Journal of Experimental Psychology:
Learning, Memory, and Cognition
2007, Vol. 33, No. 2, 297–304

0278-7393/07/$12.00 DOI: 10.1037/0278-7393.33.2.297

Forgetting and Learning Potentiation: Dual Consequences of Between-Session Delays in Cognitive Skill Learning

Timothy C. Rickard
University of California, San Diego

In the cognitive skill literature, between-session delays have been treated either as having a negligible effect on performance or as causing forgetting. In contrast, in the procedural skill literature, overnight between-session delays can result in performance gains. In 5 multi-session data sets, the author demonstrates that neither of these 2 models holds for the case of cognitive skill learning. Instead, the delay between sessions appeared to yield both forgetting and enhanced potential for new learning. Two candidate classes of explanation are considered, and implications for the empirical law of learning are discussed.

Keywords: skill, learning law, forgetting, fatigue, consolidation

Most naturalistic skill acquisition requires multiple practice sessions over many days. A complete theory of human skill must therefore account for the effects of the delays between sessions on learning and performance. Yet, in the cognitive skill acquisition literature, these effects are typically ignored, with the implicit assumption that they have negligible impact on performance. One important exception is work by Anderson, Fincham, and Douglass (1999). In a multisession problem-solving task, they showed that response times (RTs) exhibit the classic decelerating speedup function within each practice session but exhibit slowing at the start of each new session, yielding a scalloped speedup pattern over sessions. The simplest case model of this effect would assume that the (nonlinear) learning rate is constant over repetitions and that the forgetting rate is constant over time. Anderson et al. (1999) provide one possible implementation of that model in their latency equation (p. 1122). It follows from that equation that the mean RTs that are predicted by extrapolating from the fit to one session must fall below the population mean RTs of all subsequent sessions, as represented in Figure 1. Stated differently, the RTs after a delay must be above the RTs that would have been expected had all of the practice occurred within a single session.

There are two opposing traditions about the effects of delays between sessions in the procedural skill literature, in which commonly studied tasks include repetition of a sequence of finger movements (e.g., Walker, Brakefield, Morgan, Hobson, & Stickgold, 2002), movement of a stylus or cursor between specified points (e.g., Brashers-Krug, Shadmehr, & Bizzi, 1996), and rotary pursuit (e.g. Bourne & Archer, 1956). On one hand, in the older literature exploring the phenomena of reminiscence and warm-up decrements, the general finding is similar to that reached by Anderson et al. (1999); provided that practice within the first session is distributed (e.g., a 40-s break between each 10-s trial), an overnight delay between sessions can result in worsened performance (e.g., Adams, 1952; Digman, 1959). On the other hand, in the more recent literature on procedural consolidation (for reviews, see Stickgold, 2005; Walker & Stickgold, 2006), the delay between practice sessions has been shown to result in performance gains, referred to as *consolidation effects*, which appear to depend largely on sleep. At present it is not clear why some studies in these literatures have shown performance gains overnight whereas as others have shown decrements.

As treated in those literatures to date, performance decrements (forgetting) and performance gains (consolidation) following a delay are best understood as opposing forces. In this article, I demonstrate that the true effects of overnight delays between sessions are—for cognitive skills involving memory recall at least—too complex to be captured by models that assume only forgetting or only consolidation, or that assume that these forces operate in opposition along a unitary dimension. Instead, there is RT slowing on the first few item repetitions of each new practice session, which I argue is most naturally interpreted as forgetting in long-term memory, followed by pronounced RT facilitation with additional practice (to faster performance levels than would be anticipated on the basis of data from the proceeding session), which appears to reflect an increased potential for new learning following a delay.

Data Sets

Data from five multisession cognitive skill tasks were analyzed. All of these tasks (with the possible exception of the digit entry task; Data Set 3) can be characterized as requiring one or more cued-recall events on each trial. For all tasks, practice sessions were spaced 2 days apart unless otherwise stated. Experiment 1 of Rickard and Bourne (1996) involved 24 subjects and three sessions, each with 30 practice blocks. Each block involved presentation of 8 multiplication (e.g., $4 \times 7 = ?$) and 8 division (e.g., $54 \div 9 = ?$) problems, randomly ordered. The same problems were presented across all 90 practice blocks. In this and all other experiments described below, subjects began each new block of trials when they were ready to proceed. In nearly all cases, subjects advanced to the next block with little or no delay. Subjects in this

This research was supported by National Institute of Mental Health Grant R29 MH58202. I thank Harold Pashler and Denise Cai for comments on an earlier version of this article.

Correspondence regarding this manuscript should be sent to Timothy C. Rickard, Department of Psychology, 0109, University of California, 9500 Gilman Drive, La Jolla, CA, 92093-0109. E-mail: trickard@ucsd.edu

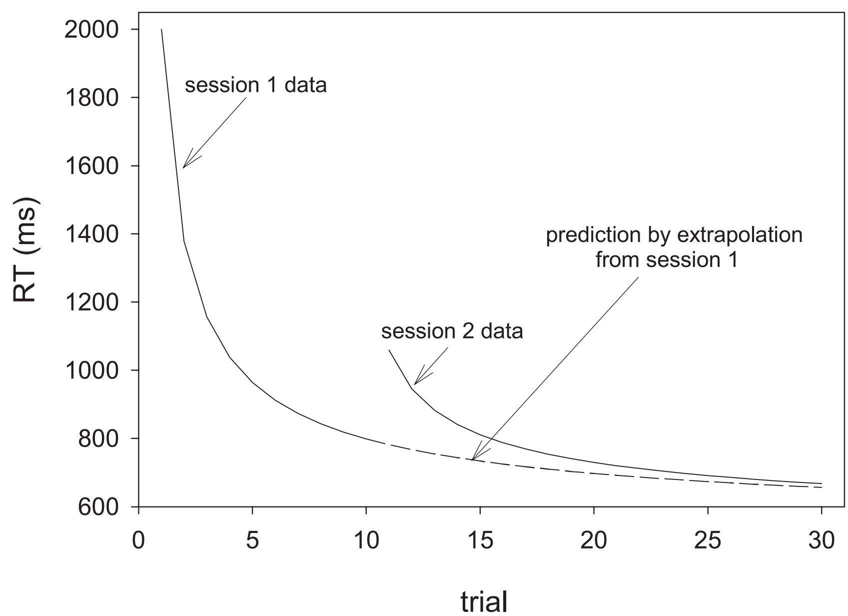

Figure 1. An example of between-session forgetting effects predicted by the model proposed by Anderson, Fincham, and Douglass (1999).

experiment entered their responses using the computer keypad. The latency between the onset of the stimulus and the pressing of the first response key was analyzed. Experiment 2 of Rickard and Bourne (24 subjects) involved two sessions of the same design as Experiment 1, each with 30 practice blocks. Each block involved presentation of 16 multiplication problems and 8 digit entry problems, in which a two-digit number was presented and subjects entered those numbers using the numerical keypad, just as for their answers to the multiplication problems. The arithmetic and digit entry data sets from this experiment are treated as Data Sets 2 and 3.

The fourth data set is from Experiment 1 of Rickard (1997). Twenty-one subjects solved novel arithmetic problems such as "4 # 17 = ?," in which responding initially required execution of a three-step algorithm involving memory retrievals: (1) subtract the smaller number from the larger one, (2) add 1 to the results from Step 1, and (3) add the result from Step 2 to the larger number. Hence, the answer for the example above is 31. In each practice block, there were six problems that required the algorithm specified above and six different problems that involved the same algorithmic relation but for which a different unknown value was solved (e.g., 5 # __ = 35). Subjects received 9, 15, 21, 24, and 21 blocks of practice in Sessions 1 through 5, respectively. Sessions 3 and 4 were separated by 3 days. The task was designed to study the shift from algorithm- to retrieval-based strategies in problem solving, and there was clear evidence that such a strategy shift occurred.

The fifth data set has not been previously published and involved three sessions of practice on 10 letter–digit or digit–letter paired associates. The 23 subjects first had one opportunity to study each paired associate for 5 s. Next, there were 50 recall blocks of 10 trials each, in which each stimulus was presented once in each block, randomly ordered. In Session 2, there were 50 additional recall blocks, and in Session 3 there were four recall blocks. Subjects spoke the response into a microphone equipped with a voice-key device. Accuracy feedback was provided if the subject's response was in error.

Results and Discussion

Four subjects in Data Set 1 and 4 subjects in Data Set 5 exhibited marked RT slowing over the course of practice in Session 2. No other subjects exhibited this trend. These subjects were assumed to have been disinterested or uncooperative, and their data were removed prior to the analysis described below. Accuracy was generally high throughout all practice sessions for Data Sets 1 through 4 (> 95%). For Data Set 5, accuracy was very low initially and was below 95% for the first 11 blocks. Data from those blocks were therefore not included in the RT curve fits described below, although they are included in the graphs for reference.

Raw RTs on correct trials were first log transformed, then averaged over items for each subject, and then over subjects (excluded from these analyses were a small number of RTs of less than 200 ms, which were clear outliers based on inspection of the distributions). A three-parameter power function ($RT = a + b \times block^{-c}$), which is the best candidate for providing good fits to speedup in mean RT within a given practice session on the basis of research to date (e.g., Newell & Rosenbloom, 1981), was then fit to the anti-log of the mean log RTs, separately for each session (except for the last session of each data set).[1] The value of the variable practice block was set to 1 for the first block of the fits to all sessions.

[1] Data Set 4 exhibited a shift from algorithm to retrieval; thus, over sessions, the RTs deviated substantially from the power function (for a discussion of distortions in power function speedup caused by a strategy shift, see Rickard, 1997, 2004). For fitting that data set in the current analyses, power functions were used only as an approximation for within-session speedup.

Results for the five data sets are shown in Figure 2. Rather than revealing a comprehensive RT slowing effect as depicted in Figure 1, or a comprehensive facilitation effect as implied by the recent procedural consolidation literature, for all 10 predicted sessions, the extrapolated fit from the previous session revealed an initial slowing effect followed by an RT facilitation (for both the slowing and the facilitation effect over the 10 sessions, a sign test yielded $p = .001$). These results are not dependent on either the approach of averaging before data fitting or the power function. Averaged item-level fits of both power and exponential functions (for a description of the technique, see Rickard, 2004, p. 77) revealed the same patterns of RT slowing followed by facilitation. These results are not surprising given that the effects are readily apparent by visual inspection of the data.

These patterns are also evident in other data sets. Both arithmetic data sets described in Rickard, Healy, and Bourne (1994) show patterns nearly identical to those in Figure 2A. There are also similar patterns for at least some of the data in Anderson et al. (1999). In their Figure 2, for example, there appear to be between-session facilitation effects in most cases, although the nature of their model fits does not reveal them directly by extrapolation of the curve fits for each session. In summary, the dual effects of RT slowing followed by facilitation after a delay between sessions are clearly robust over a range of commonly studied tasks and levels of practice (up to five experimental sessions), despite being unrecognized in the skill literature to date.

Before proceeding, however, it is important to rule out the possibility that the effects that are interpreted above in terms of between-session delays instead reflect a more general failure of the power function to fit well to data. This issue can be addressed by fitting the power function to practice blocks from the first part of each session and evaluating the quality of its extrapolated fit to the remainder of the data from the same session. If the extrapolated fits are good, then the results outlined above can be confidently interpreted as resulting from the between-sessions delay. These analyses were limited to Data Sets 1 through 3 and the first two sessions of Data Set five, for which there were a relatively large number of practice blocks per session. For all of these data sets, fits to the initial series of practice blocks (20 blocks for Data Sets 1–3 and 40 blocks for Data Set 5) were extrapolated to the last 10 practice blocks of the session. In the between-sessions extrapolations (Figure 2), both the initial slowing and the subsequent facilitation effects were clearly evident within the first 10 blocks of each new session. If those effects reflect a general failure of the power function to characterize speedup, rather than the effect of the delay between sessions, similar effects should be evident in the extrapolation to the last 10 blocks within each session. The results are shown in Figure 3. In five cases, the extrapolated curve runs

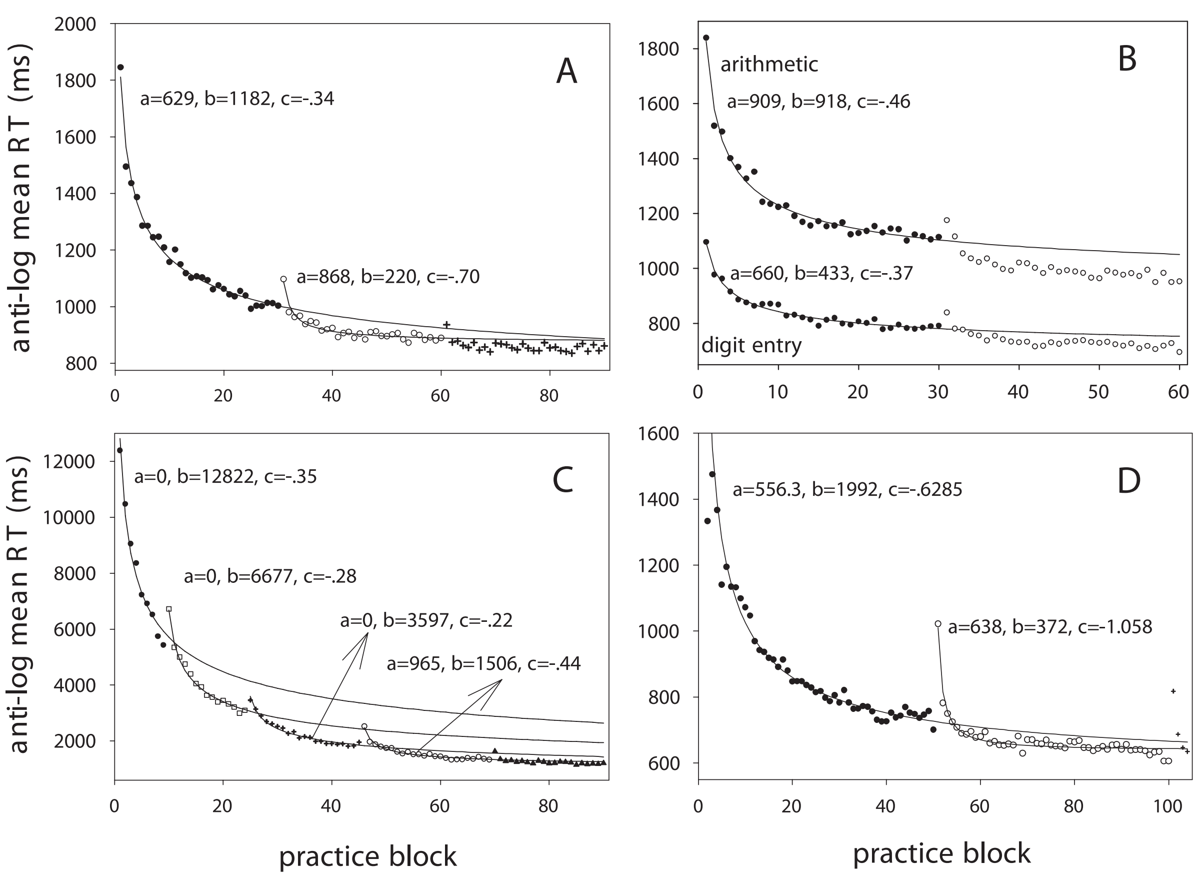

Figure 2. Anti-logs of the mean log response time (RT) speedup curves along with separate three-parameter power functions fits to each session. Panel A shows Data Set 1, Panel B Data Sets 2 and 3, Panel C Data Set 4, and Panel D Data Set 5.

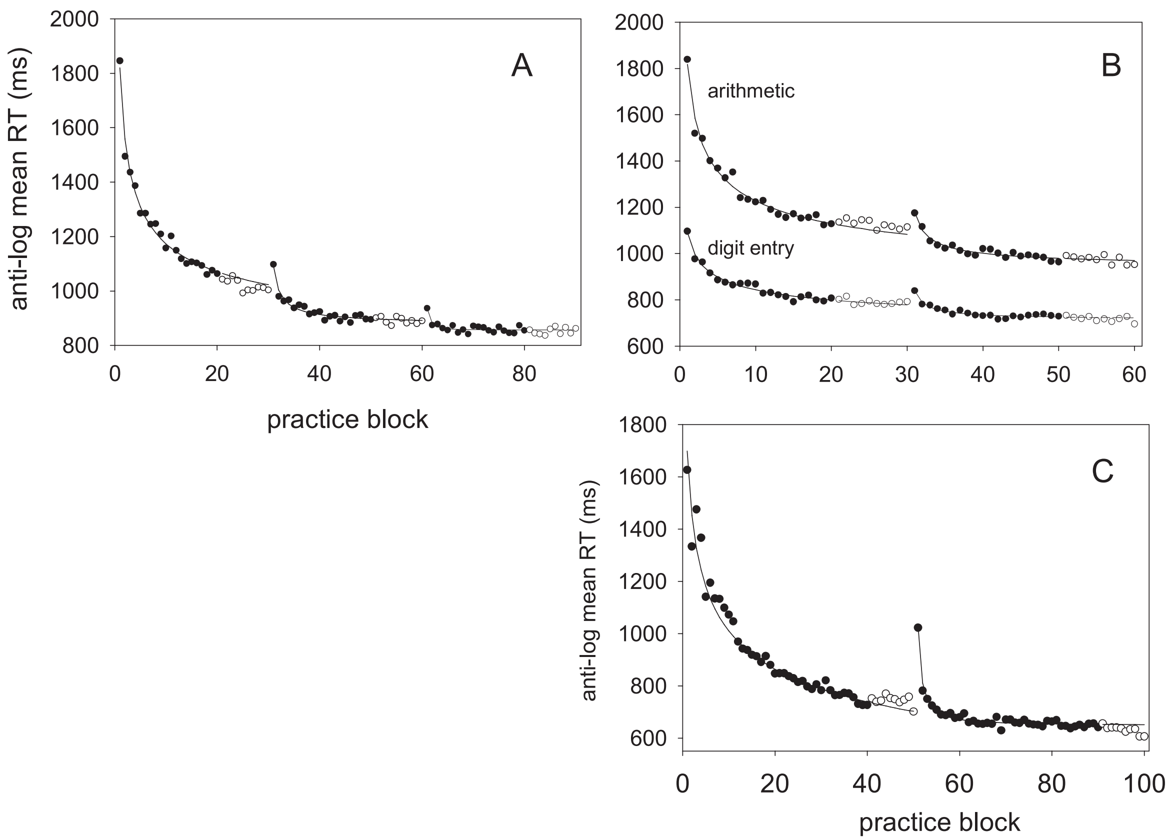

Figure 3. Anti-logs of the mean log response time (RT) speedup curves along with separate three-parameter power functions fits to the first 20 (Panels A and B) or 40 (Panel C) blocks of each session. Fits to the last 10 blocks of each session (open circles) are extrapolations of the fits to data from the earlier part of the same session (closed circles). Panel A shows Data Set 1, Panel B Data Sets 2 and 3, Panel C Data Set 5.

through the data points, in two cases it is somewhat above the data, and in two cases it is somewhat below the data. The fact that these biases in fit are not consistent over data sets suggests that they do not reflect a problem with the power function as a model of within-session speedup, but rather the sensitivity of the parameter estimates to noise in the relatively small number of fitted data points. Critically, in the within-session extrapolations, there is no case in which the signature pattern of the between-sessions extrapolations shown in Figure 2 (a pronounced crossover between the actual and predicted values within the first 10 blocks of each new session) is present. It is therefore apparent that the between-session extrapolation effects shown in Figure 2 are causally related to the delay between sessions.

Does the Initial Slowing Reflect Warm-Up or Forgetting in Long-Term Memory?

There are two broad candidate interpretations of the RT slowing at the beginning of each session relative to the end of the preceding session. One possibility is that it reflects some type of warm-up effect that is unrelated to long-term skilled memory processes. A second possibility is that it reflects a genuine long-term memory forgetting effect. The notion of warm-up can be understood cognitively at both task and item levels. At the task level, there may be general (item nonspecific) loading of task-relevant procedures, refamiliarization with task context, general priming of a memory network for all items, or even postural or muscular preparation effects at the beginning of each session. This task-level warm-up hypothesis corresponds to the set hypothesis in the warm-up decrement literature in verbal and motor learning (for a review, see Adams, 1961). Because task-level warm-up is by definition item nonspecific, it should manifest, if present at all, as speedup over items (trials) within practice block. Task-level warm-up effects were thus evaluated by plotting mean RT as a function of trial for the first and second blocks of each session. The results are shown in Figure 4, averaged over the five data sets. Separate plots are shown for the first and second blocks of Session 1, and for the first and second blocks of the average of Sessions 2 through 5. There was some speedup from the first to the second trial for Block 1 of Session 1, and to a smaller degree for Block 2 of Session 1 and for Block 1 of Sessions 2 through 5. There was no evidence of speedup from the first to the second trial for Block 2 of Sessions 2 through 5. No speedup is evident in any of these cases from Trials 2 through 8. For Block 3 onward (not shown in the figure), there was no evidence of speedup over trials within block for any session of any experiment. Task-level warm-up, then, is limited to the first trial of the first couple of blocks, and for Sessions 2

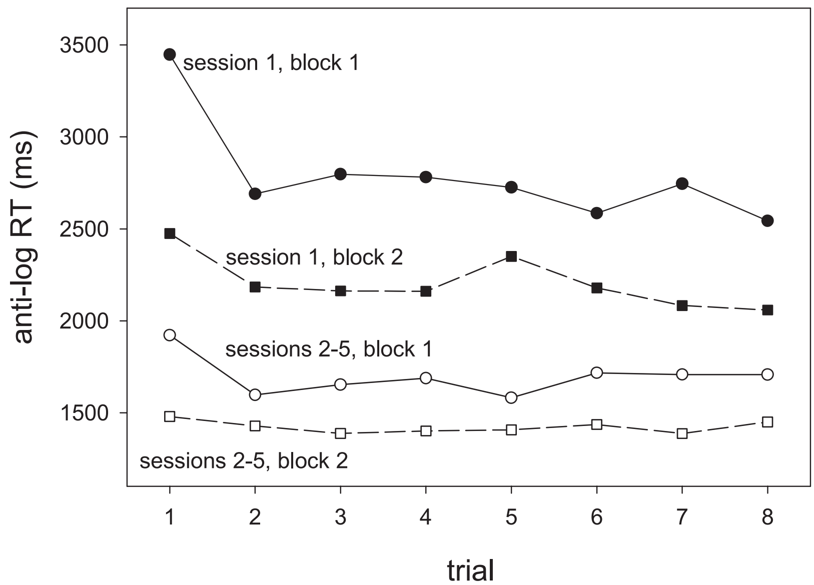

Figure 4. Anti-log of the mean log response time (RT) as a function of trial for Blocks 1 and 2 of Session 1 and for Blocks 1 and 2 of the average of Sessions 2 through 5. Session 1 of Data Set 5 was not included in these analyses because of the low accuracy rates on the first two blocks. Log RTs were averaged over subjects within each data set and then over data sets, and then the anti-log of these grand mean log RTs was computed. Only the first eight trials for each block are plotted, so that each data set could contribute equally to each data point.

through 5, it is limited to the first trial of the first block only. All other speedup effects over blocks in those sessions can be considered to be item specific. In light of these results, the first trial of the first block of each session was not included in the data shown in Figure 2, and thus the task-level warm-up effect is not present for the predicted sessions, 2 through 5, in that figure.

Warm-up could also occur at the item level, perhaps as some form of activation-based item priming that dissipates over the delay between sessions but is not related to long-term memory strength. Assuming that such priming saturates after the first trial for each item, its effect on the RT curve can be eliminated by simply ignoring the first practice block from each predicted session. Inspection of the fits in Figure 2 shows that, even with the first block ignored, mean RTs are slower than, or about the same as, those predicted by extrapolating from the previous session. In four cases, RTs on the first three blocks are slower than that prediction, in three cases RTs on the first two blocks are slower, and in three cases RTs on the second block are roughly equal to the extrapolated prediction. It thus appears that neither task-level nor item-level warm-up effects are sufficient to account for the initial RT slowing after a delay, unless item-level warm-up does not run to completion until several repetitions of each item have occurred. It is of interest to note that the most pronounced slowing effect occurred for Sessions 2 and 3 of the novel paired-associate task (Panel D), the only task among those considered here for which subjects would have had no item-relevant pre-experimental experience. This result is consistent with the possibility that rate of forgetting decreases with increasing skill level (e.g., Adams, 1952).

Another way to evaluate the item-level warm-up account of the initial RT slowing is to determine whether the rate of learning beyond the first few blocks of each session is consistent with what would be expected by extrapolation of the fit to the previous session, under the assumption of passive learning (consolidation) between sessions. The simplest way to model such learning would be to assume that there are effectively extra "mental practice blocks" between sessions, occurring outside of consciousness and perhaps during sleep (e.g., Sejnowski & Destexhe, 2000). To fit this idea quantitatively, the range of values of practice block that best fits a session can be found, using the parameter values for the power function fit to the proceeding session. Consider for example the Session 1 arithmetic data in panel A of Figure 2. The best fitting power function parameters had values of $a = 629$, $b = 1{,}182$, and $c = .34$. Using these parameter values, the function $629 + 1{,}182 \times (\text{block} + x)^{-c}$ can be fitted to Session 2 of that data set, where block is the actual practice block being fitted (31–60 in this case) and x is a free parameter indexing the number of hypothesized mental practice blocks between sessions. In these fits, the first three blocks of each fitted session were removed to minimize the chance that any of the speedup in the data being fitted reflected warm-up effects. In each fit, the power function parameters for the fit to the immediately proceeding session were used. The residuals of these fits for Sessions 2 onward of all five data sets are shown in Figure 5. For eight of the nine sessions (the exception being Session 3 of Data Set 1 in Panel A), the residuals are positive toward the beginning of each session and negative toward the end of the session (sign test, $p < .02$), and linear regressions on the residuals yielded a significant negative slope for all eight of those sessions ($\alpha = .05$ for each fit). [2] Thus, throughout eight of the nine sessions, speedup was faster than could be predicted by the hypothesis of passive practice between sessions, even when the first 3 practice blocks of the pre-

[2] For session three of Data Set 1 (Panel A of Figure 2), the residuals were mostly negative. This reflects the fact that the asymptote estimate of the power function fit for Session 2 of that data set was larger than the value of most RTs in Session 3.

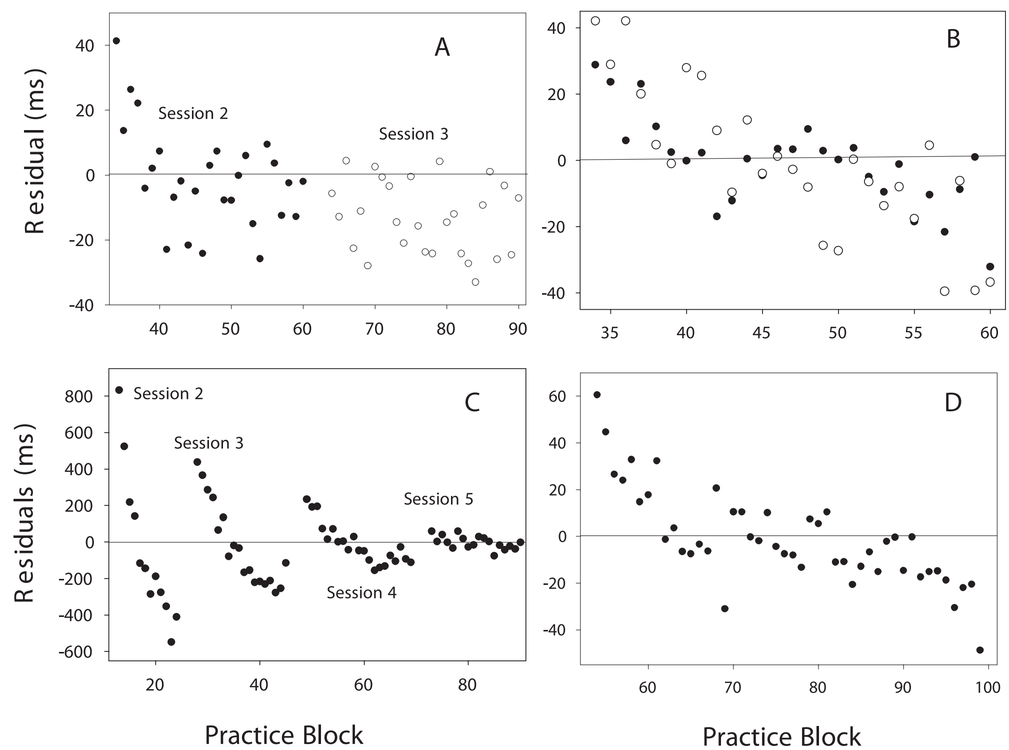

Figure 5. Residual plots for extrapolated fits from the proceeding session. Panel A shows Data Set 1, Panel B Data Sets 2 and 3, Panel C Data Set 4, and Panel D Data Set 5. In Panel B, closed circles represent the arithmetic data and open circles the digit entry data. Session 3 of Data Set 5 is not shown as there were only four practice blocks in that session.

dicted sessions are removed. Note that the same result is obtained in most cases if the first 5, or even the first 10, practice blocks of the fitted sessions are removed.

The results of the residual analysis speak against item-level warm-up as an account of the initial RT slowing in each session. Instead, these results motivate a two-component model of the effects of between-session delays on the long-term representation of cognitive skills. First, there is forgetting in the associative pathways in long-term memory that support performance, as Anderson et al. (1999) postulated, resulting in the initial slowing at the beginning of each session. This forgetting could be global, or it could be isolated to a subcomponent of the skill. Second, there is increased potential for new learning as indexed by RT (learning potentiation) that results in faster performance than would be expected by extrapolation from the proceeding session.

The novel treatment of forgetting and learning potentiation as separable factors (presumably reflecting separate mechanisms) in this article might help resolve the apparent contradictory findings in the literatures that were noted earlier. One source of the different outcomes over studies may simply be the use of different measurement techniques. If the focus is on comparison of the first trial or block of trials of Session 2 to the last trial or block of trials of Session 1, without consideration of the speedup curve in Session 2, then the forgetting effect may dominate and performance may be worse after the delay. If, however, the comparison involves substantial averaging of data, as in much of the procedural consolidation literature (e.g., Ammons, 1950), then learning potentiation effects may dominate and immediate performance gains will be erroneously inferred. This dual-factor model also allows for the possibility that forgetting will have a stronger impact in some tasks and designs, whereas learning potentiation may have a stronger impact in other circumstances, although the model leaves open why that would be the case.

More generally, the current results highlight the importance in future work of directly comparing between-session delay effects for cognitive and procedural skills. It may be that, for procedural skills, patterns very similar to those observed in Figure 2 will become evident given a sufficiently fine grain-size analysis, suggesting that similar mechanisms underlie the effects of delays for cognitive and procedural skills. Alternatively, if in the procedural skill literature the overnight facilitation effect is indeed immediate, then different mechanisms might be implicated.

Candidate Theoretical Accounts

Although a thorough theoretical investigation of these between-session delay phenomena is beyond the scope of this observation, here I briefly consider two broad candidate classes of theories. First, there may be some mechanism by which the rate of learning or the efficiency of performance as indexed by RT (or both) decreases monotonically over the course of an experimental session but returns to its original status after the delay between sessions. One plausible psychological mechanism is fatigue, which may be grounded in motivational, affective, or inhibitory processes. Related mechanisms have been proposed in the literature on reminiscence in motor skill learning (for a review, see Coppage & Payne, 1981). By definition, fatigue increases over the course of a session and should be eliminated by a sufficient delay between sessions. Between-session forgetting would account for the initially slowed RTs after the delay between sessions, and release from fatigue at the beginning of each new session would account for the increased rate of speedup over the first portion of that session. In this account, the learning potentiation effect for a given session would be defined relative to the later part of the proceeding session, in which trial-to-trial learning potential is diminished as a result of fatigue. For a model that implements similar mechanisms in accounting for the effects of spaced practice on accuracy in foreign vocabulary learning, see Pavlik and Anderson (2005). Alternatively, or in addition to its effect on learning rate, fatigue may result in slowed (i.e., less optimal) performance toward the end of a practice session.

A second class of explanations assumes consolidation between sessions. All of the tasks studied here involved at least 2 nights of sleep between sessions, so sleep consolidation may apply. Any consolidation account must contend with the forgetting effects evident at the beginning of each session. Thus, consolidation in this case could not take the form solely of passive overnight learning, which could only oppose or offset the forgetting effect, as noted earlier. Instead, consolidation in this case would take the form of learning potentiation. By this account, the neural links (or some subset of them) that support performance are weakened by the delay, resulting in the initial slowing, but the system has nevertheless prepared for the possibility that the task will be encountered again by increasing the potential for new learning in some way yet to be determined.

Implications for the Empirical Law of Learning

For more than a century, psychologists have sought a simple and universal empirical law of practice, focusing mostly on the function describing speedup (for reviews, see Newell & Rosenbloom, 1981; Heathcote, Brown, & Mewhort, 2000). A primary motivation behind this work has been to guide theory development, and a number of theories of skill learning have been influenced heavily by the prevailing view of what function best describes speedup (Anderson, 1982, 1993; Anderson & Schooler, 1991; Cohen, Dunbar, & McClelland, 1990; Logan, 1988, 1995; Newell & Rosenbloom, 1981; Palmeri, 1997; Rickard, 1997). In nearly all curve-fitting efforts to date, the effects of the delay between practice sessions have been ignored, with the implicit assumption that they are negligible (cf. Anderson et al., 1999). The foregoing analyses demonstrate, however, that those effects must be included in any successful effort to identify the empirical law of speedup, particularly if that law is to be used as a constraint on theory development.

Fitting of separate three-parameter power functions to each session, with all parameters free to vary in each session, appears to provide a good empirical account of speedup in mean RT, as shown in Figure 2. I refer to this as the unconstrained, session-specific power function. As of this writing, this appears to be the only proposed law of learning with potential to provide a sufficient account of mean speedup in the ecologically realistic case of multisession skill practice. Although there may be a more constrained model that will also fit well to multisession data, our results appear to eliminate a number of possibilities. First, as noted earlier, any constrained version of the session-specific power law that predicts only slowing after a delay, relative to the expectation based on extrapolation (as portrayed in Figure 1), can be rejected. Another plausible constraint on the empirical learning function that was considered earlier and that can be rejected assumes that the same three-parameter power function describes speedup in all sessions and that the effect of delay between sessions is solely to induce passive additional practice between sessions.

I also considered whether one or more parameters of the power function can be constrained to be the same for each session while still allowing for good fits. Clearly the parameter b, which along with the asymptote parameter, a, determines the initial RT of each session, must be allowed to take different values for each session to accommodate the substantially faster RTs at the beginning of each session compared with the beginning of the previous session (relatively small variations in a from session to session could not account for these effects).

Estimates of a were quite variable, as is often the case with fits to relatively short practice series (e.g., Heathcote et al., 2000), so no strong inferences about possible constraints on that parameter can be made. However, based on the near certainty that subjects will eventually suffer from performance-worsening fatigue if forced to practice such tasks for much more than 1 hr per session, it seems likely that the effectively achievable asymptotic performance will become progressively lower with each new practice session, necessitating that a be allowed to vary for each session.

The nonlinear rate parameter, c, exhibited an interesting and systematic pattern of becoming larger with each successive practice session. Setting aside the first three sessions of Data Set 4, in which pronounced speedup effects due to the strategy shift to retrieval are a contaminating factor, and Session 3 of Data Set 5, for which there were only 4 blocks, the estimated value of c became larger from session to session in all six cases. In fact, in five of the six cases, the estimated value of c for a given session was larger than the upper bound of the 95% confidence interval for c for the immediately proceeding session. Larger values of c correspond to a faster rate of nonlinear speedup, and they manifest visually as a more distinctive "elbow effect" in the learning curve. This effect is evident in Figure 2 (particularly in Panels A and D). It thus appears that, with each new practice session, fewer practice repetitions are required for subjects to approach their within-session asymptotic performance level. Theoretically, this effect might reflect faster relearning of the forgetting between sessions and/or an activation-based priming effect underlying some of the initial speedup in each session. If such priming constitutes a larger proportion of total speedup in each progressive session, then larger values of c would be obtained, other factors held constant. Consistent with these possibilities, the magnitude of the increase in c from session to session was smaller in supplementary power function fits wherein the first block of each session was first removed prior to fitting, and no trend toward increasing values of c was discernible when the first 2 blocks of each session were removed (again ignoring the first three sessions of Data Set 4, and also all of Data Set 5, for which the first 11 blocks of Session 1 had been removed already due to high error rates, and for which Session 3 contained only 4 blocks).

It is also of interest that the estimate of c for a given session was smaller for 9 of the 10 sessions (ignoring the first 3 sessions of Data Set 4 and the 1st and 3rd sessions of Data Set 5, for reasons noted above) with the first block removed (sign test, $p = .01$). The value of c did not continue to decrease systematically, however, when the initial two, three, or four blocks of each session were removed (all ps $> .17$). This result suggests that the three-parameter power function may be subtly ill-fitting for mean RT data from the first block of each session, even when all of its parameters are allowed to vary independently for each session. This result is consistent with the possibility that speedup from the first to the second block of each session is partly driven by item-specific, activation-based priming, which appears to saturate after one block.

It should be noted that the conclusion that all three parameters must be allowed to vary in session-specific power function fits does not necessarily imply that the most parsimonious empirical learning function for mean RT data must have $3 \times N$ parameters, where 3 is the number of parameters in each power function and N is the number of practice sessions. Both the forgetting and learning potentiation effects presumably reflect some underlying construct that operates as a function of time, sleep, or both. By analogy to the Anderson et al. (1999) model, it may be possible in future work to model each of these constructs with one or more free parameters, where the number of parameters is independent of the number of practice sessions in an experiment.

Finally, note that Heathcote et al. (2000) have recently argued that when learning functions are fit to item-level rather than mean RT data, the three-parameter exponential function fits better than the three-parameter power function. Their conclusions were based on fitting of a global three-parameter function to multisession data, however, and it is unclear whether the advantage for the exponential function at the item level will hold when data are fitted separately for each session. To explore this issue, I performed analyses comparing three-parameter power and exponential functions at the item-level. The exponential function did tend to fit better—albeit only slightly better—than the power function for nearly all sessions of all experiments. Thus, in accordance with Heathcote et al., 2000, it appears that the session-specific, item-level learning function is better described as exponential rather than as power. For mean RTs, however, the power function clearly provides the better fit.

References

Adams, J. A. (1952). Warm-up decrement in performance on the pursuit-rotor. *American Journal of Psychology, 65,* 404–414.

Adams, J. A. (1961). The second facet of forgetting: A review of warm-up decrement. *Psychological Bulletin, 58,* 257–273.

Ammons, R. B. (1950). Acquisition of motor skills: III. Effects of initially distributed practiced on rotary pursuit performance. *Journal of Experimental Psychology, 40,* 777–787.

Anderson, J. R. (1982). Acquisition of cognitive skills. *Psychological Review, 89,* 369–406.

Anderson, J. R. (1993). *Rules of the mind.* Hillsdale, NJ: Erlbaum.

Anderson, J. R., Fincham, J. M., & Douglass, S. (1999). Practice and retention: A unifying analysis. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 25,* 1120–1136.

Anderson, J. R., & Schooler, L. J. (1991). Reflections on the environment of memory. *Psychological Science, 2,* 396–408.

Bourne, L. E., & Archer, J. (1956). Time continuously on target as a function of distribution of practice. *Journal of Experimental Psychology, 51,* 25–33.

Brashers-Krug, T., Shadmehr, R., & Bizzi, E. (1996, July 18). Consolidation in human motor memory. *Nature, 382,* 252–255.

Cohen, J. D., Dunbar, K., & McClelland, J. L. (1990). On the control of automatic processes: A parallel distributed processing account of the Stroop effect. *Psychological Review, 97,* 332–361.

Coppage, S. J., & Payne, R. B. (1981). An experimental test of current theories of psychomotor reminiscence. *Perceptual and Motor Skills, 52,* 343–352.

Digman, J. M. (1959). Growth of a motor skill as a function of degree of verbal learning. *Journal of Experimental Psychology, 57,* 257–261.

Heathcote, A., Brown, S., & Mewhort, D. J. K. (2000). The power law repealed: The case for an exponential law of practice. *Psychonomic Bulletin and Review, 7,* 185–207.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review, 95,* 492–527.

Logan, G. D. (1995). The Weibull distribution, the power law, and the instance theory of automaticity. *Psychological Review, 102,* 751–756.

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 1–55). Hillsdale, NJ: Erlbaum.

Palmeri, T. J. (1997). Exemplar similarity and the development of automaticity. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 23,* 324–354.

Pavlik, P. I., Jr. & Anderson, J. R. (2005). Practice and forgetting effects on vocabulary memory: An activation-based model of the spacing effect. *Cognitive Science, 29,* 559–586.

Rickard, T. C. (1997). Bending the power law: A CMPL theory of strategy shifts and the automatization of cognitive skills. *Journal of Experimental Psychology: General, 126,* 288–311.

Rickard, T. C. (2004). Strategy execution in cognitive skill learning: An item-level test of candidate models. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 30,* 65–82.

Rickard, T., & Bourne, L. E., Jr. (1996). Some tests of an identical elements model of basic arithmetic skills. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 22,* 1281–1295.

Rickard, T. C., Healy, A. F., & Bourne, L. E., Jr. (1994). On the cognitive structure of basic arithmetic skills: Operation, order, & symbol transfer effects. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 20,* 1139–1153.

Sejnowski, T. J., & Destexhe, A. (2000). Why do we sleep? *Brain Research Interactive, 886,* 203–223.

Stickgold, R. (2005, October 28). Sleep-dependent memory consolidation. *Nature, 437,* 1272–1278.

Walker, M. P., & Stickgold, R. (2006). Sleep, memory, and plasticity. *Annual Review of Psychology, 57,* 139–166.

Walker. M. P., Brakefield, T., Morgan, A., Hobson, J. A., & Stickgold, R. (2002). Practice with sleep makes perfect: Sleep-dependent motor skill learning. *Neuron, 35,* 205–211.

Received May 4, 2006
Revision received August 15, 2006
Accepted September 13, 2006 ■