Contextual Interference Effect in Motor Skill Learning: An Empirical and Computational Investigation

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Abstract

To efficiently learn and retain motor skills, we can introduce contextual interference through interleaved practice. Interleaving tasks or stimuli initially hinders performance but leads to superior long-term retention. It is not yet clear if implicitly learned information also benefits from interleaving and how interleaved practice changes the representation of skills. The present study used a serial reaction time task where participants practiced three 8-item sequences that were either interleaved or blocked on Day 1 (training) and Day 2 (testing). An explicit recall test allowed us to post-hoc sort participants into two groups of learners: implicit learners recalled less items than did explicit learners. Significant decreasing monotonic trends, indicating successful learning, were observed in both training groups and both groups of learners. We found support for the benefit of interleaved practice on retention of implicit sequence learning, indicating that the benefit of interleaved practice does not depend on explicit memory retrieval. A Bayesian Sequential Learning model was adopted to model human performance. Both empirical and computational results suggest that explicit knowledge of the sequence was detrimental to retention when the sequences were blocked, but not when they were interleaved, suggesting that contextual interference may be a protective factor of interference of explicit knowledge. Slower learning in the interleaved condition may result in better retention and reduced interference of explicit knowledge on performance.

Keywords: Bayesian theory; motor skill learning; sequential learning; implicit learning; serial reaction time task

Introduction

In everyday life, we perform and demonstrate a variety of motor skills that have been acquired gradually through practice and interactions with our environment. These include the use of smooth coarticulation of finger movements into a specific sequence, multi-joint movement synergies, or eye-body coordinated actions. Complex and simple skills alike rely on motor dexterity, sequence memorization, perceptual acuity, and both explicit and implicit learning. Given the importance of motor skill learning to quality of life, it is essential to investigate an optimal practice schedule for greatest long-term retention. Decades of psychology research suggests that using contextual interference by interleaving tasks or stimuli may lead to enhanced long-term retention of motor sequence learning.

Contextual interference (CI) is the phenomenon in which interference during practice is surprisingly beneficial to skill learning. In the short term it leads to poorer practice performance but superior retention and transfer performance in the long term. Interleaving stimuli or tasks is a way to introduce contextual interference. In trying to optimize learning by decreasing learning difficulty, retention may be negatively affected. Introducing "desirable difficulties," enhances learning, rather than impedes it. In addition to contextual interference, "desirable difficulties" include varying the conditions of learning, spacing study or practice sessions, and using tests and retrieval practice as learning events (Bjork, 1994). The benefits of contextual interference on memory performance were first observed in verbal learning and subsequently in motor skill learning (Battig, 1966; Shea & Morgan, 1979).

There are multiple hypotheses surrounding the mechanism behind the CI effect. The two most popular, the elaboration-distinctiveness view and the forgetting-reconstruction view, are not mutually exclusive. The elaboration-distinctiveness view posits that it is easier to focus on the unique aspects of each task or stimulus when experiencing them intermixed together (Shea & Zimny, 1983; Shea, Hunt, & Zimny, 1985). Under high contextual interference during acquisition, information about multiple tasks is present in working memory and thus more elaboration is required to distinguish one task from another, leading to a more durable encoding. Originally, this hypothesis was partially informed by participants' recall of motor movements, a measure of explicit memory (Shea & Zimny, 1983).

The forgetting-reconstructive hypothesis attributes the CI effect to the process of "refreshing" working memory on every trial (Lee & Magill, 1983, 1985). With interleaved practice, the learner must "dump" a motor pattern from working memory after every trial in order to plan and execute subsequent trials (Lee & Simon, 2004). Therefore, the learner must retrieve a motor pattern into working memory or construct one on every trial. This lack of forgetting and subsequent reconstruction is presumably why blocked practice is inferior to interleaved practice for long-term retention. In contrast, sequences that are blocked allow a sequence pattern to be maintained in working memory across trials. This hypothesis may account for the learning and performance dissociation often seen in CI research.

However, neither of these proposed mechanisms specifically account for implicit processes, and motor skills are often implicitly learned. Research concerning the CI effect and implicit motor learning has largely focused on gross motor skills like those used when playing sports (French et al., 1990; Goode & Magill, 1986; Menayo et al., 2010). Furthermore, research investigating the CI effect in fine motor sequence learning has largely focused on explicit memory (Wright et al., 2016). Though research has explored the effect of contextual interference in implicit motor learning, few specifically investigate fine motor sequence learning over a substantial delay and is thus a primary aim of this paper (Dang et al., 2019; Sekiya, 2006).

Mathematical models can help us understand the different constraints memory has and how it adaptively functions (Anderson & Milson, 1989). For example, Burrell's mathematical model on borrowing books from a library can be informative from an information-retrieval systems standpoint (1985). Anderson & Milson (1989) suggest from Burrell's model that if use is massed, the intervals between successive uses can predict the probability of the item need. For example, if one item has been steadily used n times over many months (spaced), this item would be more likely to be needed when compared to an item that was used n times all in one month (massed/blocked). As such, the model would predict better memory for spaced items as compared to massed items, consistent with empirical research concerning the aforementioned contextual interference effect.

In this paper, we propose an alternate way to model the contextual interference effect using a Bayesian theory of sequential learning. This model uses prediction errors and uncertainty to model how probability distributions of parameter weights are updated from trial to trial. As trials go on, Bayes' theorem updates prior beliefs after considering new information. Using a Bayesian framework can address some shortcomings of sequential learning models. The Rescorla-Wagner model is a well-known sequential learning model of animal conditioning in which cue-outcome weights are updated incrementally at every trial based on prediction errors (Rescorla & Wagner, 1972). This model does not account for learner uncertainty, so more complex sequential learning models have addressed this deficit using a Bayesian framework (Dayan & Kakade, 2000; Dayan, Kakade, & Montague, 2000). The model we use is an iteration of the Bayesian sequential learning model proposed in Lu et al., 2016). The current paper explores how interleaving and blocking three motor sequences affects learning and retention of these sequences and how a computational model may help us understand how memory strength for these sequences differentially fluctuates over time depending on condition.

Experimental Design & Methods

To investigate if contextual interference enhances long-term retention of motor sequences, we utilized the serial reaction time (SRT) task. Participants sat with four fingers of the right hand on four keys on a keyboard (U,I,O,P) that corresponded to the four outlined, unfilled circles on a blue computer screen. One of the circles turned white to act as a cue to press the corresponding key (i.e., the first circle on the screen corresponds with "U"). After the button press, another circle turned white and the first circle reverted to being unfilled. Participants received audio feedback if they failed to press a button or pressed an incorrect button. Reaction time (RT) and accuracy were measured. Participants practiced three 8-item sequences that were either interleaved or blocked on Day 1 (training) and Day 2 (testing). Participants were randomly assigned to a training condition. In the blocked condition, they received 80 repeated presentations of each sequence (i.e., AAA...BBB...CCC). In the interleaved condition, they received 3 sequences interleaved for a total of 240 trials (i.e., ACBABCBAC....). Day 2 was the same as Day 1, participants were randomly assigned to either the blocked or the interleaved condition. There were four conditions: Interleaved-Interleaved (II), Blocked-Blocked (BB), Blocked-Interleaved (BI), and Interleaved-Blocked (IB). The sequences were randomized so that no two participants had the same sequences. Each participant received the same three sequences both days. Critically, the participants were never told there were sequences, only to respond to each cue as quickly and as accurately as possible. To measure explicit learning, a questionnaire was administered after the second session comprised of three questions which prompted the participants to recall the sequences.

Analysis

We summed the 8 key presses in the accurate sequences only for a mean sequence RT. We took an average of mean sequence RTs of the last ten trials per sequence (A,B,C) for the blocked training condition, for a total of thirty trials. For the interleaved training condition, we took an average of mean sequence RTs of the last thirty trials. For the blocked testing condition, we used the same procedure but looked at the *first* ten trials of each sequence, for a total of thirty trials. Similarly, for the interleaved testing condition, we studied the *first* thirty trials. To measure retention, we computed difference scores by subtracting the mean sequence RTs of the last thirty trials from Day 1 from the RTs of the first thirty trials from Day 2. We also assessed learning over time by looking at mean sequence reaction time every twenty trials on Day 1 using a Mann-Kendall trend test, a nonparametric test for monotonic trends, where Kendall's Tau (τ) is a measure of the strength and direction of the trend. To measure explicit representation of motor sequences, we compared subjects' recall of sequences to the actual sequences and computed a score. For example, if a participant correctly recalled half of one sequence and two items of another, their score would be an average of (0.5+0.25+0)/3 for a score of

0.25. To determine chance performance a priori, we ran a Monte Carlo simulation in which we compared three randomized "test" sequences to 1,000,000 randomized sequences. We found that on average, they matched around two of the eight items just by chance. The implicit-explicit memory distinction may lie on a continuum, with participants having varying amounts of explicit knowledge. However, since we were interested in purely implicit learners, we dichotomized our sample and post-hoc sorted participants based off of the Monte Carlo cutoff determined a priori. This allowed us to examine fully implicit learners separately from those who may have some explicit sequence knowledge. Implicit learners were participants who recalled on average, 0-3 items per sequence (at chance) while explicit learners recalled 4 or more items per sequence (above chance).

Participants

We collected data from 100 UCLA undergraduates, who received course credit for participation. A total of 17 participants were excluded for low accuracy (i.e., 80% or lower; n=8), computer error (n=5), or failing to complete the experiment (n=4). Our final subject pool consisted of 83 right-handed young adults. (n_{II}=22; n_{BB}=19; n_{I} =21; n_{BI}= 21; ages 18-43, M=20.6, SD=3.2). Participants were sorted into two groups based on their explicit recall score: implicit (n=40) and explicit (n=43). Thus, our four groups were divided into eight groups to account for both types of learners in all four conditions (implicit learners: n_{II}=14; n_{BB}=7; n_{IB}=9; n_{BI}=10; explicit learners: n_{II}=8; n_{BB}=12; n_{IB}=12; n_{BI}=11).

Experimental Results

On Day 1, participants who practiced interleaved sequences were significantly less accurate (M=92.34, SD=4.38) than participants who practiced blocked sequences (M=94.22, SD=4.13; t(81)=2.013, p=.047). However, on Day 2, a Mann-Whitney test indicated that there was no significant difference in accuracy between those who performed interleaved sequences (M=94.02, SD=4.27) and those who performed blocked sequences (M=95.59, SD=2.51; U=992.50, p=.229). Those who were tested on interleaved sequences either received blocked or interleaved training the day before, however training condition did not impact accuracy on Day 2 (M_{II}=93.34, SD_{II}=4.44; M_{BI}=94.74, SD_{BI}=4.06; t(41)=1.08, p=.287). Similarly, training condition did not impact accuracy on Day 2 for those who were tested on blocked sequences (M_{BB}=95.67, SD_{BB}=2.32; M_{IB}=95.52, SD_{IB}=2.72; t(38)=0.18, p=.859).

Participants who received blocked practice explicitly recalled on average more items per sequence (M=4.18, SD=2.48) than those who had received interleaved practice (M=3.17, SD=2.13; t(81)=-1.996, p=.049).

Before categorizing participants into implicit or explicit learners, we conducted a two-way ANCOVA to control for recall score. We found a significant main effect of training condition (F(1,78)=38.06, p<.001), a significant main effect of testing condition (F(1,78)=10.895, p=.001), and a significant interaction after controlling for recall score (F(1,78)=11.565, p=.001). The covariate was not significantly related to performance, indicating that a participants' knowledge about the sequence had little impact on performance and the benefit of interleaved practice (F(1,78)=3.02, p=.086). Since our original interest was implicit motor sequence learning, we then separated groups based on a cutoff score denoting chance performance.

All groups learned over Day 1, as evidenced by significant decreasing trends in mean sequence RT. Significant decreasing monotonic trends were observed in both the blocked training group (τ= -.442, p < .0001) and interleaved training group (τ= -.242, p < .0001) in explicit learners (Fig. 1). In implicit learners, there was also a significant decreasing monotonic trend for both the blocked training group (τ = -.336, p=.001) and the interleaved training group (τ = -.272, p< .0001) (Fig. 1).

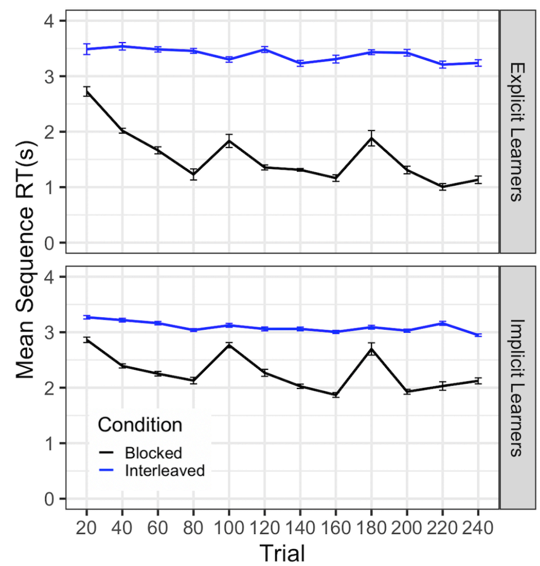

Figure 1. Learning over Day 1.

We then examined mean difference scores in all four groups separated by explicit and implicit learners. Difference scores were calculated by subtracting the mean sequence reaction time of the last thirty trials on Day 1 from the mean of the first thirty trials on Day 2. A positive difference score indicates poorer performance on Day 2, a negative difference score indicates improvement on Day 2, while a difference score of zero indicates retention. A three-way ANOVA was conducted to examine the effect of training condition, testing condition, and learner type (explicit, implicit) on mean RT difference scores (Fig. 2). There was a significant main effect of training condition on difference scores, (F(1, 75)=39.539, p <.001, η^2=0.274), with less forgetting from Day 1 to Day 2 for participants who had received interleaved training. Participants who trained in the interleaved condition had a negative difference score, indicating improved performance (M=-0.313, SD=0.554). Participants who trained in the blocked condition instead showed a positive difference score, indicating forgetting from Day 1 to Day 2 (M=0.726, *SD*=0.938). There was also a significant main effect of testing condition, (F(1, 75)=9.538, p=.003, η^2=0.066), with greater forgetting for participants who received interleaved testing on Day 2. Participants who received interleaved testing had a mean positive difference score (M=0.408, SD=1.017), while participants who tested with blocked sequences had a negative mean difference score (M=-0.049, SD=0.748).

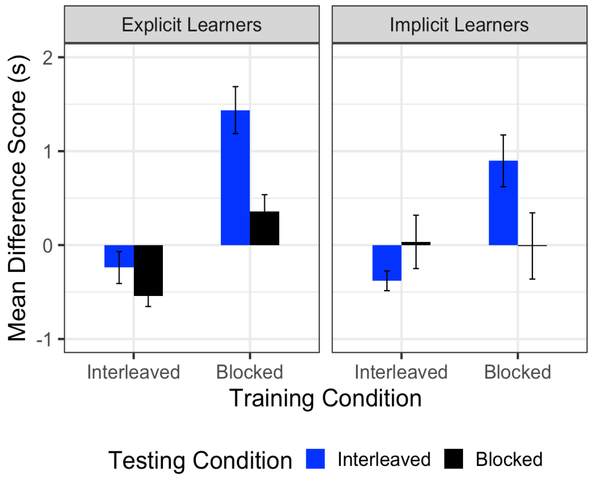

Figure 2. Mean difference scores to measure sequence retention. Higher scores indicate greater forgetting.

These main effects were qualified by two statistically significant interactions. We observed an interaction between the effects of training condition and testing condition on difference scores, F(1,75)=11.948, p<.001, η^2=0.083. An analysis of simple effects showed that testing condition did not significantly affect difference scores when participants were trained in the interleaved condition (F(1,75)=0.027, p=.870). However, testing condition did significantly affect the difference scores when participants were trained in the blocked condition (F(1,75)=20.056, p<.001). Participants who trained with interleaved sequences were able to retain or improve performance regardless of testing condition, while participants who trained with blocked sequences did worse when tested with interleaved sequences.

Additionally, we observed an interaction between the effects of training condition and learner type on difference scores, F(1, 75)=4.915, p=.03, η^2=0.034. Simple effects analysis showed that learner type did affect difference scores when subjects practiced blocked sequences (F(1,75)=4.529, p=.037), but not when subjects practiced interleaved sequences (F(1,75)=1.082, p=.302). Explicit learners in the blocked training condition had higher difference scores than implicit learners, suggesting that explicit learning of the sequences might hinder subsequent learning, especially when these sequences are practiced in a blocked fashion.

With one sample t-tests, we found there was a significant slowing of performance across the delay for subjects who were trained using blocked sequences and tested using interleaved sequences, regardless of whether they gained explicit knowledge of the sequences (t(10)=5.757, p=.0001, for explicit learners; t(9)=3.255, p=.0099 for implicit learners). For subjects who practiced interleaved sequences, there was significantly faster performance when the sequences were blocked if they had some explicit knowledge of the sequences, perhaps reflecting facilitated performance of blocked sequences (t(11)=-4.849, p=.0005).

Interestingly, the participants who practiced interleaved sequences and gained no awareness of the sequences showed faster performance after the delay when tested on interleaved sequences (t(13)=-3.633, p=.003). Subjects who practiced and were tested using blocked sequences had similar levels of performance across the delay regardless of awareness. Subjects who gained some awareness of the sequences showed no forgetting if trained and tested using interleaved sequences, and subjects without awareness showed similar performance pre and post delay if they practiced interleaved sequences and tested with blocked sequences (p's >.1).

Bayesian Theory of Sequential Learning

To understand how memory strength for each sequence evolves in both the interleaved and blocked conditions, we used a sequential Bayesian learning model. The implementation is based on particle filtering which has been widely used to model learning, such as conditioning (Daw, & Courville, 2008), category learning (Sanborn et al., 2010), causal learning (Lu et al., 2016). It is a general probabilistic approach for estimating and updating probability distributions of hidden variables by recursively applying two computational steps described below (Ho & Lee, 1964; Meinhold & Singpurwalla,1983). Though there are many iterations of this type of model, the current paper adopts the model proposed by Lu, Rojas, Beckers & Yuille (2016) as it introduces a learning mechanism and accounts for trial order effects. The prediction step uses past observations to predict the states of hidden variables. Specifically, the distribution of hidden variables x (i.e., memory strength in our application) at time point k can be predicted using observations Z in the past. In our study, x represents the memory strength for each of the three sequences, k corresponds to trials, and Z represents performed motor sequences. The prediction step can be defined as:

$$\boldsymbol{p(x_k|Z_{k-1}) = \int p\,(x_k|x_{k-1})p(x_{k-1}|Z_{k-1})dx_{k-1}} \quad \textbf{(1)}$$

in which the first term is a temporal prior following a Gaussian distribution with the mean as the memory strength in the past trial $\boldsymbol{x_{k-1}}$, and standard deviation as a temporal smoothness parameter α. The temporal prior allows memory strength to vary while still maintaining similar values for neighboring trials. When α is small (i.e., close to 0), the memory strength would not change too much from trial to trial; while larger values of α allow for significant changes in memory strength from one trial to the next. The temporal smoothness parameter can be viewed as controlling the rate of learning. Larger values indicate fast learning, and smaller values correspond to slow learning.

The model then applies the Bayes rule to update the posterior distribution of memory strength using the observations in the current trial k and predictive distribution derived in the prediction step:

$$\boldsymbol{p}(\boldsymbol{x_k}|\boldsymbol{Z_k}) = \frac{\boldsymbol{p}(\boldsymbol{Z_k}|\boldsymbol{x_k})\boldsymbol{p}(\boldsymbol{x_k}|\boldsymbol{Z_{k-1}})}{\boldsymbol{p}(\boldsymbol{Z_k}|\boldsymbol{Z_{k-1}})} \qquad \textbf{(2)}$$

The sequential model iteratively performs the two steps to update the distribution of the memory strength associated with each of the motor sequences. This model is ideal for the SRT task because it does not require perfect memory of all preceding trials and is sensitive to the order of data presentation. The learning of the memory strength is driven by the discrepancy between what is predicted to happen and what is actually observed. If the Bayesian sequential model provided a good approximation to an internal cognitive model for the SRT task, we would expect that the model could qualitatively account for human performance.

Model Simulation Results

We conducted model simulations for both training groups (Interleaved, Blocked) and for both groups of learners (Implicit, Explicit). The model predicts "memory strength" measured in arbitrary units. "Memory strength" is assumed to be the inverse of human reaction time, as reaction time will decrease when participants memorize the sequence better with higher memory strength. In the blocked condition, sequences were blocked into 80 trial presentations as in the experimental design. The standard deviation for likelihood was set to 10 in the simulation. To determine the temporal smoothness parameter α (analogous to learning rate) for implicit and explicit learners, we performed a grid search from 0-1 with a step size of .1. We found that α=.5 provides the best fit between estimated memory strength with human RT for implicit learners (r=-.653), and α=1 showed the best fit for explicit learners (r=-.928). These two parameters control learning rate and thus were altered for the two different groups of learners. This model was run 1,000 times and memory strength was averaged across runs. Model parameters for the interleaved condition were the same except the input sequences were intermixed for 240 trials rather than three blocks of 80 trials.

As higher memory strength corresponds to a faster reaction time, we added a non-linear transformation to memory strength, $e^{(1-0.1*Memory\ Strength)}$, to show the change of inversed memory strength as a function of training trials in Figure 3. The model's Day 1 performance is similar to experimental data for both explicit and implicit learners (Fig. 3). The model results with α=1 exhibited significant decreasing monotonic trends in the blocked training group (τ =-.392) and interleaved training group (τ =-.537) just as explicit learners. This was also the case for the model results with α=.5 in the blocked (τ=-.432) and interleaved (τ=-.889) training groups as did implicit learners (all p's <.0001). Importantly, model results with α=1 for explicit learners showed a larger difference between blocked training and interleaved training, than did α = .5 for implicit learners.

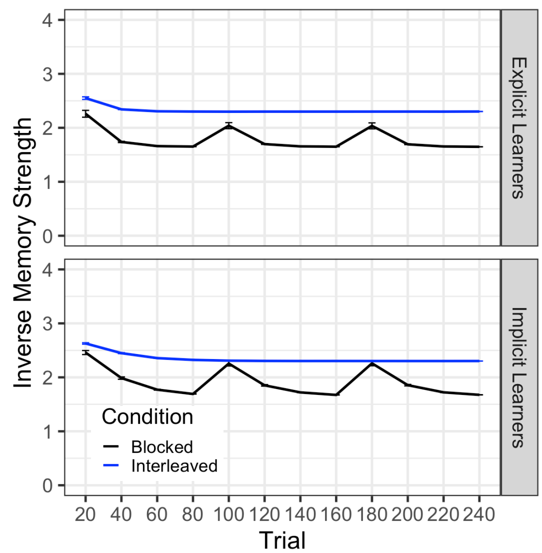

Figure 3. Inversed memory strength for both groups of learners during Day 1 training.

To directly compare model predictions and human performance, we found a strong negative correlation in the blocked training group in explicit learners for the memory strength predicted by the model and human RT in experimental data (r=-0.78, p<0.0001). We found a weak negative correlation in the interleaved training group in explicit learners (r=-0.33, p<0.0001). In implicit learners, we found a strong negative correlation between the model and experimental results in the blocked training group (r=-0.78, p<0.0001) and a moderate correlation in the interleaved training group (r=-0.44, p<0.0001).

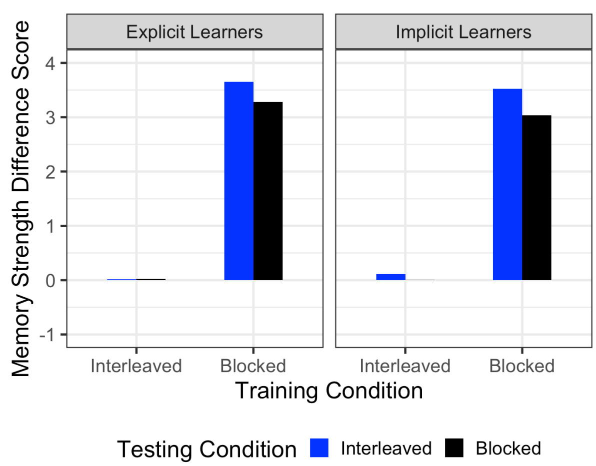

Figure 4. Model predictions of memory strength difference score. Higher scores indicate greater forgetting.

To model memory retention, we simulated Day 2 data to calculate difference scores. We modelled Day 2 similarly to Day 1, except that the prior was the posterior distribution of memory strength at the end of Day 1. Qualitatively, the model mimics the pattern observed in the experimental data (Fig. 4).

The model predicts more forgetting in the blocked training condition, and less forgetting in the interleaved training condition, consistent with experimental results. The model also shows large positive differences in the BB conditions, for both types of learners. However, the large positive difference score for the BB groups is inconsistent with our experimental results. In the experimental data, these groups had much smaller difference scores and thus better retention than the model predicted. Though the model "forgets" from Day 1 to Day 2, participants still retain procedural memory.

Discussion

The benefits of interleaving are well-documented and span multiple diverse domains (Brady, 1998). Research regarding contextual interference in motor skill learning has primarily focused on explicit sequence learning or gross motor learning (e.g., sports). However, it is as of yet unclear if the benefits of interleaving extend to implicit fine motor sequence memory after a substantial delay. Our study investigated the benefits of introducing contextual interference in a popular implicit motor learning task, the SRT task. Sequences were either blocked or interleaved in a two-day experiment. Explicit recall was probed at the end of the experiment.

We aimed to investigate the CI effect in purely implicit learners and set a recall score cut-off based on a Monte Carlo simulation that determined chance performance. Using this criterion many participants gained some explicit sequence knowledge. As we were interested in whether the CI effect persists in the absence of explicit knowledge, we dichotomized our sample. Dichotomizing resulted in a loss of power and small sample sizes, so our results should be cautiously interpreted, and it is possible that explicit knowledge could lead to greater benefits of CI in the SRT task. Future work could examine the effects of CI when learning is more clearly implicit, such as learning with a concurrent task or a more complex probabilistic sequence.

We found a main effect of practice schedule on retention, with interleaved practice leading to better retention of practice over the delay. However, this effect was qualified by an interaction between practice and test conditions: when sequences were tested in blocks, there was no effect of practice schedule, retention was good regardless of how sequences were practiced. However, there were large differences when the practiced sequences were interleaved at test. Participants who received interleaved practice showed excellent retention, and even consolidation of sequence knowledge at test. In contrast, participants who practiced the sequences in a blocked fashion showed substantial forgetting when tested in the interleaved condition. It appeared that blocked practice left participants unprepared for performance of interleaved sequences.

Finally, we found an interaction between training condition and learner type. When subjects trained with interleaved sequences, retention was similar for both implicit and explicit learners. However, subjects who trained with blocked sequences showed worse performance on Day 2, especially explicit learners. This was not the case for explicit learners in the interleaved group, suggesting that explicit knowledge of the sequences may hinder learning only when sequences are presented in a blocked fashion. Our results suggest that the benefits of interleaving do not require explicit retrieval.

The transfer-appropriate processing (TAP) principle refers to the phenomenon where task performance is best when the practice and test conditions are the same (Morris et al., 1977). Our results do not fully conform to the TAP framework, since participants with explicit knowledge who practiced interleaved sequences do better when tested with blocked sequences. However, implicit learners who practiced interleaved sequences perform better with interleaved sequences at test. Alternative TAP frameworks attempt to account for the differences in implicit and explicit learning by distinguishing between perceptual and conceptual processes, or between integrative and elaborative processes (Graf & Ryan, 1990; Roediger & McDermott, 1993). However, these proposed processes are mostly founded on perceptual priming research, so future research should aim to explain how the TAP principle differs in implicit and explicit motor learning, and how this may change with contextual interference.

We used the Bayesian Sequential Learning model and manipulated the temporal smoothness prior to model implicit and explicit learners. We altered this parameter because it relates to the rate of learning. In the motor learning literature, a multiple-process framework has been proposed where explicit processes correspond to "fast" learning and rapid forgetting, while implicit processes resemble "slow" learning and slow forgetting (McDougle et al., 2015; Smith et al., 2006). The model was mostly successful in qualitatively predicting the human data, as we found significant negative correlations when comparing the model results ('memory strength') to the experimental data (RT). However, though the model replicated the general pattern of retention results, it attributed poorer retention to both BB groups, which was not observed in our experimental data. Our model did not aim to provide a quantitative fit to the learning curves (RT), but rather a qualitative account of the differences observed in the interleaved and blocked conditions. In addition to not knowing the exact transformation from memory strength to RT, it is evident that the model has clear differences from human learning. First, the model doesn't consider any motor or perceptual uncertainty, though human participants may need practice trials to get familiar with how the visual cues correspond to the key presses. Furthermore, the model doesn't include other factors like spontaneous rehearsal, fatigue, and accuracy. Overall, the model predicts more forgetting when sequences were blocked on Day 1, as compared to interleaved sequences, which conforms to our main experimental finding.

Given the limitations of small sample sizes and a lack of experimental manipulation of explicit knowledge, our results do not offer definitive conclusions about the contextual interference effect in implicit motor sequence learning and long-term retention. However, our experimental and computational results suggest that contextual interference may protect against interference of explicit knowledge. We observed a contextual interference effect in implicit learners, as subjects who were trained in the interleaved condition showed less forgetting and subjects who were trained in the blocked condition were left unprepared for interleaved testing, indicating that they may have learned a sequence-specific rather than a general rule.

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