from the widely different probabilities with which items from different positions are recalled first. The predicted FRPs in Figure 6 show that most of the time, the first-recalled item will be from terminal list positions; in consequence, when lag-CRPs are aggregated across serial positions,

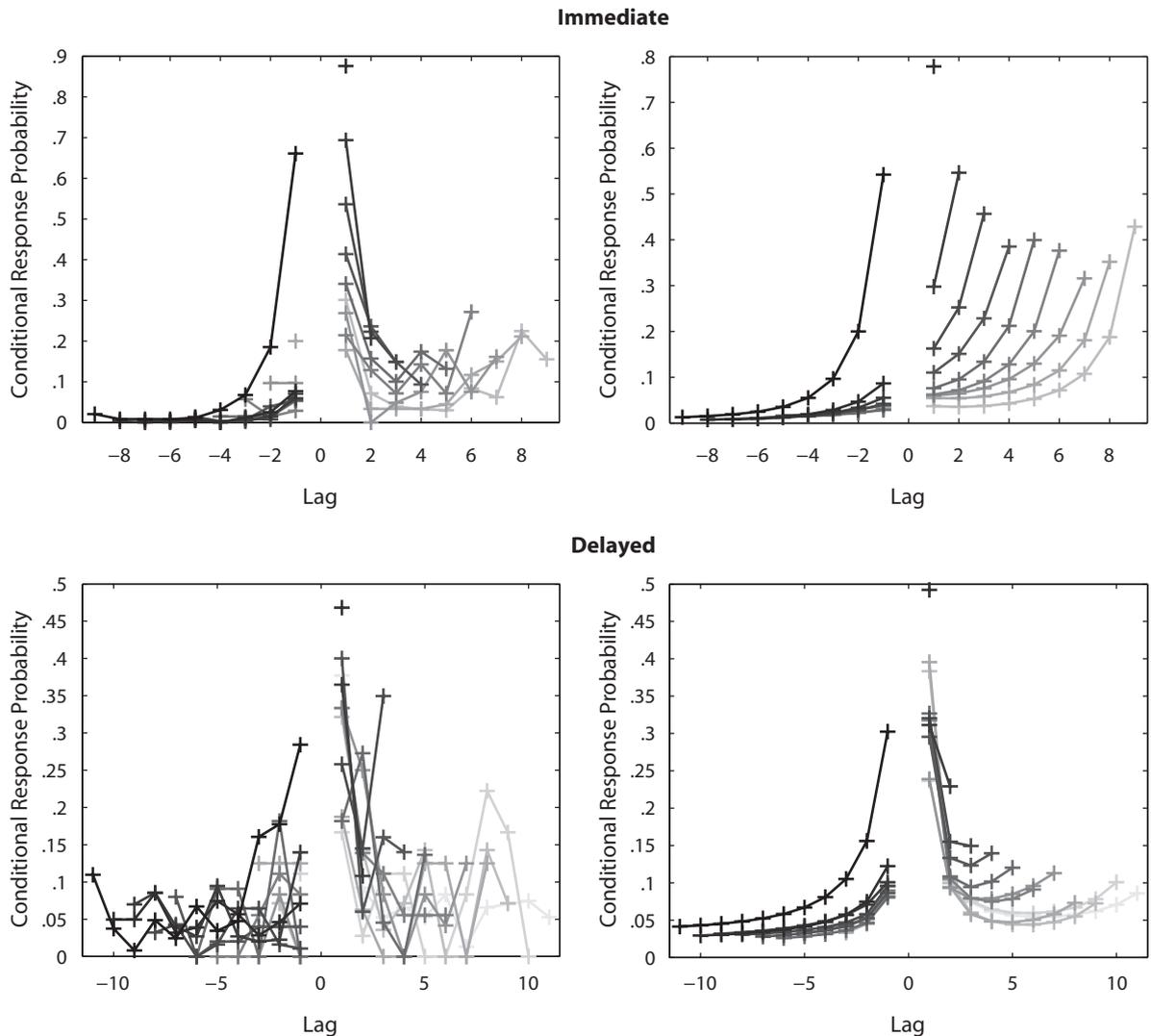


Figure 7. Lag-CRP functions for immediate recall (top panels) and delayed recall (bottom panels), broken down by serial position of the previously recalled item. The darkest line represents the case in which the last item was recalled first (this line is only present for negative lags because no forward transition is possible after recall of the final item), and successively lighter lines represent successive serial positions back in the list of the first-recalled item (the single unconnected data point in each panel represents the case in which the penultimate list item was recalled first, for which the only possible forward transition was +1). The data are shown on the left, and TCM_{evo} 's predictions are shown on the right. The immediate recall data are from Howard et al. (2007); the delayed recall data are from Experiment 1 of Howard and Kahana (1999).

the darker lines in Figure 7 (i.e., later positions) are weighted far more heavily than the lighter lines (early positions), which in turn engenders a monotonic decline across lags upon aggregation.

The preceding analysis of lag-CRPs by serial position is informative in three ways. First, it underscores the general importance of analyzing transition probabilities at a fine level of detail for both data and predictions. For example, the apparent ability of models to account for changes in lag recency across output positions (see, e.g., Davelaar et al., 2005) might simply reflect decreasing susceptibility to aggregation artifacts with increasing delay. Second, our analysis shows that, for immediate recall, the behavior of TCM_{evo} is characterized solely by

recency—irrespective of which item was recalled first, the next item recalled will tend to be from one of the terminal list positions. At the level of each serial position, no set of increasing lags, however constrained or selected, produces decreasing predicted transition probabilities. We have carried out similar analyses for the remaining experiments modeled here, and in all instances of immediate recall the same behavior was produced. We conclude that the decline in transition frequency across small lags in the aggregate lag-CRPs predicted by TCM_{evo} arises from averaging and does not reflect the deep properties of the model. Note, however, that for delayed recall, TCM_{evo} does qualitatively produce lag recency in the lag-CRP functions for individual serial

positions. Third, the behavior of TCM_{evo} identified by this analysis applies to *all* forward transitions, including those with lags of 5 or less. It follows that this problem cannot be circumvented by questioning the generality of the nonmonotonicity identified in our reanalysis.

That said, we reiterate that the TCM has not previously been applied to lag-CRP functions in immediate recall. One might therefore claim that our analysis is not very informative, because it relates to a phenomenon outside the model's scope. Our response is twofold: First, existing justifications for the exclusion of immediate lag-CRPs have focused on the change of empirical CRPs with output position—hence, on the data—rather than on a fundamental problem with the model. It follows that our analysis is informative, even if only proactively, because it presents a strong constraint that further model development must accommodate; continued dismissal of a reliable empirical phenomenon merely because it challenges one's model appears unwise and ultimately unsustainable. Second, given the explicit admonitions that the TCM is *not* a theory of free recall (see, e.g., Howard & Kahana, 2002a), one must be concerned by further reductions in its explanatory scope. As it stands, the TCM has been identified as “a model . . . to describe the recency effect and associative effects in immediate, delayed and continuous-distractor free recall experiments” (Howard, 2004, p. 234); in light of the existence of other, widely encompassing theories of free recall (e.g., Brown et al., 2007; Davelaar et al., 2005), it appears unwise—and ultimately unsustainable—to rule that associative effects are within the purview of the TCM only if accompanied by long retention intervals. Ultimately, a theory's power is proportional to what it can explain; whether it fails to explain a phenomenon (as we have just shown) or whether that phenomenon is arbitrarily put outside the theory's scope (as in previous applications of the TCM), both cases have equal limiting impact on the theory's explanatory power.

DISCUSSION

Our work has departed from three assumptions that appeared to be solidly entrenched in the literature: (1) During free recall, when people transition from one item to the next, they favor transitions across a small number of intervening serial positions over longer transitions, a tendency captured by monotonically decreasing lag-CRP functions. (2) Since its inception, the TCM has reliably and repeatedly captured this pattern of lag-CRPs, at least in delayed recall. (3) The TCM simultaneously accounts for the recency observed in first-recall probabilities. This article has identified all three of those assumptions as subject to qualification or revision.

First, we reanalyzed 14 data sets that have been used to adduce support for these three assumptions, and we discovered that many empirical lag-CRP functions are not monotonic, contrary to the previous consensus in the literature. Our reanalysis differed from the precedents by considering all possible transitions, thus including a

substantial proportion of the data that have been ignored in the past. We suggest that a proper characterization of lag-CRPs in free recall must acknowledge their frequent nonmonotonicity, which in turn reflects the contributions of primacy and recency effects to these conditional analyses.

Second, we confirmed by simulation that the published version of the TCM cannot accommodate the widespread nonmonotonicity in the empirical lag-CRPs, thus revealing a qualitative disparity between the model's predictions and the actual shape of the data that it was designed to explain.

Third, we noted that the TCM has hitherto used two distinct assumptions about context to model FRPs and CRPs, respectively. In so doing, a desirable core property of the model—namely, the gradual evolution of context—has been omitted from all published modeling. This omission compromises the utility of the TCM, irrespective of how well it might fit the data. In response, we implemented an evolving context, in line with the description of the theory, in TCM_{evo} . This modified version performed better than TCM_{pub} , but still without providing a satisfactory account of the data: TCM_{evo} underpredicted the frequency of ± 1 transitions in the CRPs and vastly exaggerated the extent of nonmonotonicity in the lag-CRP functions.⁷ Finally, a more detailed analysis of immediate recall revealed that TCM_{evo} 's lag-CRP predictions at the level of individual serial positions were in exact opposition to the data: Whereas the empirical forward lag-CRPs have a strong declining component, from immediate (+1) transitions to moderately large lags (e.g., +5), the predicted forward lag-CRPs are monotonically increasing. TCM_{evo} thus predicts that once an item has been recalled, the next item reported will be from the end of the list, irrespective of the serial position of the preceding recall.

What implications do our results have for the TCM and for our understanding of free recall in general? Concerning the latter question, irrespective of one's preferred theoretical stance, this article suggests that the hitherto accepted consensus about the shape of lag-CRPs must be revised, or at least qualified. Theoreticians can no longer assume that transitions during free recall solely involve items in close proximity; in a significant number of cases, people are more likely to transition across a large number of serial positions than across an intermediate number.

Turning to the implications for the TCM, we suggest that the model cannot describe the evolution of context while simultaneously accounting for monotonic recency and lag recency effects in free recall. As Figure 5 shows, even under the most favorable parameter values, the model produces behavior that is incommensurate with either its previously published behavior or—in many instances—the data. Note that this conclusion can be drawn without considering immediate free recall; all panels in Figure 5 involve delayed recall. Does our analysis necessarily call into question the overall architecture of the TCM? Might the theory be able to accommodate the data with a few simple modifications?

First, we do not believe that our analysis necessarily calls into question all core principles of the model. The recency that is observed in experiments with continuous distractor tasks certainly favors explanations based on temporal distinctiveness or contextual overlap (e.g., Brown et al., 2007; Davelaar et al., 2005; Glenberg et al., 1980; Glenberg & Swanson, 1986; Neath, 1993), and the lag recency effect, particularly evident in ± 1 transitions, suggests some local associations between items on lists (either direct or mediated by temporal context; Howard & Kahana, 1999; Kahana, 1996); both of these assumptions are embodied in the TCM. However, in light of our simulations, the exact instantiations of these principles in the model may need to be revisited.

Second, concerning such possible modifications, we note that the problems we have identified with the TCM are revealed by the very data that have constituted its principal support. In consequence, we have limited ourselves to exploring only solutions that could arguably be implicit in the TCM's present formulation. One modification, already reported, was to develop TCM_{evo}, which instantiates the available explicit descriptions of the model. We have also explored another parameterization of TCM_{evo} in which the parameter that governs the balance between the retrieved and carryover contexts was allowed to vary between study and test.⁸ We do not report those additional simulations because they do not materially affect our conclusions. We conclude that theoreticians may have to look farther afield to enable the TCM to handle lag-CRP and FRP functions in free recall.

AUTHOR NOTE

Collaboration on this project was assisted by an Australian Research Council international linkage grant to S.L., Gordon Brown, and S.F. The second author was supported by an Australian professorial fellowship from the Australian Research Council. We thank Marc Howard for his clarification of some details of the operation of the TCM. Correspondence should be addressed to S. Farrell, Department of Psychology, University of Bristol, 12a Priory Road, Clifton, Bristol BS8 1TU, England (e-mail: simon.farrell@bristol.ac.uk).

REFERENCES

- AKAIKE, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, **19**, 716-723.
- BROWN, G. D. A., NEATH, I., & CHATER, N. (2007). A temporal ratio model of memory. *Psychological Review*, **114**, 539-576.
- BROWN, G. D. A., PREECE, T., & HULME, C. (2000). Oscillator-based memory for serial order. *Psychological Review*, **107**, 127-181.
- BURNHAM, K. P., & ANDERSON, D. R. (2002). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd ed.). New York: Springer.
- DAVELAAR, E. J., GOSHEN-GOTTSTEIN, Y., ASHKENAZI, A., HAARMANN, H. J., & USHER, M. (2005). The demise of short-term memory revisited: Empirical and computational investigations of recency effects. *Psychological Review*, **112**, 3-42.
- DENNIS, S., & HUMPHREYS, M. S. (2001). A context noise model of episodic word recognition. *Psychological Review*, **108**, 452-478.
- ESTES, W. K. (1955). Statistical theory of spontaneous recovery and regression. *Psychological Review*, **62**, 145-154.
- FARRELL, S. (2006). Mixed-list phonological similarity effects in delayed serial recall. *Journal of Memory & Language*, **55**, 587-600.
- GLANZER, M., & CUNITZ, A. R. (1966). Two storage mechanisms in free recall. *Journal of Verbal Learning & Verbal Behavior*, **5**, 351-360.
- GLENBERG, A. M., BRADLEY, M. M., STEVENSON, J. A., KRAUS, T. A., TKACHUK, M. J., GRETZ, A. L., ET AL. (1980). A two-process account of long-term position effects. *Journal of Experimental Psychology: Human Learning & Memory*, **6**, 355-369.
- GLENBERG, A. M., & SWANSON, N. G. (1986). A temporal distinctiveness theory of recency and modality effects. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **12**, 3-15.
- HOWARD, M. W. (2004). Scaling behavior in the temporal context model. *Journal of Mathematical Psychology*, **48**, 230-238.
- HOWARD, M. W., FOTEDAR, M. S., DATEY, A. V., & HASSELMO, M. E. (2005). The temporal context model in spatial navigation and relational learning: Toward a common explanation of medial temporal lobe function across domains. *Psychological Review*, **112**, 75-116.
- HOWARD, M. W., & KAHANA, M. J. (1999). Contextual variability and serial position effects in free recall. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **25**, 923-941.
- HOWARD, M. W., & KAHANA, M. J. (2002a). A distributed representation of temporal context. *Journal of Mathematical Psychology*, **46**, 269-299.
- HOWARD, M. W., & KAHANA, M. J. (2002b). When does semantic similarity help episodic retrieval? *Journal of Memory & Language*, **46**, 85-98.
- HOWARD, M. W., KAHANA, M. J., & WINGFIELD, A. (2006). Aging and contextual binding: Modeling recency and lag recency effects with the temporal context model. *Psychonomic Bulletin & Review*, **13**, 439-445.
- HOWARD, M. W., VENKATADASS, V., NORMAN, K. A., & KAHANA, M. J. (2007). Associative processes in immediate recency. *Memory & Cognition*, **35**, 1700-1711.
- HOWARD, M. W., YOUKER, T. E., & VENKATADASS, V. S. (2008). The persistence of memory: Contiguity effects across hundreds of seconds. *Psychonomic Bulletin & Review*, **15**, 58-63.
- KAHANA, M. J. (1996). Associate retrieval processes in free recall. *Memory & Cognition*, **24**, 103-109.
- KAHANA, M. J., & HOWARD, M. W. (2005). Spacing and lag effects in free recall of pure lists. *Psychonomic Bulletin & Review*, **12**, 159-164.
- KAHANA, M. J., HOWARD, M. W., ZAROMB, F., & WINGFIELD, A. (2002). Age dissociates recency and lag recency effects in free recall. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **28**, 530-540.
- KLEIN, K. A., ADDIS, K. M., & KAHANA, M. J. (2005). A comparative analysis of serial and free recall. *Memory & Cognition*, **33**, 833-839.
- LAMING, D. (1999). Testing the idea of distinct storage mechanisms in memory. *International Journal of Psychology*, **34**, 419-426.
- LEWANDOWSKY, S., & FARRELL, S. (2008a). Phonological similarity in serial recall: Constraints on theories of memory. *Journal of Memory & Language*, **58**, 429-448.
- LEWANDOWSKY, S., & FARRELL, S. (2008b). Short-term memory: New data and a model. In B. H. Ross (Ed.), *The psychology of learning and motivation* (Vol. 49, pp. 1-48). San Diego: Academic Press.
- MURDOCK, B. B. (1962). Direction of recall in short-term memory. *Journal of Verbal Learning & Verbal Behavior*, **1**, 119-124.
- MURDOCK, B. B. (1974). *Human memory: Theory and data*. Potomac, MD: Erlbaum.
- MURDOCK, B. B. (1997). Context and mediators in a theory of distributed associative memory (TODAM2). *Psychological Review*, **104**, 839-862.
- MURDOCK, B. B., & OKADA, R. (1970). Interresponse times in single-trial free recall. *Journal of Experimental Psychology*, **86**, 263-267.
- NEATH, I. (1993). Contextual and distinctive processes and the serial position function. *Journal of Memory & Language*, **32**, 820-840.
- NELDER, J. A., & MEAD, R. (1965). A simplex method for function minimization. *Computer Journal*, **7**, 308-313.
- POSTMAN, L., & PHILLIPS, L. W. (1965). Short-term temporal changes in free recall. *Quarterly Journal of Experimental Psychology*, **17**, 132-138.
- RAAIMAKERS, J. G. W., & SHIFFRIN, R. M. (1981). Search of associative memory. *Psychological Review*, **88**, 93-134.
- SIROVIN, Y. B., KIMBALL, D. R., & KAHANA, M. J. (2005). Going beyond a single list: Modeling the effects of prior experience on episodic free recall. *Psychonomic Bulletin & Review*, **12**, 787-805.
- TAN, L., & WARD, G. (2000). A recency-based account of the primacy

- effect in free recall. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **26**, 1589-1625.
- WAGENMAKERS, E.-J., & FARRELL, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review*, **11**, 192-196.
- ZAROMB, F. M., HOWARD, M. W., DOLAN, E. D., SIROTIK, Y. B., TULLY, M., WINGFIELD, A., ET AL. (2006). Temporal associations and prior-list intrusions in free recall. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **32**, 792-804.

NOTES

1. For simplicity of exposition, we use the term "lag" from here on to refer at once to both positive and negative transitions. Hence, "increasing lags" is a shorthand way of referring to "increasing absolute lags." Where necessary, we will differentiate between the directions of transition by referring specifically to "positive lags" (for forward transitions) and "negative lags" (for backward transitions).
2. None of the conclusions offered in this article would change materially if the analyses or model fitting had included all output positions.
3. Further details about how transitions were corrected for chance can be found in the supplementary materials for this article at the Web address provided at the end.
4. None of the conclusions would be substantially altered if lags ± 1 were included in the fitting.
5. To conserve space, a formal description of both models and their fits to empirical data is given in the Web-based supplementary materials, along with figures for all model fits.
6. An additional set of unreported simulations fitting all legitimate responses, not just those from the first two output positions, led to the same conclusions.
7. In an attempt to increase the proximity of transitions in the TCM, we devised one other version that assumed that an orthogonal carryover context was used for all recalls, including the first output position. (This

basically generalized the assumption used in TCM_{pub} for lag-CRPs to all output positions.) This version of the model is not presented in detail here, because it performed significantly worse than the other versions considered; in particular, the model predicted perfectly flat FRP functions, which clearly does not accord with the extensive recency in the data. Thus, irrespective of whether the disjointed assumptions about temporal context in TCM_{pub} are reconciled within TCM_{evo} or by generalizing the orthogonality assumption to both phenomena under consideration, no common set of assumptions about temporal context will enable the TCM to simultaneously handle the two phenomena—FRPs and CRPs—that provide its foundational support.

8. We thank Marc Howard for suggesting this modification in a review of an initial version of the manuscript.

ARCHIVED MATERIALS

The following materials associated with this article may be accessed through the Psychonomic Society's Norms, Stimuli, and Data Archive, www.psychonomic.org/archive.

To access this file, search the archive for this article using the journal name (*Psychonomic Bulletin & Review*), the first author's name (Farrell), and the publication year (2008).

FILE: Farrell-PBR-2008.zip.

DESCRIPTION: The compressed archive folder holds a single file, Farrell2008supp.pdf, containing a detailed description of the two models examined here, TCM_{pub} and TCM_{evo}, further details about the data-fitting procedures, and the detailed results of all of the reanalyses and model fits reported here.

AUTHOR'S E-MAIL ADDRESS: simon.farrell@bristol.ac.uk.

(Manuscript received July 11, 2007;
revision accepted for publication March 27, 2008.)