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Explicit pre-training instruction does not improve implicit perceptual-motor sequence learning

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ABSTRACT

Memory systems theory argues for separate neural systems supporting implicit and explicit memory in the human brain. Neuropsychological studies support this dissociation, but empirical studies of cognitively healthy participants generally observe that both kinds of memory are acquired to at least some extent, even in implicit learning tasks. A key question is whether this observation reflects parallel intact memory systems or an integrated representation of memory in healthy participants. Learning of complex tasks in which both explicit instruction and practice is used depends on both kinds of memory, and how these systems interact will be an important component of the learning process. Theories that posit an integrated, or single, memory system for both types of memory predict that explicit instruction should contribute directly to strengthening task knowledge. In contrast, if the two types of memory are independent and acquired in parallel, explicit knowledge should have no direct impact and may serve in a "scaffolding" role in complex learning. Using an implicit perceptual-motor sequence learning task, the effect of explicit pre-training instruction on skill learning and performance was assessed. Explicit pre-training instruction led to robust explicit knowledge, but sequence learning did not benefit from the contribution of pre-training sequence memorization. The lack of an instruction benefit suggests that during skill learning, implicit and explicit memory operate independently. While healthy participants will generally accrue parallel implicit and explicit knowledge in complex tasks, these types of information appear to be separately represented in the human brain consistent with multiple memory systems theory.

1. Introduction

Neuropsychological research has provided abundant and strong evidence for separate implicit and explicit memory systems in humans (Reber, 2008). Conscious, explicit memory that is dependent on the medial temporal lobe (MTL) memory system can be dissociated from implicit memory that influences behavior from outside of awareness (Squire, 2004). This neuropsychological dissociation may be reflected in the curious inability of experts to verbally communicate the basis of their skill acquired from extensive practice. However, unlike laboratory memory studies, complex skill learning is not acquired in a process-pure manner; both explicit instruction and practice are important parts of acquiring expertise. To understand the neurocognitive basis of skill learning, it will be necessary to identify the role of both memory types and also their interaction in learning complex tasks.

Theories of the interaction between implicit and explicit knowledge depend critically on a detailed model of the underlying representations of these types of memory. Theories that focus on separate neural systems for implicit and explicit knowledge have typically argued for independent operation (Reber & Squire, 1994, 1998; Stark & Squire, 2000; Willingham, 1998) or even competitive interactions

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(Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Poldrack & Packard, 2003) between memory systems. However, studies of healthy participants have frequently been interpreted as supporting a memory model based on a single, or tightly integrated system (Cleeremans & Jiménez, 2002; Shanks, 2005; Shanks & Perruchet, 2002) in which explicit awareness may be a property of the memory strength or quality of implicit representations. These two approaches make very different predictions about how the course of skill learning should be reflected in human memory. With independent systems, the direct role of explicit knowledge in skill learning should be a modest one, possibly just providing initial guidance to help establish a practice regime – effectively acting as a "scaffold" for the subsequently trained procedure (Petersen, van Mier, Fiez, & Raichle, 1998). Over subsequent practice, implicit learning mechanisms would then be responsible for honing and refining execution. With a single or integrated memory system model, expertise arises from a transformation of the explicit knowledge into a state that can support later rapid, expert performance. This model is similar to theories of automaticity that posit that increasing the strength of a memory should generally benefit performance and lead towards automation, without regard to the representational form of the memory being acquired (e.g. Logan's Instance Theory, 1988). In this case, effects of initial explicit knowledge should generally be visible throughout the course of learning since this is part of the eventual underlying expert knowledge representation.

Examination of the performance of skilled experts provides some evidence for separate representations of memory. For instance, when preparing for a performance, expert musicians describe very distinct processes to "learn" to play a piece and to "memorize" the score consciously (Chaffin, Logan, & Begosh, 2009). Overshadowing effects have also been reported that describe conditions in which explicit cognition can harm the expression of skilled performance (Beilock, Carr, MacMahon, & Starkes, 2002; Flegal & Anderson, 2008), suggesting that the two types of memory arise from separate, possibly competing, sources. However, the idea of *deliberate practice* (Ericsson, Krampe, & Tesch-Römer, 1993) is important in skill learning, in which an emphasis is placed on explicit instruction and top-down control to achieve optimal performance. The importance of explicit knowledge reflected in deliberate practice suggests less independence between memory types and a more active role for explicit memory than simply scaffolding. In this case, explicit knowledge may provide more direct support for skilled performance by allowing for the correction or alteration of learned movements in order to prevent arrested development and/or to enhance the level at which movement automation occurs.

The neuropsychological studies that support the dissociation between memory systems seen in patients with neurological damage do not rule out the possibility that these types of memory may operate differently when the neural systems are fully intact (e.g., in cognitively healthy adults). For example, there may be two systems that normally operate in a tightly linked fashion, like the two eyes that move together, except in cases where dysfunction might cause them to become uncoupled (Perruchet & Gallego, 1993). Complete system integration has been suggested by Shanks and colleagues (Shanks, 2005; Shanks & Perruchet, 2002; Shanks & St. John, 1994) who argue for a unitary memory framework whereby a single, largely explicit system supports all learning. The dynamic frameworks model by Cleeremans and Jiménez (2002) describes a model of tightly-integrated representations in which explicit and implicit cognition are aspects of a single set of underlying neural mechanisms. In this approach, certain low-level mechanisms (weight-learning) operate outside of awareness but complex symbol manipulation operates on the same basic information with explicit awareness. The commonality across these unitary frameworks that distinguish them from multiple systems models is that both skill instruction and performance are supported by a shared and singular underlying memory representation.

In the single-system theoretical accounts, implicit learning cannot be fully dissociated from explicit learning because experience leads to increased knowledge in a common representational store (in healthy participants). From this perspective, it is argued that dissociations among tests of implicit and explicit knowledge appear due to characteristics of the particular test measures used to assess implicit or explicit memory (see, Shanks et al., 1994). Implicit memory tests are thought to be more sensitive to low levels of information, leading to occasional observations of implicit knowledge without explicit knowledge. A key prediction of this general approach is that there should always be evidence for explicit knowledge whenever implicit learning is observed because this explicit knowledge significantly contributes to task performance. In healthy participants, this finding is generally observed. Across implicit learning paradigms, some memory for the learning context is almost always observed, and even when a subset of participants exhibit implicit knowledge without explicit memory, a sizeable percentage of participants typically exhibit both (Sanchez, Gobel, & Reber, 2010; Shanks & Johnstone, 1999; Willingham, Greeley, & Bardone, 1993), raising questions of test sensitivity.

However, the existence of explicit memory after practice is consistent with both theoretical approaches. The intact MTL memory system in healthy participants may be acquiring explicit memory during practice that does not actually contribute directly to performance. Under a model of separate, independent systems, this explicit memory will accrue in parallel (Song, Marks, Howard, & Howard, 2009; Willingham & Goedert-Eschmann, 1999) and although it does not improve skilled performance, it supports performance on post-training tests of explicit knowledge. Of note, this approach counter-intuitively implies that the human brain acquires task-relevant knowledge (e.g., explicit memory) that is not applied to current performance. This idea, plus the rhetorical point that a single system model is a more parsimonious explanation, has been used to argue in favor of a single or tightly integrated model of memory use (Shanks et al., 1994). However, the organization of human memory systems may reflect neurobiological and information processing constraints (e.g., Attalah, Frank & O'Reilly, 2004; Henke, 2010) that are not yet well perfectly understood.

A key question for understanding the role of implicit and explicit knowledge in complex cognition, such as skill learning, is to determine whether explicit knowledge information contributes directly to learning to perform or whether it reflects concomitant knowledge in a separate representational system that is epiphenomenal to task performance. This is a difficult question and most prior studies have attempted to address this by looking for process-pure demonstrations of robust implicit learning in the total absence of explicit memory. As noted by Merikle (1994) and Dienes and Berry (1997), the challenge of proving process-purity in implicit learning may be essentially impossible (but see a subsequent overview in Dienes, 2012). This has led these attempts to generally not be definitive (with the process-dissociation procedure of Destrebecqz & Cleeremans, 2001, probably coming closest).

Here we take an alternate approach to this question by providing participants with abundant explicit knowledge prior to engaging in an otherwise implicit learning task. In a single-system model (or tightly coupled representations), the acquisition of task-relevant information in either implicit or explicit form should lead to better performance on the task because there is a shared underlying representation of sequence knowledge. Thus, anything that contributes to or strengthens knowledge should improve performance, especially on the relatively sensitive implicit memory test. Alternately, if implicit and explicit learning lead to completely separate representations, then increasing one will not automatically lead to an increase in the other or in general memory measures. If there are two independent representations, then explicit knowledge may only contribute to the MTL-dependent representations that contribute to performance on recognition or recall tests, but not produce any impact on the implicit learning process that depends on brain regions outside the MTL.

This approach was previously examined in Reber and Squire (1998) where healthy participants were instructed about the explicit sequence in a Serial Reaction Time (SRT) task at the very beginning of training, but exhibited no benefit on sequence-specific reaction time performance. However, this effect was only observed during the first 60 trials ($\sim$30 s to 1 min) of practice, and in other studies sequence-specific reaction times have been shown to be enhanced when implicit training is accompanied by explicit knowledge (e.g., Curran & Keele, 1993; Frensch & Miner, 1994; but also see Mathews et al., 1989 for a similar approach with artificial grammar learning). The structure of the SRT task is that it could potentially be performed entirely on the basis of explicit knowledge, e.g., as a prediction task about where the next cue will appear rather than a reaction to the cue onset. Thus, a benefit of explicit knowledge on performance does not necessarily imply explicit knowledge affects implicit knowledge, but could instead reflect switching to a consciously driven strategy. The same difficulty in characterizing strategy use has been noted in tasks of visual categorization, with the difficulty of determining participant strategy without additional information such as neuroimaging data (Reber, 2009; Reber, Gitelman, Parrish, & Mesulam, 2003).

For the current study, we use the recently described Serial Interception Sequence Learning (SISL) task (Sanchez et al., 2010), which is closely related to the SRT task in that perceptual cues are used to guide participants through a covertly embedded sequence of responses. In the SISL task, however, participants observe a moving cue and attempt to time a motor response to the arrival of the cue over a target region. This changes the task from being based on wait-and-respond to a more continuous performance task that is a better analog of real-world performance tasks thought to be influence by implicit learning (e.g., physical skills, music performance, language processing). An important difference from the SRT task is that SISL task performance is assessed by whether the correct response was made at the appropriate time to a continuous stream of cues, resulting in a binary hit-or-miss response to each item (measured as percent of correct responses). Sequence-specific learning is assessed in the SISL task in a similar manner to the SRT task with performance during the embedded repeating sequence contrasted with performance during an unfamiliar sequence. This provides a measure of implicit learning which occurs without explicit knowledge in some participants, in the same kind of partial dissociation (Sanchez et al., 2010) seen with the SRT task, but with a higher percentage of participants exhibiting this effect.

This type of partial dissociation can be accommodated by a single or integrated system model by hypothesizing that the participants who only exhibit implicit knowledge had some covert explicit knowledge and simply failed to express it on the explicit test, or that these same participants simply had a weaker form of the underlying knowledge. To better contrast between hypotheses about representations, rather than continuing to search for evidence for the complete absence of explicit knowledge, here we examine the contribution of high levels of explicit knowledge to performance. Before beginning practice, participants were given full explicit knowledge about the repeating sequence, i.e., they are told the precise order and relative timing between cues in order to anticipate and guide the sequence of responses they will have to make during task performance. If participants are able to bring this explicit memory to bear on performance, they should exhibit further increases in accuracy of responding for the repeating sequence. If performance improvements are based on an integrated memory representation, then the addition of relevant explicit (E) knowledge to repeated implicit (I) learning trials would predict a benefit of this instruction, $(E + I) > I$. Alternately, if participants are generally unable to benefit from additional explicit knowledge, this suggests that the two types of memory are relatively encapsulated such that, $(E) + (I) = I$.

The pre-training instruction approach also mimics the methods by which skill learning is typically taught: explicit instruction about the procedure followed by repetitive practice. The current paradigm uses the SISL task as a model of skill learning for this purpose. However, since the SISL task is one that allows for direct implicit learning by cuing the motor responses of the repeating sequence with perceptual information, unlike most skill learning, performance does not absolutely depend on initial pre-training instruction. This makes it possible to contrast implicit (I) learning with implicit plus explicit ($I + E$) learning, because there is no need for explicit pre-instruction to guide initial performance, unlike many physical skills (e.g., juggling). If the two memory systems operate independently then no performance advantage will be seen for the explicit pre-training instruction condition ($I + E$) compared to an implicit learning condition (I) without the additional explicit instruction. Under a single memory system or tightly integrated systems model, the addition of explicit memory should raise the total amount of available information and produce an improvement in performance.

To test whether explicit pre-training instruction leads to enhanced learning and performance on an implicit skill learning task, a group of participants were explicitly instructed on the embedded repeating sequence prior to SISL practice. Based on preliminary data suggesting that explicit knowledge can be difficult to retain over the course of training, additional explicit instruction was also provided halfway through practice. In contrast to traditional skill instruction methods whereby the learner may be provided with explicit rules or algorithms to guide performance, the explicit instruction provided here was the specific sequence of repeating actions that were to be learned. Both forms of instruction require explicit memory, but the instruction used here was designed to provide exactly the most relevant explicit knowledge for the task to best see how it might affect implicit learning and performance. Learning in this group of participants was compared to a control group who learned under traditional incidental learning conditions. In addition to comparing learning across groups, explicit memory for the repeating sequence was assessed after practice to verify that the pre-training instruction manipulation produced high levels of explicit sequence knowledge. If sequence knowledge relies on a shared implicit and explicit ($I + E$) knowledge representation, or if the representations between memory systems interact in a beneficial manner, participants in the explicit condition should exhibit a benefit during the SISL training and in the post-training test.

2. Method

2.1. Participants

Thirty-one undergraduate students at Northwestern University received course credit for participation. Two participants from each condition were removed from the data due to cessation of responding leading to unusually low performance during SISL test blocks, leaving 27 participants in the final analysis (19 female, M_{age} = 18.48 years). The SISL task is similar in format to popular rhythm music games (e.g. Guitar Hero, Tap Tap Revenge), so participants' video game experience was assessed. Participants were familiar with popular video games of the same format (i.e. rhythm games) and one participant reported regular play.

3. Materials

3.1. The Serial Interception Sequence Learning (SISL) task

Participants observed circular cues scrolling vertically down a monitor in one of four horizontal locations towards corresponding yellow target rings located near the bottom of the screen (Fig. 1). Beneath each ring was a letter (D, F, J, or K) indicating which keyboard button corresponded to each of the locations. Participants were instructed to make a keypress response when a cue overlapped a target ring. Responses were considered correct if the appropriate key was pressed while the cue was within one cue-length of the target ring (half a cue length on either side of the proper target location), so that the initial window for a correct response was approximately 140 ms. A response was considered incorrect if the key was pressed while the cue was outside of the acceptable response window, if the wrong key was pressed, or if more than one keypress was made within a single target response window. For direct response feedback, incorrect responses caused the corresponding target ring to flash red, and if a response was correct, the target ring flashed green and the cue disappeared. A performance meter located on the left side of the screen increased in size by about 1% for each correct response and decreased in size for each incorrect response. A numerical score box on the right side of the screen displayed a number that increased with each correct response. The performance meter and score were indicative of performance, providing participants with constant feedback.

The cues moved down the screen with an initial velocity of 12.6°/s, reaching the target zone 850 ms after appearing on the screen (time-to-target). To maintain a reasonable level of task difficulty and reduce ceiling effects, the percentage of correct responses was assessed after every 30

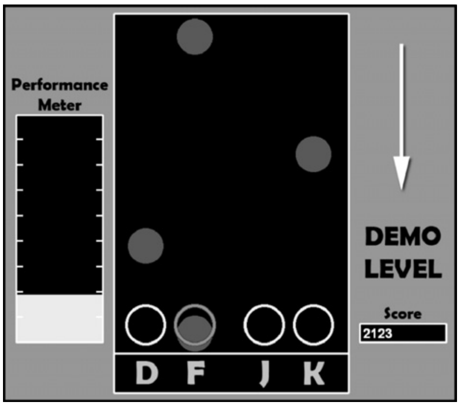

Fig. 1. The Serial Interception Sequence Learning (SISL) task. Circular cues scroll down the computer screen toward target rings at the bottom. Participants attempt to intercept circles as they cross the target rings by pressing the corresponding keyboard button. For example, this participant just responded with an *F* keypress, and would be readying responses for *D*, then *K*, then *F*. The colored bar within the performance meter increases for every correct response and decreases for every incorrect response and the score increases based on the accuracy of correct responses.

trials during training and the cue velocity was adjusted accordingly. When performance was at 85% correct or higher, the time-to-target decreased by 3.2% and when performance was between 70% and 84%, the time-to-target decreased by 1.6%. Conversely, when performance was between 26% and 69% correct, the time-to-target increased by 1.6% and if performance was 25% or lower the time-to-target increased by 3.2%. Time-to-target never increased above 1200 ms.

Unbeknownst to participants, the cue order followed a repeating sequence that was 12 cues in length for 80% of the training trials, while 20% of the trials were novel, non-repeating sequences. All sequences were constructed following second-order conditional (SOC) structure (see Reed & Johnson, 1994). SOC structure restricts cues from repeating (e.g. D–D) and prevents paired cues (e.g. K–D) from appearing more than once per sequence, making a trigram (e.g. D–K–F) the smallest statistically predictable structure. All sequences were selected from a pool of 256 unique 12-item SOC sequences and were not repeated for any participant during the experiment. In addition to the repeated order of the cues, the cues within the sequence followed a specific interval pattern of short and long inter-stimulus intervals (ISIs). The ISIs were either 2.5 or 5 cue lengths, respectively. The ISIs adjusted with the velocity of the task, such that the ISIs remained a constant visual distance (2.5 or 5 cue lengths) throughout the task.

3.2. Procedure

Participants were randomly assigned to either an explicit pre-training instruction condition, in which they attempted to memorize their 12-item sequence before the SISL training, or to an implicit knowledge condition, in which they were not told about the repeating sequence. In the explicit condition, participants were allowed to watch (without responding) as their repeating sequence scrolled down the screen five times prior to training, and were instructed to memorize the sequence. Additionally, a static image of the 12-item repeating sequence was displayed on the left side of the screen, with each of the corresponding response letters (D, F, J, K) overlaid on the circles. This allowed the participant to see the sequence in its entirety, along with the corresponding responses, while watching the sequence scroll down the screen in order to achieve a robust explicit representation of the repeating sequence. This portion was self-paced as participants were allowed to press the spacebar every time they wanted to view the sequence scroll down the screen, and were allowed as much time as they needed to encode and memorize the sequence. In order to ameliorate forgetting, half-way through SISL training participants watched their sequence scroll down the screen five more times, but without the static image during pre-training instruction. They were also notified that their repeating sequence would not always be present during training. Participants in the implicit condition did not receive the verbal explanation or instruction and were not given the opportunity to view their sequence, as to be kept naïve to the repeating sequence. To familiarize themselves with the task prior to SISL training, all participants completed a short demonstration of the SISL task, which included 24 random cues.

The training portion of the SISL task contained six 480-trial blocks which consisted of 384 trials of the repeating sequence and 96 novel, unrepeated SOC trials. Therefore, participants received 192 sequence repetitions during training (32 repetitions per block). The blocks were constructed such that a novel sequence appeared once per 60 trials, or four repetitions of the trained sequence for one presentation of a novel sequence. Novel sequences during training never repeated, and were not used as foils during the implicit or explicit knowledge tests. In between blocks, participants were offered a 15 second break that could be bypassed by pressing the space bar.

A 540-trial test block followed directly after training, with no indication that it was different from the preceding training blocks. The test block consisted of 15 repetitions of the trained sequence along with 15 repetitions each of two novel SOC sequences. The test block was structured so that every 60 trials (five sequence repetitions) represented performance on one of the three sequences, and the order of sequence presentation was randomized. The SOC sequences assigned to training and test were completely orthogonal so that no sequence shared any of the same trigrams. For example, if D–F–K appeared in one sequence, the other two sequences would not contain this trigram, but would instead have D–F–D or D–F–J. Implicit knowledge of the trained sequence was assessed by comparing percentage correct performance on the trained sequence to performance on the novel sequences.

Upon completion of the SISL task, participants in the implicit condition were informed that a repeating sequence was present in the task they had just completed. All participants then completed a recognition test to assess their explicit recognition knowledge of their trained sequence. The recognition test was the first explicit test administered – directly after the SISL task – because it has been shown to be highly sensitive to explicit knowledge in perceptual-motor sequence learning tasks (e.g. Willingham et al., 1993). For the recognition test, participants performed the SISL task with their trained sequence and four completely novel SOC sequences separately. Each sequence was presented in a 24-trial (two-repetition) block and participants were asked to consider whether or not the sequence they had just performed was the repeating sequence from the training trials. Participants rated their confidence on a scale from 10 (absolutely was the sequence) to -10 (absolutely not the sequence).

Lastly, participants completed an explicit recall task in which they saw only the yellow target rings on the screen and were instructed to generate the repeating sequence using the keyboard buttons. The recall test ended after a participant entered 24 responses. Recall knowledge was assessed by identifying the longest matching subsequence between the participant's response and the trained sequence. To assess baseline recall knowledge, the generated sequence was also compared to the remaining 201 novel SOC sequences (of 256, 55 had already been used for novel training sequences and tests) and the average matching subsequence was calculated.

4. Results

Sequence-specific learning was calculated as the percentage correct difference between SISL performance on the trained sequence and the foil sequences across training and analyzed with a mixed 2×6 ANOVA of condition (explicit, implicit) and training block (one through six). A linear increase in sequence-specific performance across training was found, $F(1,25) = 28.33$, $p < .001$, such that both groups exhibited a trained sequence performance advantage during the last training block (explicit, $M = 14.96\%$, $SE = 2.71\%$; implicit, $M = 13.39\%$, $SE = 2.14\%$; $ts > 5.53$), but there was neither a main effect of condition nor an interaction effect ($Fs < 1$), suggesting both groups learned at similar rates. A mixed 2x2 ANOVA of condition (explicit, implicit) and sequence type (trained, foils) at test revealed a main effect of sequence type, $F(1,25) = 21.34$, $p < .001$, as participants performed the trained sequence ($M = 63.33\%$, $SE = 1.27\%$) significantly better than the novel sequences ($M = 53.65\%$, $SE = 1.98\%$). However, there was no main effect of condition, nor an interaction ($Fs < 1$), indicating that sequence-specific performance improvements were not different between the explicit instruction ($M = 9.32\%$, $SE = 3.29\%$) and implicit ($M = 10.10\%$, $SE = 2.63\%$) conditions (Fig. 2).

Not only was the effect of explicit knowledge on SISL performance minimal, but the explicit group actually demonstrated a slightly lower sequence-specific performance advantage at test (Cohen's $d = -.08$). The small decrease in the sequence-specific performance advantage seen in both groups between the last training block and test likely reflects the fact that the foil sequences repeat during test, as opposed to being completely novel during training, and small learning effects for the foils may occur. Despite this difference, the correlation between the trained sequence performance advantage at the end of training and during test is very high, $r = .65$, suggesting that these measures are reliable estimates of implicit learning.

The sensitive recognition test revealed that healthy participants in both conditions were capable of recognizing the trained sequence, $F(1,25) = 75.54$, $p < .001$. Participants in the explicit condition gave slightly higher ratings to the trained sequence ($M = 8.08$, $SE = .80$) and lower ratings to the foil sequences ($M = -2.88$, $SE = 1.25$) compared to participants in the implicit condition ($M = 7.50$, $SE = .64$; $M = -1.46$, $SE = 1.06$, respectively), but these differences did not reach significance (interaction and main effect of condition, n.s.). On the recall test, there was a main effect of sequence type, $F(1,25) = 27.53$, $p < .001$, and condition, $F(1,25) = 17.06$, $p < .001$, and an interaction, $F(1,25) = 12.42$, $p < .01$ – indicating that the sequences generated by the explicit instruction participants matched the trained sequence ($M = 9.54$, $SE = .87$) better than the foil sequences ($M = 4.54$, $SE = .19$), as compared to the participants in the implicit condition (trained, $M = 5.36$, $SE = .64$; foils, $M = 4.38$, $SE = .13$). Thus, the explicit instruction led to a large effect (Cohen's $d = 1.35$) on the ability for participants to recall the trained sequence in the explicit group. A clear summary of the implicit and explicit test scores can be seen in Table 1.

Potential performance effects of explicit knowledge were additionally assessed by post hoc sorting participants into groups based on levels of explicit knowledge demonstrated at test. When participants were post hoc sorted into high- and low-recognition groups based on the median of the recognition score in the explicit ($Mdn = 12.50$) and implicit ($Mdn = 9.00$) conditions, there were no significant main effects or interactions (n.s.), showing that the ability to recognize the sequence was not correlated with performance ($r = -.02$). In addition, seven of the 13 participants in the explicit condition displayed robust explicit knowledge and were capable of recalling the entirety of their 12-item trained sequence, but this did not lead to better sequence-specific performance at test ($M = 7.94\%$, $SE = 4.90\%$).

Cue velocity, measured as time-to-target, increased in a linear trend throughout training, $F(1,25) = 32.66$, $p < .001$, such that the time-to-target at test was 790 ms ($SE = 30$ ms) and did not differ between conditions (interaction and main effect of condition, n.s.).

5. Discussion

Participants developed robust explicit sequence knowledge as a result of the explicit instruction, but this did not lead to better performance on the trained sequence during

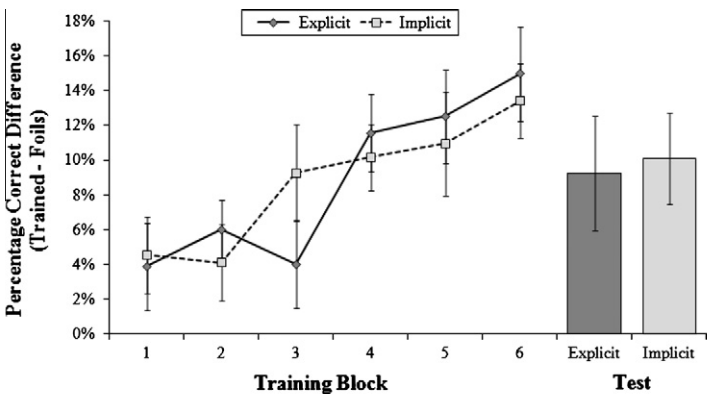

Fig. 2. Sequence-specific performance benefits across SISL training and test. The learning curve across the six training blocks and the percentage correct difference between the trained sequence and foil sequences at test show no difference between the explicit instruction and implicit conditions.

Table 1
SISL, recognition, and recall test results. The SISL scores reported are the percent correct performance for the trained sequence and foil sequences at test, for both training conditions (implicit, explicit). Recognition test values are confidence ratings (from +10 to −10) to trained and foil sequences provided by participants in regards to how likely they believed the current sequence was the sequence during training. Recall values represent the longest matching subsequence of the generated sequence to the trained and foil sequences.

	SISL		Recognition		Recall	
	Sequence	Foils	Sequence	Foils	Sequence	Foils
Implicit	63.81% (1.64)	53.71% (3.01)	7.50 (0.64)	−1.46 (1.06)	5.36 (0.64)	4.38 (0.13)
Explicit	62.82% (2.02)	53.59% (2.66)	8.08 (0.80)	−2.88 (1.25)	9.54 (0.87)	4.54 (0.19)

Mean (SEM).

learning or test. Even for the seven participants (of 13) in the explicit instruction condition who could recall the entirety of the trained sequence, no advantage in performance was observed. These participants had complete explicit knowledge of the repeating sequence, plus the same amount of practice as the participants who learned the sequence in typical implicit learning conditions. However, this increase in the total amount of knowledge held by the participants led to no additional performance advantage. The absence of an advantage of very strong explicit knowledge suggests that SISL test performance is driven almost entirely by implicit learning gained during practice.

Although participants in the incidental (implicit) group also exhibited a tendency to acquire some concomitant explicit sequence knowledge of the repeating sequence, the participants with much higher levels of explicit knowledge did not exhibit an advantage on the implicit test. This likely reflects the common finding that healthy participants often acquire incidental explicit knowledge of the trained sequence during implicit perceptual-motor sequence learning (Willingham et al., 1993). This reported lack of correlation between performance on implicit and explicit tests is frequently found (e.g., Gobel, Sanchez, & Reber, 2011; Sanchez & Reber, 2012; Sanchez et al., 2010), and has been suggested to support generally independent operation of the two types of memory (Song, Howard, & Howard, 2007; Willingham & Goedert-Eschmann, 1999). Occasionally an association between the two measures of memory has been reported (Perruchet & Amorim, 1992), which has been used to support the idea of a common knowledge representation. The inconsistency of this finding may indicate that there are experimental or individual factors that affect both types of memory (e.g., vigilant attention to the task) which does not necessarily imply a single or integrated memory. If the relationship between explicit and implicit knowledge test scores reflected integration of information across memory types during skill learning, it should be consistently observed.

Although multiple memory systems theory accounts for the results found here based on the encapsulation of memory representations, theories that posit a singular memory representation for both implicit and explicit knowledge cannot easily account for the lack of any benefit from explicit pre-training instruction. Under a shared representation approach, increasing the total amount of knowledge ($I + E$), should increase performance. Strict unitary frameworks (e.g., Shanks, 2005) would suggest that robust explicit knowledge that is demonstrable through a recall test (as shown here) represents an enhanced sequence memory strength, which should have benefited the sensitive implicit memory test. Likewise, if explicit knowledge can arise from weaker underlying implicit representations and, when provided, can possibly negate the need for direct experience (Jiménez, Vaquero, & Lupiáñez, 2006; following Cleeremans & Jiménez, 2002) then it would have been expected to find enhanced sequence-specific performance during the SISL task in the explicit condition. However, the current results found that significantly robust explicit knowledge did not benefit the trained sequence performance.

With an approach based on integrated representations, it might still be argued that there is an important issue regarding the applicability of knowledge, along the lines of "transfer appropriate processing" (e.g. Blaxton, 1989). However, the requirement that one type of knowledge must be transferred in order to be applicable to another task depends on an assumption that there are multiple kinds of information that can be differentially applied across tasks. That assumption implies a framework that includes multiple types of knowledge in the same manner as the multiple memory systems theory, as recently noted in Henke (2010). A theory that requires transfer of memorized explicit sequence knowledge to task performance, as found here, is making the same assumption that there are separate representations for knowing what to do and how to do it. In multiple memory systems theory, the representation for explicitly knowing what to do is based on the MTL memory system for facts and events while implicit knowledge of how to perform is based on a separate memory system, such as cortico-striatal learning mechanisms of the basal ganglia (Doyon et al., 2009). A single-system theorist might posit that both types of information are accumulated within a single system that has different kinds of representations that apply to performance versus explanation. However, this form of "single system" model has become nearly indistinguishable from a multiple memory systems model (different types of memory in a single system versus different types of memory in separate systems), except for the fact that the neural basis of this kind of memory is not specified in the "single-system" model.

A key remaining point of theoretical difference could lie in the character of the information acquired of each type. In the multiple memory systems theory, the practice-based performance memory is entirely implicit while conscious verbalization of the sequence is explicit; representative of separate underlying memory systems with unique operating characteristics. Alternately, a theory of multiple kinds of knowledge within a single system suggests that the knowledge acquired through explicit instruction is different than the implicit knowledge acquired through practice. However, explicit knowledge may also emerge from the implicit practice-based knowledge as well, as the memory strengthens, implying multiple kinds of memory for acquiring similar knowledge. This model gives up the core rhetorical arguments in favor of a single system: parsimony and rationality. The multiple memory systems theory predicts two types of memory that differ in neural bases and have operating characteristics matched to how they are used (performance versus explanation). Accounting for the results reported here with a single system and the idea of "knowledge transfer" requires postulating one type of memory for conscious memorization and a separate type of memory that acquires both implicit and explicit memory based on practice. Comparing these approaches, the multiple memory systems model is both more parsimonious and consistent with the neuroscientific findings about the operation of memory across separate regions of the brain.

Our finding that explicit pre-training did not benefit learning rate or test performance was obtained using our relatively novel, fast-paced SISL task. Although explicit instruction of the sequence was administered in a manner to encourage use of explicit sequence knowledge to the task as much as possible, the non-contribution of the explicit knowledge may indicate that applying explicit knowledge is a slower process than applying implicit knowledge. The instruction provided to participants went to some length to be sure that it was in exactly the format needed to relate to SISL performance. The visual stimuli and pacing of cues were displayed precisely as they were at the beginning of the training protocol, and the visual representation of the sequence in its entirety allowed participants to develop a representation of the sequence in components and as a whole. During sequence instruction, participants were fully aware of the response characteristics of the following SISL task, to the extent that they understood the response mapping of keys/fingers to the on-screen cues and were allowed to use any strategy of their choosing in order to develop explicit knowledge. Although participants did not respond to the cues during explicit instruction, participants were allowed to mime or move their fingers along with the cues in order to map the motor response to the instructed sequence. The participants are essentially told exactly what they will need to do during the SISL task, but even individuals with perfect subsequent recall of the sequence exhibited no advantage from this information. This result contrasts with previous findings of an explicit knowledge benefit to sequence-specific performance (Curran & Keele, 1993; Frensch & Miner, 1994), but these previous studies utilized the SRT task which requires reaction time responses compared to the interception responses required here.

The task demands of the SISL task feature key differences from the SRT task that has been highly studied as a model of implicit learning, in spite of the fact that both depend on implicit learning of a covertly embedded sequence. The SRT task is based on reaction time – a response is made as rapidly as possible after waiting for the onset of a cue. While learning in the SRT task is often implicit, when participants are also consciously aware of the sequence, they could potentially anticipate the next motor response and produce extremely rapid responses entirely based on explicit memory. Thus, the implicit RT performance benefits can become dominated by explicit anticipation and planning strategies. When there is one behavioral response and two potential internal processes for producing this response, it can be extremely difficult to make a reverse inference about how each process contributed to the behavioral response (also noted in Moisello et al., 2009). The SISL task removes anticipatory planning effects by requiring continuous performance and by displaying numerous upcoming cues on the screen simultaneously. The difficulty of this problem is not isolated to sequence learning tasks, and has also been noted in studies of visual categorization in which healthy participants might use either an implicit or explicit strategy that can only be distinguished with methods like functional neuroimaging that examine internal activity (Reber, 2009). Identifying the multiple brain systems that support category learning has been made possible by the development of tasks that strongly favor one system over another (Ashby & Maddox, 2005) and neuroimaging studies identifying the neural correlates of these systems (Nomura & Reber, 2008) that are guided by cognitive models of each process (Ashby et al., 1998).

The SRT task has been an excellent tool for exploring mechanisms of implicit learning, but the core structure of the task does not effectively capture the kind of online processing that reflects the role of implicit learning in tasks like language processing (e.g., Perruchet & Pacton, 2006) or motor plan execution. The SISL task is a continuous performance task that requires precisely-timed responses and, therefore, provides a better model of increasing fluidity and accuracy of skilled performance following repetition. These features may also contribute to learning depending more exclusively on implicit memory systems, e.g., if explicit memory operates more slowly in general and is difficult to apply in a rapid, continuous task. The fact that SISL allows for a more process-pure examination of implicit learning makes it particularly suitable for examining possible interactions between implicit and explicit learning. We do not feel, however, that this limits the finding of independence in the operation of implicit and explicit memory to the SISL task. Tasks that depend on rapid online processing such as language comprehension or visual categorization (object recognition) are thought to reflect implicit processes because we "just know" that a sentence is grammatical or an object is a face without access to the underlying computations that led to that inference. In experimental paradigms where participants are presented with a stimulus and given time to draw the inference, it is possible that the response made could depend solely on either implicit or explicit processing (and averaging across participants would look like an interaction between memory types). Only a task like SISL can be used to show the clear distinction between increasing explicit knowledge and task performance that indicates that the two kinds of knowledge are separate in the human brain.

This unique dissociation found with the SISL task does not imply that explicit instruction is not necessary for learning real-world skills, but demonstrates the unique contributions of different knowledge representations to skill acquisition. The role of explicit knowledge appears to primarily be for initially planning an action sequence in order to support the gradual and covert repetition-based learning in the implicit system, which eventually takes over support for performance. During skilled performance, an internally-generated motor plan is executed, but it is nearly impossible to separate the contributions of explicit and implicit knowledge to the actual movement performance. Here, it was found that by making the planning stage redundant with rapidly-paced cues that were presented with multiple visible on the screen simultaneously, that performance gains were completely dependent on implicit learning based on practice. This suggests that explicit knowledge serves the unique role of allowing the internal planning of a motor response, such as during the recall test when a participant must consciously generate the 12-item motor sequence.

This contrast in the proposed contributions of explicit and implicit memory representations fits with the theory of motor control whereby explicit knowledge is proposed to be responsible for motor planning (Tubau, Hommel, & López-Moliner, 2007), as opposed to the actual movement execution stage. Allowing for planning time has been shown to have an effect in RT based tasks (Perlman, Pothos, Edwards, & Tzelgov, 2010), and this contrast has also been demonstrated with real world golf experts, such that when they were given a new tool ('funny putter') additional time was absorbed during the motor planning, not execution, stage (Beilock, Bertenthal, Hoerger, & Carr, 2008). This internal motor planning concept is more commonly understood as a form of knowledge flexibility or top-down control. Explicit knowledge affords a flexible use of the underlying knowledge representation such that it may help recover from a break in the associative chain that implicit knowledge is dependent on. For example, when there is a failure in the chain of procedural movements supporting the performance of a musical piece, an expert must recall an explicit retrieval cue in order to keep performing the correct action sequence (Chaffin et al., 2009). This reinforces the idea that the representations of explicit and implicit knowledge are distinctly utilized for different roles in skill learning, and also that utilizing both forms of information simultaneously requires an integration of these sources that the participants here were unable to accomplish.

While the SISL task lends itself to examining explicit and implicit memory contributions separately, a question might be raised whether more complex skill learning tasks might lead to a greater contribution of explicit knowledge during practice. It has been suggested that multiple memory systems can be recruited during the learning of motor sequences (Albouy et al., 2008; Ghilardi, Moisello, Silvestri, Ghez, & Krakauer, 2009), and the idea of *deliberate practice* (Ericsson et al., 1993) in expertise implies an important role for explicit, top-down processes even at high levels of performance excellence (Yarrow, Brown, & Krakauer, 2009). However, there have been several reports that explicit knowledge can actually interfere with the expression of skilled knowledge (Beilock et al., 2002; Flegal & Anderson, 2008) suggesting that memory system interactions may not be cooperative in these cases either. The scaffolding model (Petersen et al., 1998) is consistent with a role for explicit memory in usefully directing practice even though the benefits of repetitive practice may depend entirely on implicit learning mechanisms. In this case, as mentioned above, explicit knowledge is useful for directly planning a movement, such as preventing the improper form or arm movement in a golf swing (i.e. deliberate practice). This top-down control in preventing improper movements is extremely important because performance gains are typically considered to be a function of repetitions practiced (Heathcote, Brown, & Mewhort, 2000; Newell & Rosenbloom, 1981; Sanchez & Reber, 2012), and practicing a sub-optimal sequence likely leads to sub-optimal performance. What this model suggests is that both types of knowledge are important for skill learning, but the two types of knowledge serve unique roles and exist as separate representations based in multiple memory systems.

The same interplay between memory systems likely occurs in the acquisition of cognitive skills, even though the action sequences for a cognitive skill may be more abstract and less dependent on perceptual cues to drive motor responses. Similarities between perceptual-motor skills and cognitive skills have been observed previously (Rosenbaum, Carlson, & Gilmore, 2001) and sequential learning has been observed in problem solving tasks (Reber & Kotovsky, 1997). Computational models of skill learning such as ACT-R (Anderson & Lebiere, 1998) have a theory of interactions between explicit knowledge (declarative chunks) and implicit processing (production rules) as a major architectural element. The ACT-R model proposes a specific form of interaction between memory types with production rules compiled from explicit knowledge, as in learning following instruction. Further improvements in speed and accuracy could reflect modification of production rule firing parameters that would appear to be an implicit learning process. It is not entirely clear how ACT-R would capture the phenomenon of learning without awareness observed in SISL since this would appear to require development of new production rules for sequential performance without explicit sequential knowledge. The CLARION model (Sun, Slusarz, & Terry, 2005) also directly examines interactions between explicit and implicit knowledge in skill learning, although the focus of this model is on bottom-up learning of action-oriented knowledge (procedural) that is separate from, but contributes to later, declarative learning. Either of these modeling approaches could be used to naturally extend the results here to more cognitive tasks using an approach where initial performance is guided by explicit, top-down processes followed by gains from repetition based entirely on bottom-up, implicit learning.

The results here are consistent with a multiple memory systems theory that supports the scaffolding model of skill learning (e.g., Petersen et al., 1998). In this model, explicit memory initially guides performance during the learning of physical and cognitive skills, but as practice accrues, implicit learning that operates separately and in parallel eventually comes to take over support for rapid, expert performance. In the SISL task used here, the perceptual cues replace the initial explicit scaffolding. In skill learning outside the laboratory, this is usually provided by instruction, but here the perceptual cues allow for performance largely dependent on implicit learning. Under these conditions, even very strong and accurate extra explicit sequence knowledge provided no benefit to enhancing motor skill performance during practice, consistent with our hypothesis that these types of memory are separate and distinct. In contrast, memory systems theories that rely on a single system require an alternate model of skill learning whereby practice leads to the transformation of explicit knowledge into a more efficient form. This approach predicts that additional explicit knowledge would improve performance. The lack of a performance benefit due to explicit sequence knowledge found here argues against this single-system transformation model and instead demonstrates that implicit and explicit memory depend on separate mental representations that affect behavior independently. The inability to utilize the extra explicit knowledge available implies that these independent knowledge representations interact in limited ways, suggesting that although both explicit and implicit knowledge contribute materially to the normal development of expertise, these separate and encapsulated memory representations serve unique and distinct roles in skill acquisition.

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