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Investigating Individual Differences in Implicit Learning

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Kelsey R. Thompson

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Abstract

Memory systems research has established the importance of two distinct types of memory systems in the brain: explicit and implicit. While a robust literature exists on individual differences in the explicit domain (Chapter 3), research on individual differences in implicit learning remains relatively limited. The key question guiding the investigation into individual differences described in this dissertation lies in the arguably natural assumption that certain individuals are more equipped to learn particular skills, such as in sports or music, that are supported by implicit learning mechanisms. Historically, researchers have assumed that individual differences in implicit learning are relatively small or nonexistent due its reliance on evolutionarily older neural mechanisms and its incidental or "automatic" nature. Such an automatic process should not be able to translate into individual advantages or weaknesses in implicit learning. However, the body of research investigating "automaticity" in implicit learning has proved inconclusive in many ways.

Furthermore, researchers who study the types of real-world skill learning that implicit learning is thought to support have argued in favor of individual differences. In particular, consideration of the nature of skill expertise has led some to argue that innate talent does play an important role in skill learning. This suggests that implicit learning, as a key component of skill learning, may vary across individuals in a similar way to constructs with a much deeper history of individual differences research, such as fluid intelligence or working memory capacity. In other words, particular individuals may simply be more gifted when it comes to skill learning, a notion that likely seems logical or even obvious to most.

In my own research using an implicit sequence learning task, I have found that altering participants' mental state (e.g., depleting mental resources, inducing a particular motivational state) can impact the expression of implicit knowledge, providing a firmer argument against the notion of "automaticity" in implicit learning (Chapter 2). In addition, other researchers have begun to investigate the relationship between individual differences in working memory capacity and individual differences in implicit learning (Chapter 3). Together, these studies led me to ask the question: is implicit learning ability a reliable trait measure that differs across individuals? Surprisingly, the results from the four experiments at the core of this dissertation (Chapter 4) suggest that the answer is a resounding no. Evidence from both correlational and factor analyses indicated that sequence-specific learning ability is not a stable individual trait. This finding adds significantly to the discussion of the nature of skilled expertise by implying that the basic implicit learning mechanism underlying skill learning is a universally shared process—all individuals have an equal capacity to learn.

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Chapter 1: Implicit Learning—An Automatic Process?

Memory systems research has established the importance of two distinct types of memory systems in the brain: explicit and implicit. The explicit memory system holds conscious memories for fact and events, and upon retrieval these memories are readily available for conscious control and verbal report. Therefore, the explicit system contains much of what are conventionally thought of as “memories”. Seminal research by Scoville and Milner (1957) on the patient H.M. provided the first evidence that explicit memories rely on the hippocampus and related structures contained within the medial temporal lobe (MTL). In particular, storage of explicit memories is dependent on an intact MTL, with long-term memory retrieval gradually becoming MTL independent through consolidation (Reber, 2008).

In contrast to explicit memory, implicit memory is thought to operate largely outside of conscious awareness. These types of memories are thought to reflect changes in plasticity that occur throughout the cortex independent of the explicit, medial temporal lobe system. Through experience, patterns are extracted from the environment and predictable structures that emerge can be used to guide future behavior. For example, some aspects of language learning (e.g., early learning of word segmentation and grammatical structure) are thought to occur in the automatic fashion that is considered a hallmark of implicit learning (Saffran, Aslin, & Newport, 1996). Artificial grammar learning tasks (e.g., Reber, 1967) have been commonly used to investigate implicit learning of language. A wide range of other phenomena have also been classified as types of implicit learning, including priming, habit learning, sequence learning, and some forms of category learning (Reber, 2008; Reber, 2013). Additionally, this type of learning is thought to underlie a wide array of skills, such as learning to ride a bike or play a sport or musical instrument. Thus, skill learning research is related to implicit learning research in that it focuses on the study of the types of complex, real-world skills that are thought to be supported by implicit learning mechanisms.

A further contrast between implicit and explicit memory concerns the manner in which learning is thought to occur. Explicit learning occurs intentionally, such as when participants attempt to discover a task-based rule through hypothesis testing. Individual events are rapidly learned and stored in the MTL memory system, which is highly specialized for pattern separation such that many similar events can be stored and retrieved separately with relatively low interference (McClelland, McNaughton, & O’Reilly, 1995). Implicit learning, on the other hand, is assumed to be incidental and not based on a conscious intention to learn. Learning in this system is slower, with information accumulated in an incremental fashion across a number of repetitions. This more gradual learning is what allows for the extraction of underlying statistical co-occurences that can then lead to greater processing fluidity and accuracy.

For example, priming can be elicited in a word stem completion task where participants read a list of words and are then asked to complete a list of partial word stems with the first word that comes to mind. Participants are more likely to complete the word stems with words from the list they read earlier, even if they were not told to remember these words and even if they are given explicit instructions to avoid completing the word stems with words from the list (Reber, 2008; Schacter, 1987). The studied words appear to unconsciously “intrude” to influence participants’ word stem completions, even if the participants believe they are avoiding using the words they read earlier.

However, this type of performance test is by nature an indirect measure of the learning process (in this case, greater activation of the words read earlier is thought to produce the priming effect by making these words more likely to come to mind when reading the word stems). Indeed, it is difficult if not impossible to directly measure implicit learning since the learning occurs incidentally and outside of awareness. Another example of an indirect assessment comes from research on implicit motor sequence learning. Participants make motor responses to a series of on-screen cues in which a repeating sequence has been embedded. Though participants are not made aware of the presence of the repeating sequence, they tend to show improved performance over time for the repeating sequence compared to novel or random sequences (Nissen & Bullemer, 1987; Sanchez, Gobel, & Reber, 2010). Thus, participants appear to extract and learn the embedded pattern even though they are not aware of its existence.

Historically, the incidental nature of implicit learning has led researchers to assume that individual differences in implicit learning are relatively small or nonexistent. Many have referred to implicit learning as an "automatic" process that occurs regardless of constraints imposed on processes that can impact explicit learning, such as attention or working memory. Additionally, many have cited the reliance of implicit learning on evolutionarily older neural mechanisms as evidence that this type of learning should not differ among individuals in the way that explicit learning does (Kaufman et al., 2010; Reber, 1989; Reber & Allen, 2000). However, imaging studies have shown that implicit learning processes involve not only older structures such as the basal ganglia, but areas of the more newly formed neocortex as well (Gobel, Parrish, & Reber, 2011). Furthermore, research on implicit learning under dual task conditions have challenged strict interpretations of automaticity as it relates to implicit learning.

The notion that implicit learning occurs “incidentally” and outside of awareness led many to assume that attention was not required for this type of learning. Several researchers have explored this idea in implicit sequence learning by looking at learning under dual-task conditions. The added secondary task (typically tone counting) is presented to participants as the primary task. This prompts participants to divert most their attention away from the sequence learning task, allowing researchers to measure subsequent effects on sequence learning through indirect tests of performance (typically measured as the difference in reaction times to the repeating sequence compared to a random sequence introduced towards the end of training).

Schumacher and Schwarb (2009) provide a comprehensive review of studies that investigated dual-task effects on implicit sequence learning in the Serial Reaction Time (SRT) sequence learning task developed by Nissen and Bullemer (1987). The results of many of these studies are conflicting, with some finding interference from a secondary task and others observing intact learning. Schumacher and Schwarb (2009) discuss two potential reasons for this discrepancy. First, the timing of the secondary task in relation to the sequence learning task appears to affect whether impaired learning is observed. Schumacher and Schwarb found that sequence learning is impaired when the sequence learning and secondary tasks occurred simultaneously, but not sequentially. They argued that this was due to parallel processing constraints rather than a response selection bottleneck, as previous researchers had speculated. However, this may be specific to sequence learning dual-task paradigms, as the responses typically required (motor in the SRT task and verbal for the tone counting task) differ in modality and thus one might not expect response selection interference to explain the impairments observed from the addition of the secondary task.

Second, it is difficult to tease apart whether the secondary task affects the learning or expression of sequence knowledge, and this may have contributed to the varied findings in the literature. Curran and Keele (1993) suggested that a secondary task impairs learning of ambiguous sequences (where each item in the sequence can be followed by two or more other items) but not unique (each item is always followed by the same item) or hybrid (containing at least one unique transition) sequences. This led the authors to conclude that learning of ambiguous sequences, which are commonly used in implicit sequence learning paradigms, requires attention. However, others (e.g., Frensch, Lin, & Buchner, 1998; Frensch & Miner, 1994) proposed that as an automatic process, implicit sequence learning should not depend on attentional resources. They explain dual-task interference effects in terms of knowledge expression rather than learning. This theory, known as the *automatic learning hypothesis* or *suppression hypothesis*, suggests that sequence knowledge is obscured, but that learning is not necessarily impaired, by the addition of a secondary task. In support of this, Frensch et al. (1998) found that when participants learned the sequence under dual-task conditions but were given a single-task test, there was still evidence of successful learning.

There does not yet seem to be a consensus on the above question concerning whether a secondary task interferes with learning or expression. Even within research groups, such as Frensch and colleagues, seemingly contradictory claims have been made across papers. Furthermore, the idea of parallel explicit and implicit knowledge development in healthy subjects again becomes relevant here. As stated above, implicit learning is described in terms of a lack of medial temporal lobe (e.g., explicit memory system) involvement. However, this can prove difficult to tease apart with healthy subjects. Additionally, the SRT task is somewhat less effective as a “process-pure” measure of implicit learning and often leads to concurrent explicit knowledge development in participants. The combined issues of learning versus expression and parallel explicit/implicit knowledge development may be some of the key reasons researchers have struggled to develop an adequate definition of automaticity with regards to implicit sequence learning.

Though this represents an important and ongoing problem in the implicit learning literature, I do not plan to address automaticity directly in the scope of my proposed research. Rather, I discuss these points to illustrate how central assumptions about implicit learning—namely, that it is incidental and automatic—are in fact complex concepts that have proved difficult to address experimentally. The argument that implicit learning ability has relatively low between-subject variability due to its automatic nature may therefore not be as solid as it first appears.

Furthermore, skill learning research often assumes the opposite—individual differences in innate talent do influence learning. Ericsson’s popularized “10,000 hours” theory (Ericsson, Krampe, & Tesch-Römer, 1993; Ericsson, Prietula, & Cokely, 2007) originally challenged the idea of innate talent, suggesting that expertise in a particular skill was the result of years of intense, deliberate practice, with 10,000 hours as the estimated amount of practice required for attaining expertise in a given skill. Following this line of argument, individual differences should not exist in skill learning contexts—practice, and not innate learning ability, is the sole requirement for attaining expertise. In other words, the notion that an individual may be particularly better or worse at skill learning would be unfounded. This aligns with the assumption that implicit learning, a key component process of skill learning, does not function as a stable individual trait in the same manner as other cognitive abilities such as working memory or fluid intelligence (both widely studied in the individual differences literature).

However, Fernand Gobet has pushed back against the theory of deliberate practice by arguing that it is “necessary but not sufficient” in achieving expertise (Campitelli & Gobet, 2011; see also Hambrick et al., 2014). In particular, Gobet’s research into expert chess players revealed that many individuals who dedicated over 20,000 hours to chess, twice the amount that Ericsson suggested was sufficient for expertise, still failed to achieve chess master level status (recognized as the highest level of skill). In addition, Gobet noted high variability in the number of practice hours (a range of approximately 3,000 to 23,000 hours) among those who had achieved “master” status, suggesting that not all individuals benefited from deliberate practice in similar ways. Gobet therefore concluded that innate talent or ability does play a key role in expertise; certain individuals have a greater capacity for skill learning. If implicit learning ability is a key component of skill learning ability, implicit learning should thus also vary across individuals in a similar way to other cognitive skills like fluid intelligence or working memory.

Additionally, examples of individual differences even among novices are abundant in skill learning literature. Ackerman and Cianciolo (2000) found that psychomotor and processing speed abilities predicted individual differences in learning and performance on a simulated flight landing task. Groups that have use simpler sensorimotor adaptation tasks such as grip force or motor trajectory tasks have found evidence of individual differences (Golenia, Schoemaker, Mouton, & Bongers, 2014) and that trial-by-trial variability in movement accuracy may be predictive of individual learning rates (Wu, Miyamoto, Castro, Ölvecky, & Smith, 2014).

Finally, Engel and colleagues (2013) found that time to learn novel piano melodies consistently varied across their non-musician participants from one training session to the next.

Despite the evidence from the skill learning literature, individual differences in more basic experimental implicit learning tasks meant to capture the type of learning underlying these skills have remained relatively unexplored. As discussed above, this is in large part due to the reigning assumption among researchers who employ these tasks that such individual differences don't exist. While individual differences in explicit learning ability have been studied by many researchers (as discussed further in Chapter 3), the opposite—namely, that there are little or no individual differences—seems to be merely assumed to be true of implicit learning due to the further assumption that it is an automatic process that should be immune to such differences. In the next two chapters, I present evidence challenging the idea that implicit learning is fully automatic by considering factors that can affect learning and performance in implicit sequence learning (Chapter 2). The two sets of experiments on state effects described in the next chapter have particular implications for implicit knowledge expression and maximizing expertise. I then go on to review prior individual differences research (Chapter 3) as I consider whether implicit learning can behave more like an individually distinct trait.

Chapter 2: Factors Affecting Implicit Learning and Performance

Experiment 2.1: Fragment-Based Learning of Repeating Sequences

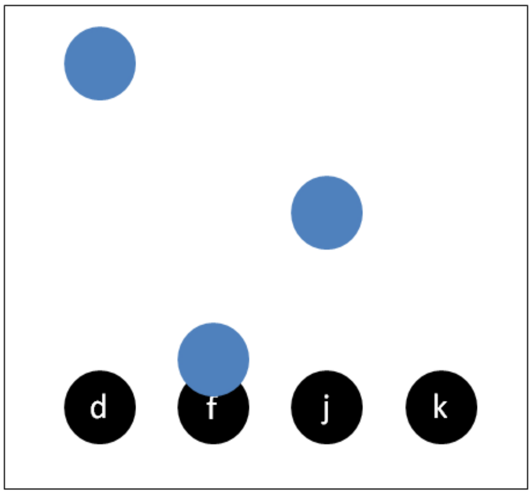

Figure 2.1. The SISL task. Blue circular cues move down the screen towards black target circles, each corresponding to a key on the keyboard—D, F, J, or K.

In my prior and current work, I have utilized the Serial Interception Sequence Learning (SISL) task (Sanchez et al., 2010) to measure implicit sequence learning. During the SISL task, participants attempt to intercept cues scrolling down a monitor by pressing a corresponding key (D, F, J, K) when the cues overlap their target rings (Figure 2.1). Responses are scored as correct if the corresponding key is pressed when the cue overlaps the target ring within one cue length (one half a cue length on either side of the optimal target response). Typically, participants are trained on a particular 12-item repeating sequence that comprises 80% of the 3240 training trials, while novel foil sequences are shown on the remaining 20% of trials. Following training, implicit sequence knowledge is tested using 3 60-trial sub-blocks of five trained sequence repetitions randomized among six sub-blocks of five repetitions of two novel foil sequences (3 sub-blocks for each foil). Participants are not made aware of the presence of the repeating sequence during training or test, nor is there any indication of when the training blocks end and the test block begins. Sequence learning is measured as the difference in accuracy (percent correct) at test for the repeating sequence compared to the foil sequences.

In some of my early work with the SISL task, I became interested in what specifically is learned about the repeating sequence to support later performance on the sequence knowledge test. As discussed in Chapter 1, the incidental quality of implicit learning and the indirect nature of tests used to measure learning make it difficult to study the learning process itself. As a way to address this issue, I developed two types of training in the SISL task that would allow me to manipulate the sequence information available to participants to determine what type of information was necessary for participants to learn the sequence (Thompson, Blake, & Reber, in preparation).

In the SISL task, the sequences used are second-order conditional in nature (Reed & Johnson, 1994), meaning that each item in the sequence occurs an equal number of times, making reliance on raw frequency or bigram information insufficient for predicting the next item in the sequence. However, each possible pair of items occurs exactly once and learning second-order information (trigrams) allows perfect prediction of the sequence. I contrasted normal 12-item sequence training with training based on sequence fragments that were 6 items long. Critically, the basic trigram information necessary to learn the sequence was matched between the two types of training. On a sequence knowledge test, the performance of all participants on the 12-item repeating sequence was contrasted with two novel 12-item foil sequences—the typical test block structure used in the SISL task. Participants displayed equivalent rates of learning (measured by the Sequence-Specific Performance Advantage, or repeating sequence performance minus average foil performance) regardless of training type, indicating that trigrams are a key piece of information participants extract to learn the sequence. Furthermore, presenting the sequence in fragments did not appear to disrupt participants' ability to extract the statistical

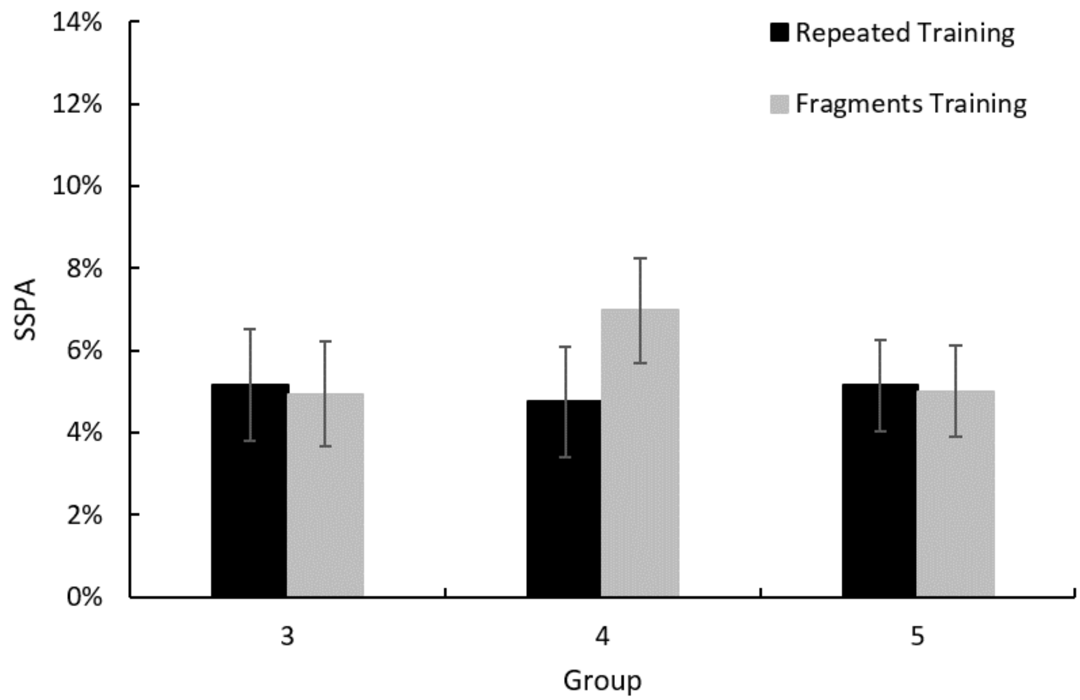

Figure 2.2. Performance during the sequence test for the repeating and fragments training groups. Regardless of training condition (Repeated/Fragments) and group (3=trigram matched, 4=4-gram matched, 5=5-gram matched), test performance indicated equivalent knowledge of the repeating sequence. SSPA = Sequence-Specific Performance Advantage. Error bars reflect SEM.

structure of the entire sequence (Figure 2.2, first pair of bars).

Two additional experimental conditions, which matched the repeating sequence and fragments conditions based on higher-order statistical information (4-grams or 5-grams), suggested that participants may also be learning more than simple trigram information (see remainder of Figure 2.2). This was confirmed through computational simulation of the data using three different learning models. Each model predicted percent correct on a trial-by-trial basis. This prediction combined the outcome from two different functions—a learning function

(Eq. 1) and a general performance function (Eq. 2). Learning in a given model was based on the number of repetitions of the particular N-gram (trigram, 4-gram, 5-gram) tracked by that model:

$$f(L) = M_3[b, cue_t]^{\lambda} \quad (1)$$

The above (Eq. 1) is an example of the learning function in the trigram (M3) model, where M_3 represents the trigram matrix. This matrix was indexed using the current bigram (b, which represents the previous two cues) and current cue (cue_t), and the resulting value was raised to the learning rate (λ) power. Therefore, the model would predict higher performance for trigrams that have been encountered more often and follow a power law function of learning based on trigram repetitions. The learning functions for the 4-gram (M4) and 5-gram (M5) models were identical in format, but the matrix instead stored the appropriate N-gram and was indexed by the current trigram or 4-gram, respectively, and current cue.

All possible N-grams were tracked and stored in the given N-gram matrix of a model. The trial order information for each participant was fed into the model, and on each trial the model would simultaneously update its count of the current N-gram and predict performance on the current trial based on the current number of N-gram repetitions. The outcome of the learning function was then modulated by the performance function (Eq. 2), which represented general task characteristics necessary to produce model predictions that matched human behavior.

$$f(P) = C - (S \times \sigma) \quad (2)$$

Here, C was a constant that represented general task performance, S represented the current speed (taken from participant data), and σ was a speed adjustment parameter that controlled how speed changes affected overall performance. Thus, the model's predicted performance for each trial was given by Eq. 3:

$$PC_t = f(L) + f(P) \tag{3}$$

Predicted performance could then be summarized across blocks for both the repeating sequence (or fragments) and foil trials, in the same manner as the behavioral data. This was repeated for all participants' trial orders, and the predictions for the group performance taken from the model were compared to the actual group data to assess the goodness of fit for each model. Using a downhill simplex search method, the parameter spaces for the three free parameters in each model (λ, C, and σ) were explored to find the set of parameter values that yielded the best-fitting version of each model (M3, M4, M5). Comparison of these models showed that a 5-gram learning model provided the best overall fit of all six datasets (trigram, 4-gram, and 5-gram repeated and fragments groups; Table 2.1).

Table 2.1

Comparison of model fits across the three learning models.

		Parameter Values		
Model	Fit (MSE)	λ	σ	C
M3	34.53	0.511	-0.510	0.301
M4	28.00	0.490	-0.413	0.339
M5	25.87	0.479	-0.371	0.443

Note: MSE = mean squared error

The modeling work provided a way to investigate the learning process and indicated that participants were utilizing higher-order information beyond the simple trigram level necessary for learning the second-order conditional sequences, which fits with previous work using more complex SISL sequences (e.g., Gobel et al., 2013). Of course, even trigram learning can be computationally complex if one considers that real-world skills involve more than the simple four keystrokes used in the SISL task. Furthermore, the number of items that must be tracked increases exponentially with each additional step size (4-grams, 5-grams, etc.). Thus, although the mechanism supporting implicit learning does not require learning the full sequence in order and can support fragment-based learning, it also requires tracking of multiple statistical relationships between cues.

State Effects in the SISL Task

Following this investigation of how participants learn the repeating sequences in the SISL task, two sets of experiments on state effects further prompted my interest in investigating individual differences in implicit learning. If one accepts that implicit learning is truly incidental and/or automatic, one would expect this type of learning to be unaffected by current mental state. However, some researchers have presented evidence for state effects by showing that mood can affect learning on the SRT task. Shang, Fu, Dienes, Shao, and Fu (2013) found that inducing a negative mood reduced learning on the SRT task. Bertels, Demoulin, Franco, and Destrebecqz (2013) also found an effect of mood on visual statistical learning of shape triplets. Participants under a sad mood induction were more likely to develop explicit knowledge of the statistical relationship among the shapes. Using the SISL task, we have also found evidence for two types of state effects that can impact the expression of implicit knowledge: ego depletion and motivation.

Experiments 2.2 and 2.3: Ego Depletion

Thompson, Sanchez, Wesley, and Reber (2014) investigated the effects of ego depletion on implicit learning using the SISL task. The core motivation for this research was to look at cognitive resource constraint effects on implicit learning (similar to the dual-task work previously described), and the phenomenon of ego depletion was chosen primarily for its implications in dopaminergic function. Muraven, Tice, and Baumeister (1998) and Baumeister, Vohs, and Tice (2007) described the phenomenon of ego depletion as a weakening of central executive functioning following the depletion of cognitive control resources. Because cognitive control has been associated with variations in dopaminergic function (Braver & Barch, 2002), it was proposed that ego depletion could produce a transitory learning effect similar to deficits in sequence learning observed in Parkinson's patients (Gobel et al., 2013; Siegert, Taylor, Weatherall, & Abernethy, 2006). An additional benefit of using this type of resource constraint induction method was that it allowed us to get away from some of the issues associated with the dual-task paradigms used previously with the SRT task (e.g., timing effects).

Experiment 2.2 methods. Thirty undergraduates at Northwestern University were compensated $10/hour for participation. Participants were randomly assigned to a Depletion (*N*=15) or Non-Depletion (*N*=15) condition. We induced ego depletion through a standard manipulation (Baumeister, Bratslavsky, Muraven, & Tice, 1998) that initially required participants to cross out every letter "e" in a page of text from a statistics textbook for five minutes. For the next five minutes, those in the Depletion condition completed a more complex regulatory control fatiguing task of crossing off every letter "e" unless it was next to or one letter removed from a vowel, while Non-Depletion participants continued to follow the easier rule of crossing out every "e".

Following the depletion/non-depletion task, participants completed six 480-trial training blocks of SISL followed by a 540-trial test block to assess sequence-specific learning. During training, the cues followed a repeating sequence on 80% of trials and novel foil sequences on

20% of trials. At test, 3 60-trial sub-blocks of five trained sequence repetitions were randomized among six sub-blocks of five repetitions of two novel foil sequences (3 sub-blocks for each foil). Participants were not made aware of the presence of the repeating sequence during training or test, nor was there any indication of when the training blocks ended and the text block began. Sequence learning was measured as the difference in accuracy (percent correct) at test for the repeating sequence compared to the foil sequences.

Cues initially scrolled down the screen at a velocity of 12.6 degrees/second, reaching the target zone .85 s after appearing on the screen. Speed was adapted based on performance, with cue velocity increasing when performance rose above 65% and dropping when performance fell below 25%. Thus, the speed adjustments prevented participants from reaching ceiling performance levels, which would prevent observation of sequence learning as this measure relies on a difference score based on the performance difference between the repeating sequence and foil sequences.

Equally importantly, the speed adjustments served as means of maintaining a consistently challenging task for participants. This component of the task is likely what accounts for the lower levels of explicit knowledge development observed among participants compared to the more traditional sequence learning task, the SRT. Indeed, even instructing participants to memorize the embedded repeating sequence does not lead to better performance compared to participants who are kept naïve to the presence of a repeating sequence (Sanchez & Reber, 2013). Thus, the SISL task is designed such that even perfect explicit knowledge of the sequence does not produce faster learning, suggesting that explicit recognition of the sequence does not influence performance on the task. This eliminates any need for concern that cognitively healthy participants likely acquire some explicit knowledge of the repeating sequence, as this type of knowledge does not appear to contribute to performance on the SISL task.

Experiment 2.2 results. Though both groups showed evidence of learning the sequence, participants in the Depletion condition displayed less sequence knowledge at test than those in the Non-Depletion condition (Figure 2.3). However, as in the initial dual-task experiments discussed in Chapter 1, we were unable to distinguish whether ego depletion negatively affected sequence learning directly or whether it impacted participants' ability to express their sequence knowledge. Therefore, a second experiment employed a pre-training/pre-test depletion design to address this issue.

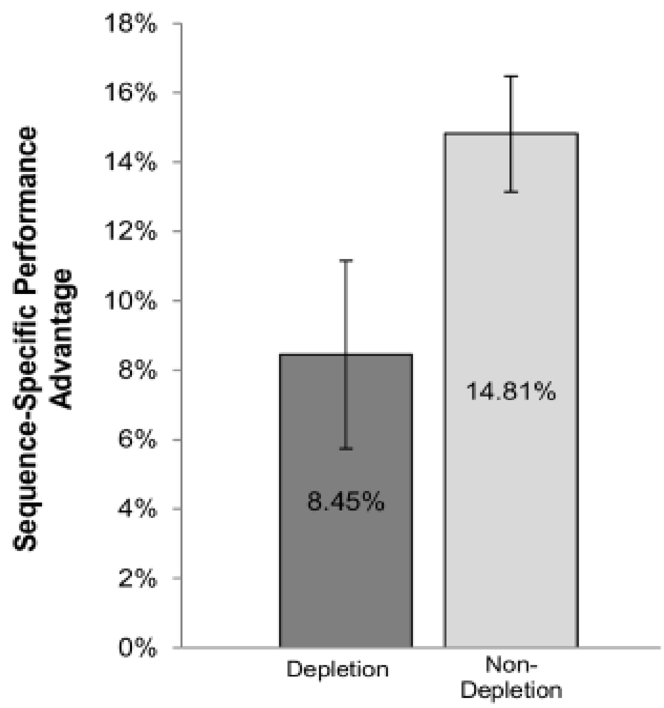

Figure 2.3. SISL test performance in Experiment 2.2. The sequence-specific performance advantage measures the improvement in SISL task execution when cues are following the repeating sequence. The Depletion group showed a significantly smaller advantage for the trained sequence at test. Error bars reflect SEM.

Experiment 2.3 methods. One hundred twenty-four participants at Northwestern University received course credit for participation. Two groups of Depletion participants received the depleting form of the task (crossing out "e's" based on the complex set of rules described above) for five minutes either before training on SISL (*N*=42) or after training but before the sequence test (*N*=41), and the non-depleting form of the task (cross out every "e") at the other time point. An additional group (*N*=41) served as a non-depletion control, completing the easier form of the task at both time points.

Experiment 2.3 results. Though not quite reliable, the Non-Depletion group again performed better on the test compared to both of the Depletion conditions. The nonsignificant results may have been due to the shortened version of the depletion task used in order to fit the two depletion time points, which may have been less effective than the design used in Experiment 2.2. In addition, participants provided self-report ratings of mental fatigue following each time point and several individuals reported depletion levels inconsistent with the experimental manipulation (e.g., reporting feeling depleted after the non-depleting task or vice versa). When participants were sorted based on a median split of their self-reported depletion at each time point, there was a main effect of pre-training depletion and a marginal effect of pre-test depletion. In particular, participants who reported feeling depleted at both time points showed the lowest performance benefit for the trained sequence, while those who were not depleted at either time point showed learning similar to the Non-Depletion participants in the Experiment 2.2. Participants who were depleted at one time point but not the other fell somewhere between the other two groups (Figure 2.4).

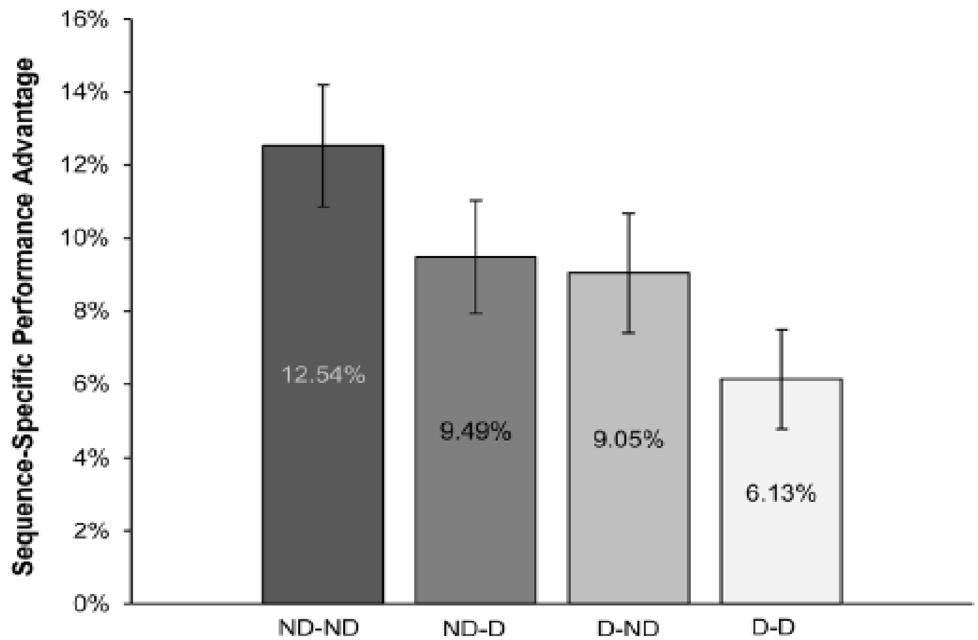

Figure 2.4. SISL test performance for post hoc conditions in Experiment 2.3. Participants in a depleted state prior to training and test (D-D) exhibited a significantly smaller sequence-specific performance advantage at test compare to those who were not depleted at either time point (ND-ND). Those who self-reported depletion at either time point (ND-D and D-ND) also displayed reduced performance benefits compared to ND-ND participants. Error bars reflect SEM.

Thus, the effects of ego depletion appeared to be additive—depletion either pre-training or pre-test produced lower test performance than no depletion, and depletion at both time points produced the lowest performance. There was no clear distinction among pre-training versus pre-test depletion, leading us to conclude that depletion may affect both sequence learning and the expression of sequence knowledge. Importantly, we also failed to find an effect of ego depletion on participants' explicit knowledge of the sequence pattern, suggesting that ego depletion affects implicit knowledge expression and/or learning directly. As mentioned above, the potential contamination of explicit knowledge represents an additional issue faced by dual-task experiments, as the SRT task tends to produce higher levels of explicit knowledge in participants. However, participants' explicit knowledge has been shown to have little or no effect on SISL task performance (Sanchez & Reber, 2013; also see Chapter 4 for a more in-depth discussion), leaving us more confident that the depletion effects we observed were specific to the implicit processes involved in the task. These findings have implications for real-world skill training, suggesting that maximizing the gains from repeated practice of a skill requires limiting the constraints placed on central executive processes, which could impact implicit learning processes by disrupting dopaminergic functioning.

Experiments 2.4 and 2.5: Motivation

In addition to mood and depletion effects, others have shown that current motivational states can also impact implicit learning. In particular, Grimm, Markman, Maddox, and Baldwin (2008) showed that inducing a regulatory "mismatch" between motivational focus (approach/avoid) and task feedback structure (gain/loss) led to improved learning on an information integration (implicitly learned) category learning task. In other words, participants who were primed to be in an approach motivational state but were given feedback focused on losses (and vice versa) showed improved learning of an implicit category. Those who experienced a regulatory "match" between feedback and motivational focus (approach motivation + gain-focused feedback or avoid motivation + loss-focused feedback), on the other hand, showed better learning of a rule-based category which can be learned explicitly.

The authors explained this effect by proposing that regulatory fit leads to greater flexibility in hypothesis testing, which would benefit a rule-based task by leading participants to find the rule more quickly. However, an information integration category learning task requires participants to learn categories that cannot be distinguished by an easily verbalizable rule, and explicitly applying different rules can actually hurt performance. Therefore, participants who experience a regulatory mismatch may be better suited to learn these more complex categories due to a reduction in elaborative processing. We aimed to expand this theory to implicit sequence learning by conducting a similar experiment with the SISL task (Chon, Thompson, & Reber, 2017).

Experiment 2.4. In a first experiment, one hundred and twenty-five participants were compensated $10/hour for participation. Participants were told that they could either win two tickets for a $50 raffle by improving their performance on the task (approach motivation induction) or were provided with an initial two tickets and told they could lose them through poor performance (avoid motivation induction). In addition, the motivation conditions were fully crossed with two feedback conditions (with 20 participants per each of the four conditions) for the SISL task—positive feedback on correct responses (by target circles flashing green and positive verbal phrases appearing on the screen) or negative feedback (red target flashes and negative verbal phrases) for incorrect responses. The regulatory "match" participants were those with avoid motivation and negative feedback or approach motivation and positive feedback. Participants with contradictory motivation/feedback pairings were considered to be experiencing a regulatory "mismatch", similar to Grimm et al. (2008). Participants were also provided with feedback on their progress towards winning or losing tickets (depending on condition) throughout the task (3240 trials of training and 540 trials of test) to ensure that the motivation manipulation remained strong (Figure 2.5). Cue speed was adjusted adaptively to maintain an overall task performance rate of 75% correct. Initially cues reached the target zone 1.5s after appearing on the screen. If performance exceeded 80% correct over 20 trials, the speed was increased by 5%. If performance fell under 70%, speed was decreased 5%. The speed adjustments were removed for the test block; test speed was set to the speed the participant had reached at the end of training.

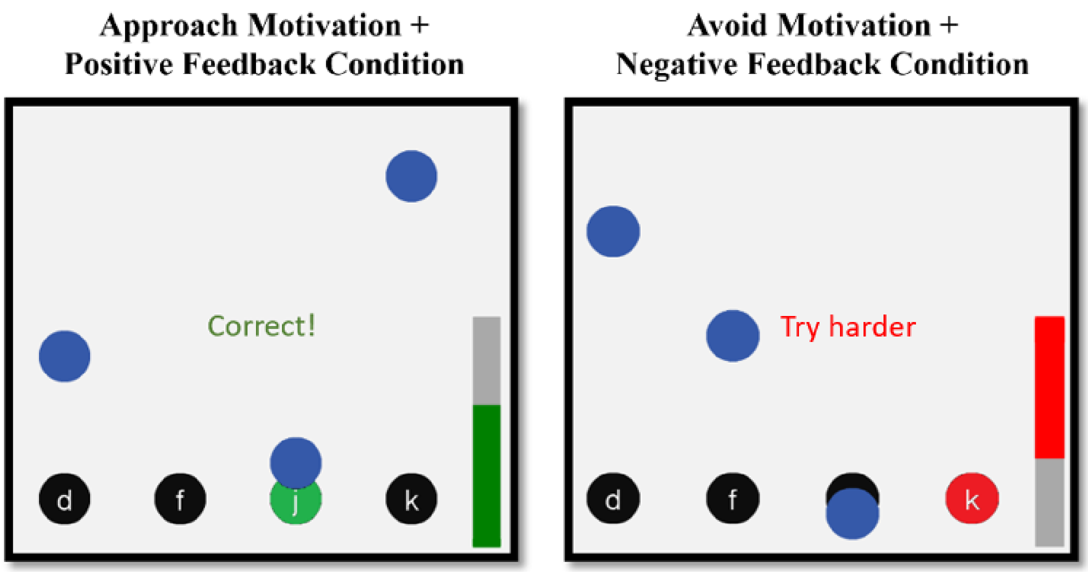

Figure 2.5. SISL task for Experiments 2.4 & 2.5. In Experiment 2.4, the Positive Feedback condition flashed positive verbal phrases (e.g., “Correct!” “Great!” or “Excellent!”) across the screen for every third correct response while the Negative Feedback condition flashed negative verbal phrases (e.g., “Missed,” “Try harder,” or “Wrong”) for every incorrect response. In the Approach Motivation condition, the progress bar filled up to the top with green color based on the correct response rate, while in the Avoid Motivation condition, the progress bar filled down to the bottom with red color based on the incorrect response rate. Movement of the progress bar was controlled based on the 75% correct response rate (controlled by adaptive speed adjustments) so that it reached the top or bottom of the bar (for the Approach or Avoid conditions, respectively) by the end of the experimental session. The figures shown above reflect the two “match” conditions. For Experiment 2.5, the verbal phrases feedback was removed.

Though we did not find a similar motivation-feedback interaction as Grimm and colleagues, we did observe that participants under an avoid motivation induction (regardless of feedback condition) showed significantly greater sequence-specific knowledge at test (Figure 2.6A). Again, we wanted to further investigate whether this effect was specific to learning or expression.

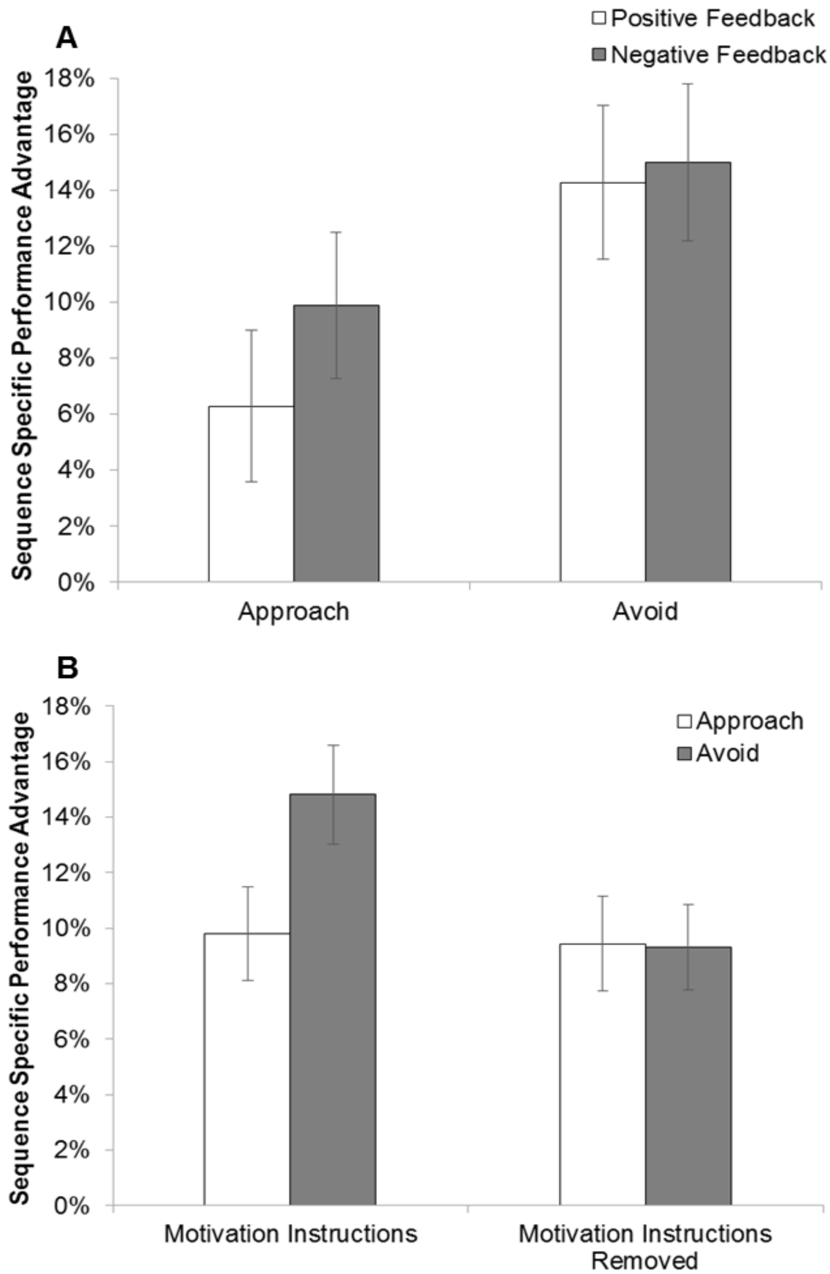

Figure 2.6. SISL test performance for Experiments 2.4 & 2.5. **A)** In Experiment 2.4, those in the Avoid motivation conditions exhibited a significantly greater performance advantage for the trained sequence than those in the Approach conditions. There was no main effect of feedback nor an interaction between feedback and motivation. **B)** In Experiment 2.5, avoid motivation participants again showed a greater sequence-specific advantage at test (left bars). However, when the motivation manipulation was removed (right bars), no reliable differences between the motivation conditions persisted. Error bars reflect SEM.

Experiment 2.5. In a second experiment, the feedback conditions were removed (since no main effect of feedback was found in Experiment 2.4, all participants received both positive and negative feedback in the form of the target circles flashing green or red) and participants were randomly assigned to either an Approach (*N*=40) or Avoid (*N*=41) condition. Participants completed 3240 trials of training and a 540-trial test block of the SISL task as in Experiment 2.4. Participants were debriefed about the motivation manipulation following the test block. They were then invited to complete a second test block, which allowed us to observe performance with the motivation effects removed. We replicated the effect from the first experiment, with participants who were directed to adopt an avoidance motivation style showing significantly greater sequence knowledge in the first test block. However, this group's performance dropped to match those in the approach motivation condition in the second test block, once the motivation manipulation had been removed Figure 2.6B).

Thus, avoid motivation appeared to produce transiently improved expression of sequence knowledge after SISL task training but did not necessarily lead to faster learning of the sequence. Nevertheless, the idea that motivation could not only affect general performance on the task but actually led participants to better express their knowledge of the trained sequence was surprising. Similar to the findings from the ego depletion experiments, these results open the possibility of identifying ideal conditions for fully capitalizing on one's implicitly acquired knowledge in guiding skilled performance in real-world skills such as music and sports. Indeed, coaches and trainers seem to regularly employ avoid motivational techniques (e.g., framing performance goals in terms of avoiding loss, whether of status, a scholarship, teammates' respect, or other valuable concepts) in pushing their trainees to perform better.

The motivation experiments, along with the ego depletion experiments discussed earlier in this chapter, provide evidence that the expression of knowledge acquired implicitly (and perhaps the learning process itself) can be enhanced or impaired by manipulating mental states. This adds to the dual-task literature reviewed in Chapter 1 by further weakening the claim that the expression of knowledge in implicit learning tasks is an automatic process that cannot be disrupted. Because automaticity is one of the main supporting arguments for the idea that implicit learning does not exhibit individual differences, it seems that a reconsideration of this claim is in order. However, the evidence for specific effects on implicit learning (in contrast to implicit performance/expression of knowledge) remains somewhat less robust even following the prior studies discussed thus far, given the inconclusive results from both dual-task experiments with the SRT task and the ego depletion experiments described in the current chapter. The next chapter reviews prior research on individual differences and more directly considers the question of whether implicit learning ability can be defined as a stable trait that varies across individuals.

Chapter 3: A Review of Individual Differences Research in Intelligence and Working Memory

While it appears that implicit learning isn't truly automatic in the sense that it is unaffected by the learner's current mental state, whether there are stable trait differences in implicit learning ability remains an open question. By contrast, explicit cognition is well known to vary among individuals. Two of the most widely studied areas of individual differences are intelligence and working memory. Conway and Kovacs (2013) provide a good review of the history of research into these constructs, emphasizing the parallel search for and subsequent rejection of a unitary source of variance among individuals.

Spearman's (1904) theory of a general factor (*g*) of intelligence has since been challenged primarily on the finding that intelligence tests within a particular domain (e.g., spatial) correlate more strongly with each other than with tests from a different domain (e.g., verbal). Various models that include both a general factor and group factors representing specific domains to explain the variance in individual test scores have been proposed as alternatives to Spearman's original model. The most influential description of the content of the group factors comes from Cattell (1971) and Horn's (1994) proposed models of fluid versus crystallized intelligence. Fluid intelligence describes the ability to solve problems in novel situations (without necessarily drawing on specific previous knowledge) while crystallized intelligence refers to the ability to solve problems using already acquired knowledge or skills. Other intelligence factors such as visuospatial intelligence and processing speed are also commonly included in updated versions of these original models.

Indeed, processing speed has its own fairly robust history in the realm of individual differences research as one of the group factors identified in the more updated models of intelligence. Some researchers have even assumed the strong position of arguing that processing speed is the basis of a general intelligence factor such as *g*. This line of argument proposes that speed of processing imposes limits on the efficiency of operating on particular types of information (e.g., verbal or visual), thus making speed key to the functioning of all cognitive processes underlying the manifestation of intelligence (Mackintosh, 2011). Whether or not this notion is correct, there have been many studies that confirm at least some relationship exists between processing speed and intelligence (see chapter 3 in Mackintosh, 2011 for a review of the history of this research), indicating that this cognitive ability does reliably vary across individuals.

To conclude their summary of intelligence research, Conway and Kovacs summarize the wealth of converging evidence from cognitive psychology, neuropsychology, and neuroscience contradicting the notion of a domain-general intelligence mechanism. It is now generally accepted that no such mechanism exists to fully and adequately explain the positive correlations observed when looking at individuals' scores on a battery of intelligence tests; rather, processes common to all tests merely gives the illusion of a general factor such as *g*.

Conway and Kovacs continue their review with a discussion of the parallels between intelligence and working memory research. The latter has also undertaken a similar debate concerning whether domain-specific or domain-general processes are responsible for determining working memory capacity. Daneman and Carpenter (1980) originally seemed to suggest the former in the paper describing their reading span task, as they specifically related their reading span measure to measures of reading comprehension. The reading span task asks participants to read a series of sentences hold the final word of the sentence in mind. After sets of sentences ranging from two to six, participants are asked to recall the final word from each sentence in the correct order. Working memory capacity is measured as the maximum set size at which participants are able to correctly recall all of the final words.

Following the creation of this first complex working memory span task (considered a more accurate measure of working memory than simple span tasks), others created similar complex span tasks, the most well-known of which is Turner and Engle’s (1989) operation span task. These authors argued instead for a more domain-general explanation of working memory capacity, citing as evidence the fact that their task, which uses mathematical operations rather than reading as the intervening task, correlated just as well with verbal SAT scores as Daneman and Carpenter’s reading span task. Eventually, working memory researchers reached a similar conclusion to those in the field of intelligence research: no single domain-general process can fully account for the correlations observed among various measures of working memory capacity.

A review of these two bodies of research would be remiss if it did not include a discussion of the relationship between intelligence and working memory. Conway and Kovacs thus conclude their review by considering the vast body of research into the link between these two constructs. Indeed, during the search for a general factor of intelligence, many proposed working memory as the likely candidate (see Conway, Kane, & Engle, 2003, for a review of this work). Certainly, working memory capacity has been related to many higher-level cognitive abilities, including reading and language comprehension (e.g., Cantor, Engle, & Hamilton, 1991;

Daneman & Carpenter, 1980; Just & Carpenter, 1992; King & Just, 1991) and inference reasoning (e.g., Barrouillet, 1996). However, more recent research has shown that, while strongly correlated, working memory and general intelligence are not identical. Rather, the central executive component of working memory, which is more directly tapped by complex span tasks, relates most closely to fluid intelligence (e.g., Engle, 2002). Again, Conway and Kovacs present converging evidence from neuroimaging studies (e.g., Kane & Engle, 2002) in support of the theory that the central executive component of working memory and the fluid reasoning component of intelligence are primarily responsible for the observed relationship between working memory and intelligence.

What About Implicit Learning?

It is important to note that what has been most commonly debated in both intelligence and working memory research concerns the source of individual differences in these abilities, rather than the existence of such individual differences themselves. Of course, the strong reliability of measures of intelligence and working memory gives ample support for the stability of such differences. By contrast, however, the leading assumption among implicit learning researchers is that this type of learning shows relatively small individual differences, though there has been a surprising lack of research aimed at directly supporting this theory. The majority of research that has been done investigated the relationship between intelligence and implicit learning, much as research on working memory and intelligence has often focused on the relationship between the two. Though no such relationship has been found (Feldman, Kerr, & Streissguth, 1995; Kaufman et al., 2010; McGeorge, Crawford, & Kelly, 1997; Reber, Walkenfeld, & Hernstadt, 1991), this is perhaps not so surprising considering that the processes tapped by intelligence tests likely share little in common with those involved in implicit learning. (One possible exception is processing speed, which may be a common process shared by both intelligence and implicit learning, as suggested in Kaufman et al., 2010).

However, some have recently begun to consider the relationship between implicit sequence learning and working memory. Indeed, this idea developed out of some of the dual-task research discussed in Chapter 2.

Working Memory and Implicit Sequence Learning

In the debate concerning the exact nature of the attentional requirements for implicit sequence learning, some have argued that a secondary task interferes with learning by disrupting the organization of the sequence and the ability to associate successive items together (e.g., Frensch, Buchner, & Lin, 1994; Jiménez & Méndez, 1999; Jiménez & Vázquez, 2005; Stadler, 1995). For instance, Stadler (1995) pointed out that participants are only required to actively update information about the secondary task on some trials (typically they are instructed to only count high tones in the tone counting task commonly used as the secondary task), thus artificially creating inconsistent timing between trials. Stadler found that similar interference effects to those observed in some of the dual-task research could be created by randomly inserting short and long response stimulus intervals between sequence trials without actually including a secondary task. Therefore, it may be that the inconsistent organization of the two tasks is what detracts from learning the sequencing task in these cases, rather than reduced attentional capacity per se.

Some of the above authors further considered the idea that working memory is essential for forming associations between successive items in a sequence (e.g., Frensch et al., 1994; Jiménez & Méndez, 1999). Successful association between all items in the sequence is important in driving the increased fluidity of responding that is thought to underlie the measured learning effects (i.e., decreased RTs) observed in studies of the SRT task. Because the addition of a secondary task induces an increase in working memory load, these authors suggest that the secondary task not only interrupts the presentation of the sequence but also increases the temporal distance between the sequence stimuli, thus negatively impacting one's ability to associate these stimuli together in working memory.

Frensch and Miner (1994) found support for the first part of this hypothesis, showing that manipulating the temporal distance between subsequent cues can influence the amount of observed learning (though they argued for an expression rather than a direct learning effect). In particular, a longer response stimulus interval (RSI) led to a smaller RT difference between the repeating and random sequence (the typical measure of learning) in their experiments, similar to the finding by Stadler (1995). However, they only found a direct correlation between working memory capacity and learning under intentional instructions, where participants were told to look for the repeating sequence. The same relationship was found for incidental learning only under dual-task conditions. Thus, they speculated that true implicit learning (e.g., learning that occurs incidentally) may rely on working memory only when task demands require some attentional control (e.g., under dual-task conditions).

Further research has also highlighted the complexity of the relationship between sequence learning and working memory. In their review of the literature, Janacsek and Nemeth (2013) discuss three key findings. First, working memory may only be required when sequence learning is intentional (as in Frensch & Miner, 1994). Unsworth & Engle (2005) also found that high working memory capacity individuals only showed differential learning rates from low capacity individuals under intentional learning instructions, while there were no group differences in learning rate for the incidental learning condition.

However, Janacsek and Nemeth (2013) also considered that the type of working memory assessment used could affect the observed relationship between working memory and incidental sequence learning. Nearly all of the studies to date have used traditional simple span measures (e.g., digit span), which tap into the maintenance aspect of working memory, but not necessarily the processing and manipulation of information held in mind. Thus, these tasks fall short of fully and accurately measuring working memory capacity (Jarrold & Towse, 2006). Furthermore, it seems more plausible that the ability to manipulate information present in working memory is key to one's ability to form the associations between cues in a sequence; it is not sufficient to merely maintain the items in memory.

In support of this idea, studies that have used more complex working memory tasks designed to tap manipulation in addition to maintenance have demonstrated a relationship between working memory and incidental (implicit) sequence learning (Bo, Jennett, & Seidler, 2011; Martini, Furtner, & Sachse, 2013). Martini et al. (2013) suggest that it is the relational integration aspect of working memory that is related to implicit sequence learning. This fits with the idea put forth in the dual-task literature that working memory is necessary to form associations between items (i.e., relational associations) in the sequence (Jiménez & Méndez, 1999). Furthermore, imaging studies using disruptive transcranial magnetic stimulation (TMS) over the dorsolateral prefrontal cortex have shown that this can disrupt implicit sequence learning. Because this region is also involved in working memory, the authors of these studies speculate that the spatial (Robertson, Tormos, Maeda, & Pascual-Leone, 2001) or the temporal sequencing aspects (Pascual-Leone, Wassermann, Grafman, & Hallett, 1996) of working memory may specifically support implicit sequence learning.

Finally, Janacsek and Nemeth (2013) discuss a further issue that arises when considering the type of working memory assessment employed—whether working memory is necessary for general task learning or sequence-specific learning. Indeed, Unsworth and Engle (2005) did find a difference between high and low span individuals in terms of overall reaction times (high span participants were faster) under both incidental and intentional learning conditions. Additionally, Bo et al. (2011) found that their measures of working memory capacity correlated with the decrease in reaction times across the experimental session even though they did not correlate with learning. However, the authors caution that this may be due to a limitation in the typical structure of the SRT task itself. Using a random sequence as comparison, rather than a sequence that is structured in the same manner as the repeating sequence but with a different order of cues, may not be an accurate measure of sequence-specific learning (Reed & Johnson, 1994).

The research on the relationship between working memory and implicit learning thus follows along the same lines as the dual-task research on automaticity in implicit learning: neither illuminate a clear conclusion to support the presence or absence of individual differences in implicit learning. Therefore, while both bodies of research address important and interesting questions, they still fall short of answering the more basic question proposed to guide this dissertation—is implicit learning ability a reliable trait measure that differs across individuals? And if so, how does one quantify those differences? The experiments conducted to answer this question and discussed in Chapter 4 aim to make a significant contribution to the implicit learning literature while also expanding on my own prior work on state effects in SISL.

Chapter 4: A Look at Individual Differences in SISL

General Methods

The following section describes the typical SISL task administration, as well as the exclusion criteria used in all experiments described in this chapter. Any specific modifications to the SISL task employed for a given experiment are described in the Methods section of that experiment.

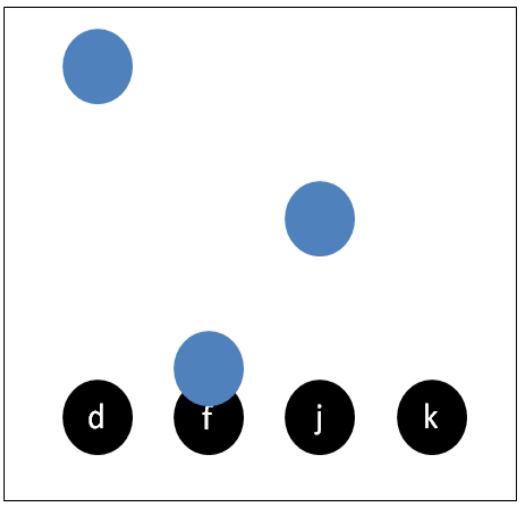

Figure 4.1. The SISL task.

As briefly described in previous chapters, the SISL task consists of blue circular cues that continuously scroll down a computer screen towards one of four target circles, each corresponding to a key on the keyboard (D, F, J, or K; see Figure 4.1 for a reminder of the task layout). Participants are instructed to time their responses to the cues such that they press the appropriate key on the keyboard as each cue crosses its target. The target circle flashes green and the blue cue circle disappears from the screen when a correct response is made. When participants make an incorrect response, the target circle flashes red and the cue remains on the screen until it passes out of the target zone.

The initial speed of the cues is set to 1.5 seconds from onset to target with an inter-stimulus interval (ISI) of 750ms (long) or 350ms (short), with a random pattern of six long and six short ISIs assigned to each sequence (see example below). The task speed is adaptive based on performance, which is assessed every twelve cues. If the participant's accuracy over the last twelve cues is 90% or higher, the speed is increased by multiplying the current time-to-target by a fraction of 20/21 (resulting in an approximately 5% change in speed). If accuracy falls below 75%, speed is decreased by multiplying the current time-to-target by a fraction of 21/20 (with ISI speed changing accordingly as the time-to-target is adjusted). This method of adjusting the speed ensures that the speed increments remain the same as the task speeds up and slows down.

The SISL task utilizes 12-item, second-order conditional (SOC) sequences (e.g., D-F-D-J-F-K-D-K-F-J-K-J). Each sequence is additionally assigned a unique pattern of long and short ISIs (e.g., L-S-L-L-L-S-L-S-L-L-S-S). The SISL task is typically divided into six 540-trial training blocks and one 540-trial test block to assess sequence-specific learning. Each of these blocks is further divided into nine 60-trial sub-blocks. During training, each of these sub-blocks contains 4 repetitions of the 12-item SOC sequence that has been selected as the training sequence and one 12-item SOC foil sequence, which always occurs at a randomly selected position (1-5) within the sub-block. A different SOC sequence is selected as the training sequence for each participant. All of the foil sequences used during the training blocks are unique; that is, they occur only once throughout the 3,240 trials of training. Thus, participants are trained with 80% repeating training sequence and 20% noise (foils).

During the test block, three of the nine sub-blocks each contain five additional repetitions of the trained repeating sequence. Participants are not made aware of the presence of a repeating sequence during training or at test. The remaining test sub-blocks contain five repetitions of one of two foil sequences, neither of which were used as foils during training. Thus, participants see fifteen additional repetitions of the trained sequence and fifteen repetitions each of two novel foil sequences. The order of the repeating sequence and foil sub-blocks are randomized for each participant. Sequence learning during training and at test is measured using a sequence-specific performance advantage (SSPA) measure. The SSPA is a subtraction score of mean accuracy (percent correct) for the foil sequences from mean accuracy for the training sequence. It is assumed that the higher the SSPA, the better participants have learned the trained, repeating sequence. Speed functions as a measure of general task learning, as it is summarized as an overall average across the test block rather than as a difference score between the trained sequence and foil sequences. The better participants are able to perform the task overall, the faster the task speed.

In the four experiments described in subsequent sections, some modifications were made to the typical structure of the SISL task; these are noted within the Methods section of each experiment.

Characteristics of the SISL Task

Explicit knowledge. In the seminal paper introducing the SISL task, Sanchez et al. (2010) found reliable sequence learning even among participants with no concomitant explicit knowledge (measured using both a recognition and recall test), suggesting that the SISL task was particularly sensitive to measuring implicit knowledge. A common issue with many implicit learning tasks concerns interference from explicit knowledge. Several studies have suggested that instructing participants to attempt to discover the sequence pattern during training (using the more common SRT task or variations on this task) or providing information about the repeating sequence can interfere with participants' ability to perform the task (Boyd & Winstein, 2004; Boyd & Winstein, 2006; Fletcher et al., 2004; Howard & Howard, 2001). Authors of these studies argue that the explicit knowledge interferes or competes with one's ability to learn implicitly. Although several of the studies cited above used older adult or patient populations, explicit interference is still a concern when designing tasks intended to solely measure implicit learning.

In the SISL task, however, explicit knowledge does not seem to interfere with nor contribute to task performance even though it may (and likely does) develop in parallel as participants perform the task. Indeed, even perfect explicit knowledge of the repeating sequence prior to training does not lead to faster learning. In Sanchez and Reber (2013), half of the participants viewed the repeating sequence prior to SISL task training and were asked to memorize it. Although these participants later scored significantly higher on an explicit recall test, they did not differ from naïve participants in their ability to learn the sequence; in other words, explicit knowledge of the sequence did not lead to any learning benefits during the SISL task. Nor, indeed, did it lead to any impairments in learning. Thus, this study further demonstrated the relatively “process-pure” nature of the SISL task, which appears to be resistant to any contributions or interference from explicit knowledge. Thus, although I did not utilize any explicit knowledge tests in the subsequent experiments due to the difficulty of delivering these types of tests remotely online, I could be relatively confident that any explicit knowledge acquired by participants would not affect their performance in a meaningful way.

Learning. Sanchez and Reber (2012) found that learning on the SISL task, as measured by the sequence-specific performance advantage for the repeating sequence (regardless of the length of the sequence), could be reliably predicted from the logarithm of the number of trained sequence repetitions occurring during the task (see Figure 4.2, taken from Sanchez & Reber, 2012). This log-linear relationship allows for a useful means of determining the reliability of the sequence learning measure obtained in the following experiments, thus preventing any doubt in the reliability of the SISL task itself from affecting the interpretation of the results on individual differences.

Rather, one potential concern with the structure of the SISL task that may impact the

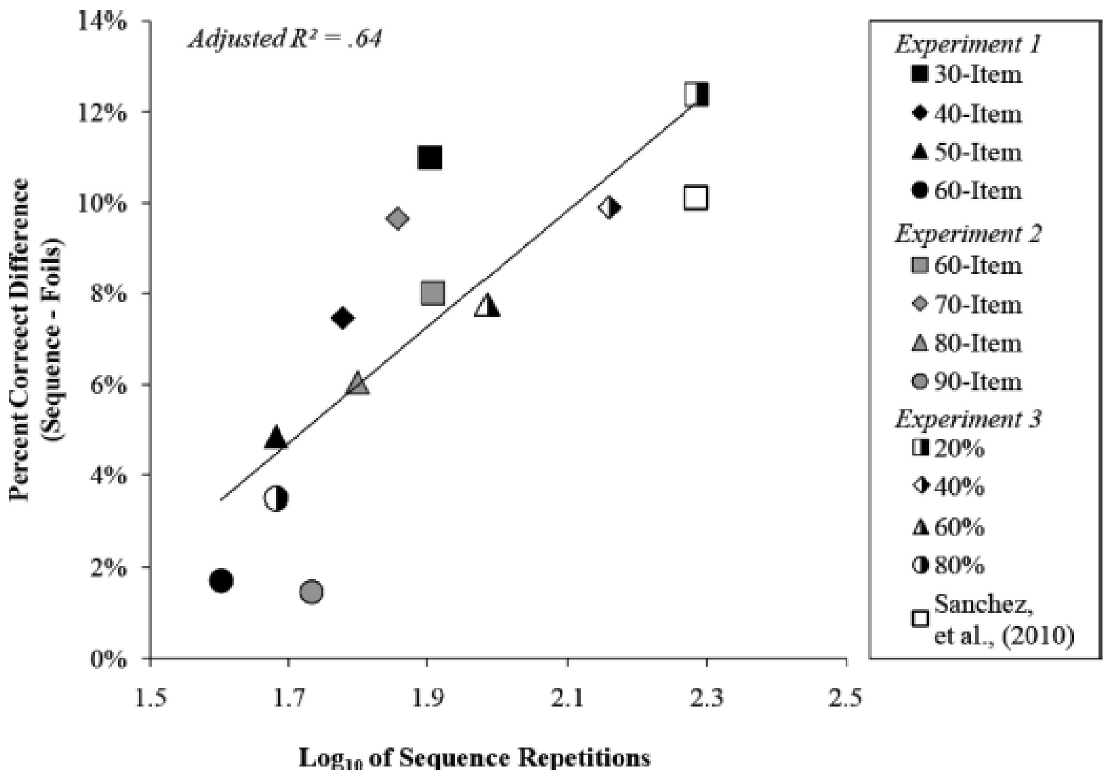

Figure 4.2. Scatterplot of the SISL test score by the $\log_{10}$ of trained sequence repetitions. The SISL test performance as a log-linear function of trained sequence repetitions is better predictive than other variables, such as sequence length. (text taken from Sanchez & Reber, 2012).

results involves the repeating foil sequences used during the SISL test. As sequence learning is log-linear based on the number of sequence repetitions (as shown in Sanchez & Reber, 2012), participants are likely demonstrating some learning of the foil sequences at test, which are themselves repeating, in contrast to the non-repeating foils used during training. This in turn may impact the subtraction measure (repeating sequence accuracy minus foil sequence accuracy) used as the indicator of learning in SISL. This point is discussed further at the end of Experiment 2 and is addressed in the design of Experiment 3.

Exclusion Criteria

In each of the experiments below, identical exclusion criteria were applied to all participants. Only those who maintained good overall task performance were included in the main analyses. Poor performance was indicated by excessive numbers of missed trials (more than 50% within a 180-trial sub-block); responding in excess of 50% above the total number of trials in a 180-trial sub-block, indicating that participants are likely hitting many keys at random in quick succession; or overall performance below 25% correct in any 180-trial sub-block. Each of these indicators reflects a lack of attention and noncompliance with the task itself and would greatly impact the accuracy of the learning score measure, particularly considering the relatively shortened amount of training and test trials used in the subsequent experiments.

Experiment 4.1

My previous research on state effects has shown that performance implicit learning tasks such as SISL can be affected by mental state. The question that naturally follows from this is whether implicit learning ability can manifest as a trait that shows stable differences across individuals, as discussed in the preceding chapter. The extent to which individuals vary significantly at the trait level in the type of skill learning that tasks such as SISL aim to measure remains to be determined. It is vital to consider the potential influence of individual differences when drawing conclusions about observed learning differences that one would like to attribute solely to experimental manipulations of interest, as individual differences in implicit learning ability offer potential confounds for such conclusions. While it has generally been assumed that implicit sequence learning (and implicit learning in general) shows little variation among individuals, few researchers have explicitly tested this theory. In addition, research on real-world skills suggests that innate talent does play a role in skill development. As researchers like Gobet have argued (e.g., Campitelli & Gobet, 2011), extensive practice, even focused and deliberate practice, does not guarantee a particular level of skill attainment.

Thus, the main goal of my thesis work was to challenge the dominant narrative that implicit learning is not subject to individual differences. One way to identify individual differences in implicit learning assessments such as SISL is to look at test-retest reliability. It is not enough to administer one assessment and assume that individual differences in scores reflect real differences among participants. As discussed above, other variables such as mental state can impact an individual's performance at any given time. In addition, no assessment is a perfect measure of the construct it aims to test. By measuring performance at multiple time points, one can determine the proportion of variance attributable to individual ability (i.e., how well current performance is predicted by previous performance) versus interference from measurement error or state effects. In working memory research, for example, commonly used complex working memory span tasks such as reading span (Daneman & Carpenter, 1980) and operation span (Turner & Engle, 1989) have both shown high test-retest reliability (Conway et al., 2005; Friedman & Miyake, 2005; Klein & Fiss, 1999). This has provided strong evidence that working memory capacity is a reliable and stable individual trait.

The goal of this and the next three experiments was to use the SISL task to look at sequence learning across several sequences and/or days. This would allow me to determine whether the learning measure used in SISL is stable within individuals across multiple learning instances. The SISL task used in the following experiments lends itself well to this type of design. There are 256 unique second-order conditional sequences making it simple to administer multiple different training and test sessions. In addition, because previous research using the SISL task has shown that prior knowledge of the sequence to be learned does not affect performance (Sanchez & Reber, 2013), if participants discover the repeating structure of the task after one or more training sessions, it is unlikely to affect future performance on subsequent sequence tests. In terms of explicit knowledge, then, performance on a particular sequence should be relatively immune to interference effects from prior learning of a different sequence.

Methods

Participants

Seventy-nine participants were recruited through Amazon's Mechanical Turk. Participants were compensated $10 for their time. Using the exclusion criteria described in the

General Methods section above, 19 participants were excluded, leaving 60 for the analyses reported in the Results section below.

Procedure

For Experiment 4.1, the SISL task was altered in the following way. Participants were trained and tested on four different sequences. For each sequence, they completed one 540-trial block of training. Each sequence training block was followed by a 540-trial test block, composed of trained sequence and foil sub-blocks as in the typical SISL task. Thus, participants completed 4,320 trials of alternating training and test blocks, with a new training sequence and a new set of foil sequences selected for each of the four training/test block pairs.

Results

Across the four sequences, the average performance advantage for the trained sequence compared to the foil sequences across all sequence tests and all participants was 5.38% (*SE* = 0.71%). A one-way repeated measures ANOVA of the SSPA scores for the four individual sequences indicated that there were no significant differences in learning between the sequences as measured by the SSPA learning score (Seq 1, *M* = 4.60%, *SE* = 1.27%; Seq 2, *M* = 5.44%, *SE* = 1.21%; Seq 3, *M* = 4.76%, *SE* = 1.47%; Seq 4, *M* = 6.71%, *SE* = 1.35%), $F(3,177) = 0.55$, $p = .648$ (Figure 4.3). Based on the log-linear relationship between sequence repetitions and the SISL learning score determined by Sanchez and Reber (2012), one should expect a performance advantage of approximately 3%; all sequence learning scores were well above this threshold. Additionally, although the final sequence test had the highest average performance, the linear trend across the four sequence tests was not significant, $F(1,59) = 0.95$, $p = .333$.

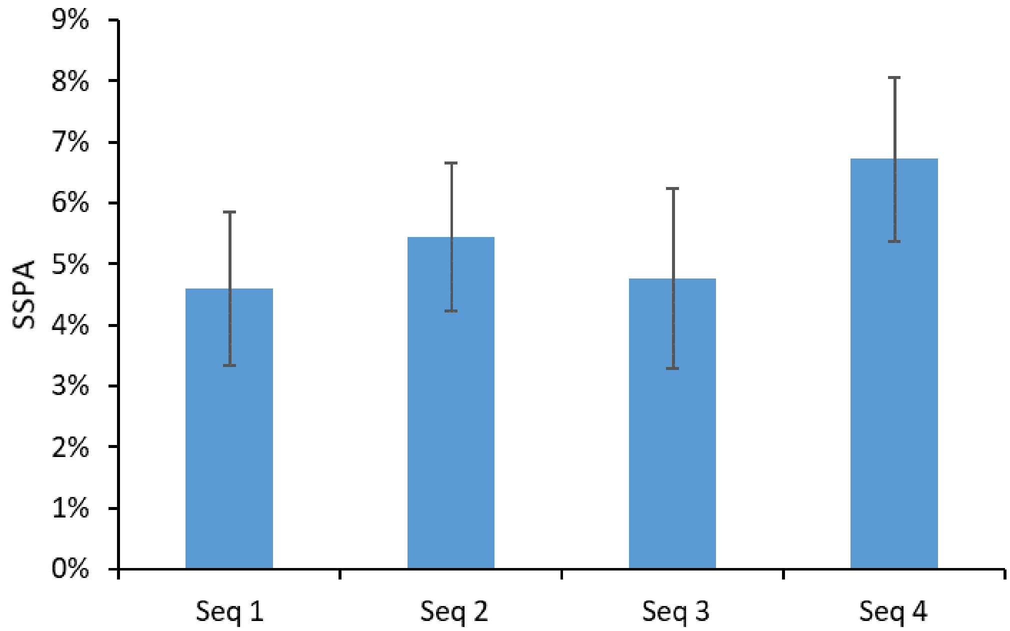

Figure 4.3. Average test sequence performance advantage for each of the four sequences in Experiment 4.1. SSPA = Sequence-specific performance advantage (trained sequence performance minus foil performance). Error bars reflect SEM.

The overall average speed at test across all four sequence tests and all participants was 0.98s (*SE* = 0.03s). A one-way repeated measures ANOVA of the speed at test for the four individual sequence tests indicated that there were significant differences in speed between the sequences (Seq 1, *M* = 1.08s, *SE* = 0.04s; Seq 2, *M* = 0.98s, *SE* = 0.03s; Seq 3, *M* = 0.93s, *SE* = 0.03s; Seq 4, *M* = 0.92s, *SE* = 0.03s), $F(3,177) = 42.01$, $p < .001$ (Figure 4.4). In particular, the time between cue onset and target decreased in a linear fashion across sequence tests ($F(1,59) = 75.94$, $p < .001$), suggesting that participants became faster at the task throughout the four training/test sessions.

To quantify individual differences in SISL performance, I looked at the correlation matrix of SSPA scores among the four sequence tests. This produced only one marginally significant correlation between performance on the first and third sequence tests (Table 4.1), indicating that participants who perform better or worse on a particular sequence test do not do so consistently. By contrast, speed was highly correlated across the four sequence tests (Table 4.2).

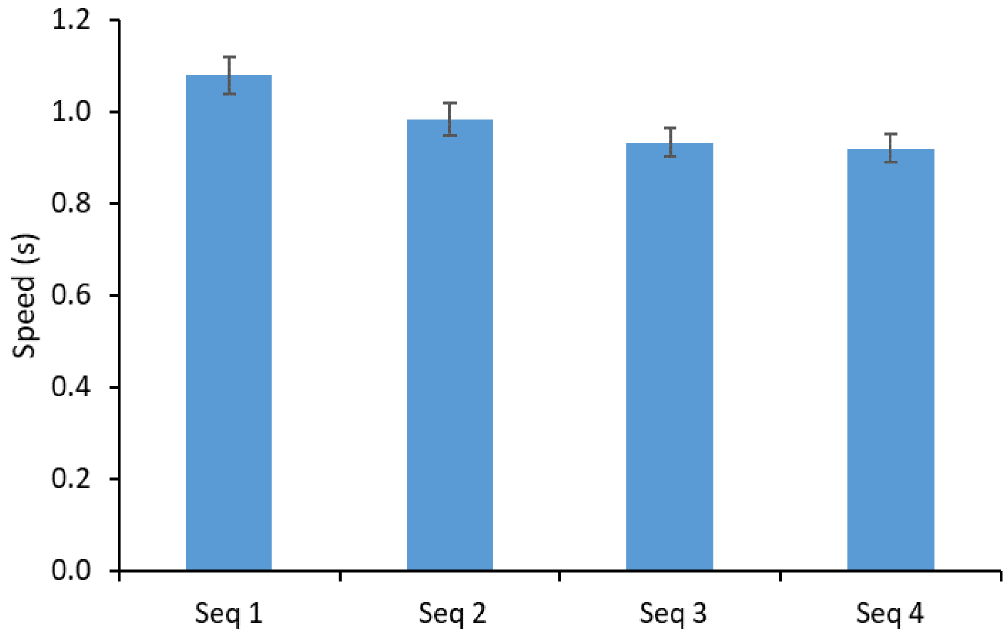

Figure 4.4. Average test speed (in seconds to target) for each of the four sequences in Experiment 4.1. Error bars reflect SEM.

Table 4.1

Correlations between the sequence-specific performance advantage (SSPA) measure for the four sequence test blocks in Experiment 4.1.

	SSPA 1		SSPA 2		SSPA 3	
	r	*p*	*r*	*p*	*r*	*p*
SSPA 2	-0.02	.858				
SSPA 3	0.24	.071	-0.11	.393		
SSPA 4	0.01	.927	-0.02	.869	0.15	.240

Table 4.2

Correlations of speed between the four sequence test blocks in Experiment 4.1.

	Speed 1		Speed 2		Speed 3	
	r	*p*	*r*	*p*	*r*	*p*
Speed 2	0.91	< .001				
Speed 3	0.91	< .001	0.92	< .001		
Speed 4	0.89	< .001	0.92	< .001	0.92	< .001

Nevertheless, average speed across the four sequence tests did significantly correlate with average sequence learning as measured by SSPA, $r(58) = -0.25$, $p = .051$[1] (Figure 4.5).

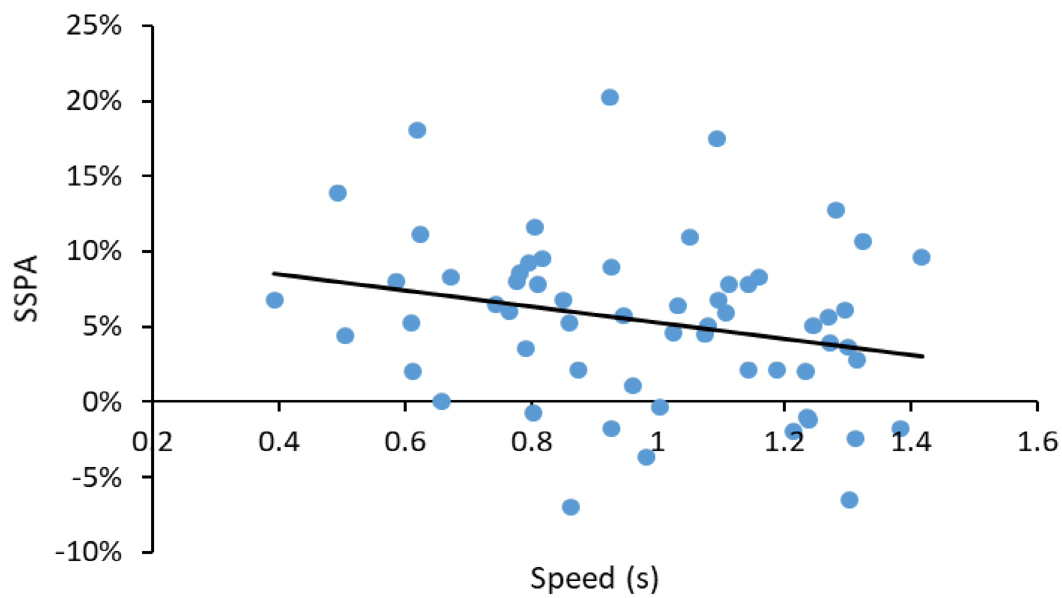

Figure 4.5. Scatterplot of average SISL SSPA score across the four sequence tests in Experiment 4.1 by average test speed across the four tests.

[1] The correlation is negative because we measure speed as the seconds to target for the cues. Thus, a lower value indicates a faster speed.

Discussion

From these results, there appear to be significant individual differences in general task performance (speed), but not necessarily sequence-specific learning (SSPA). Nevertheless, the average speed across the four sequence tests did significantly correlate with average performance, though the correlation was relatively weak. One concern with the structure of Experiment 4.1 is that assessing sequence knowledge on four different sequences with just 540 trials of training only allows investigation of individual differences very early in learning. If the individual difference effect is small, it likely would not have been measurable with just one block of training. Experiment 4.2 aimed to reduce the number of sequence assessments and increase the number of sequence training and test blocks to address this issue.

Experiment 4.2

The goal of Experiment 4.2 was to determine whether training on fewer sequences but with more training and test blocks produced greater evidence of stable individual differences in sequence learning compared to shorter assessments of four different sequences.

Methods

Participants

Seventy-four participants were recruited through Amazon's Mechanical Turk to participate in Experiment 4.2 and were paid $10 for their time. Participants were not allowed to participate in this experiment if they had previously participated in Experiment 4.1. Fourteen participants were removed based on the performance exclusion criteria, leaving 60 participants for the analyses reported below.

The SISL Task

The SISL task was identical to that used in Experiment 4.1, apart from the specific training and test parameters laid out below.

Procedure

In Experiment 4.2, participants were trained on two different sequences. For each sequence, they completed two 540-trial training blocks followed by two 540-trial test blocks. Thus, participants completed the same number of trials as well as the same number of training and test blocks as in Experiment 4.1, but instead were only trained and tested on two different sequences with twice the number of training/test trials for each sequence.

Results

The average performance advantage for the trained sequence across both sequence tests and all participants was 6.74% (*SE* = 0.76%). This is higher than in Experiment 4.1, which would be expected based on the log-linear relationship between sequence repetitions and learning (the expected learning score for this experiment would be approximately 6.5%). Although the average group performance for the second sequence test (*M* = 5.79%, *SE* = 1.09%) was lower than that of the first sequence test (*M* = 7.69%, *SE* = 1.10%), this difference was not reliable, $t(59) = 1.21$, $p = .232$ (Figure 4.6).

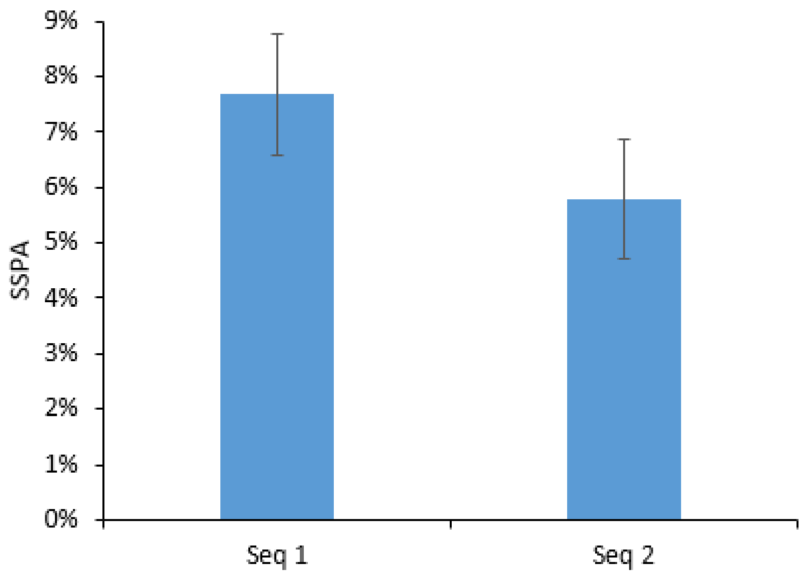

Figure 4.6. Average test SSPA for the two sequences in Experiment 4.2. Error bars reflect SEM.

The average test speed across both sequence tests and all participants was 1.01s (*SE* = 0.04s). Similar to Experiment 4.1, participants were significantly faster on the second sequence test (*M* = 0.97s, *SE* = 0.04s) compared to the first (*M* = 1.05s, *SE* = 0.04s), $t(59) = 5.18$, $p < .001$ (Figure 4.7).

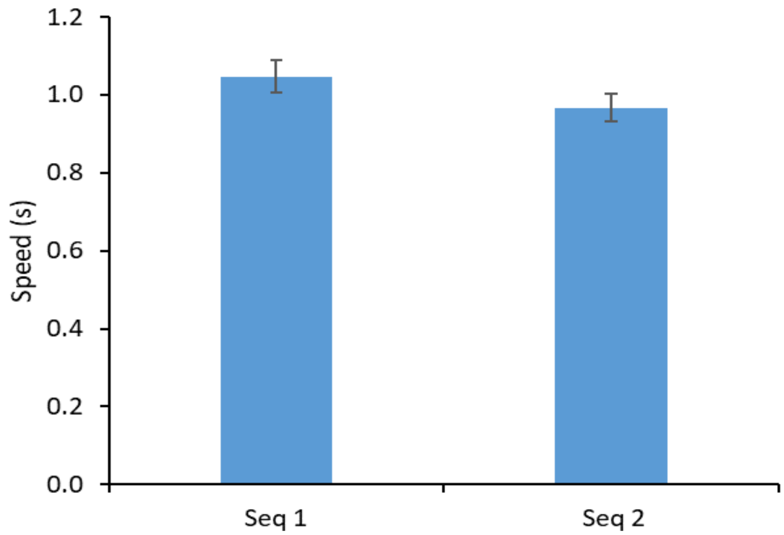

Figure 4.7. Average test speed (in seconds to target) for each sequence in Experiment 4.2. Error bars reflect SEM.

Also similar to Experiment 4.1, the correlation between the two SSPA measures for each of the sequence tests was not significant [$r(58) = -0.03$, $p = .817$], while speed was highly correlated between the two sequence tests [$r(58) = 0.93$, $p < .001$]. However, the correlation between average speed across the two blocks and average performance was not significant [$r(58) = -0.19$, $p = .137$] (Figure 4.8).

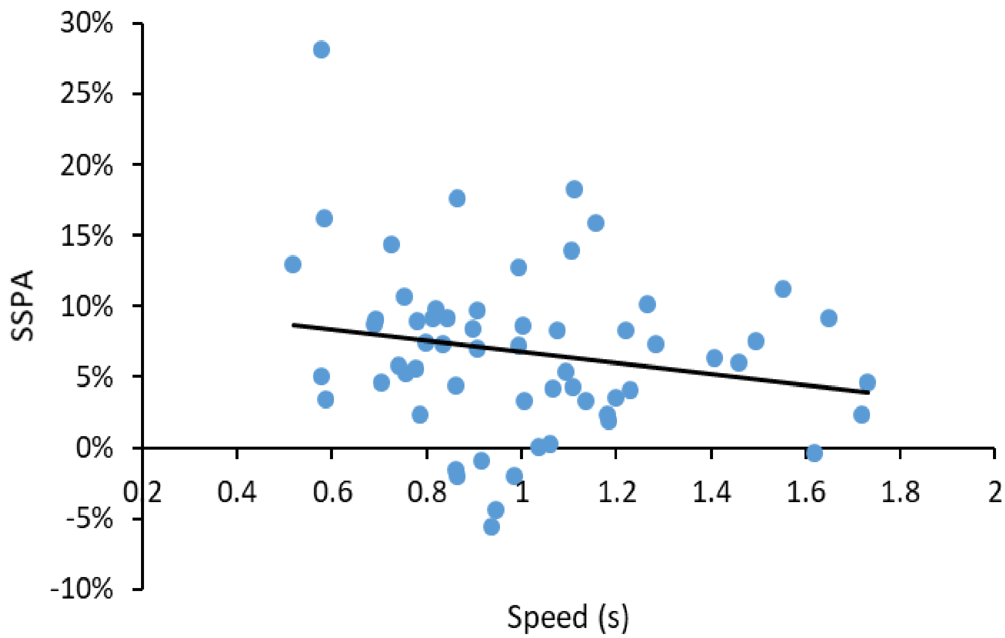

Figure 4.8. Scatterplot of average SISL SSPA score across the four sequence tests in Experiment 4.2 by average test speed across the four tests.

While the SSPA data in Experiments 4.1 and 4.2 did not point to any stability in learning across sequences, I also wanted to examine the possibility of performance instability within a given sequence masking individual differences in learning. To test this, I looked at split-half correlations between trained sequence performance on the two blocks of each sequence test. One should expect performance to correlate when looking at the same sequence. For the first sequence, participants' performance (accuracy) during block 1 correlated signficantly and robustly with their performance during block 2 ($r(58) = 0.70$, $p < .001$). Sequence peformance on the two blocks of the second sequence test was not as strongly, but still significantly, correlated ($r = 0.39$, $p = <.01$). Figure 4.9 shows the comparison between the split-half tests correlations and the cross-sequence test correlation.

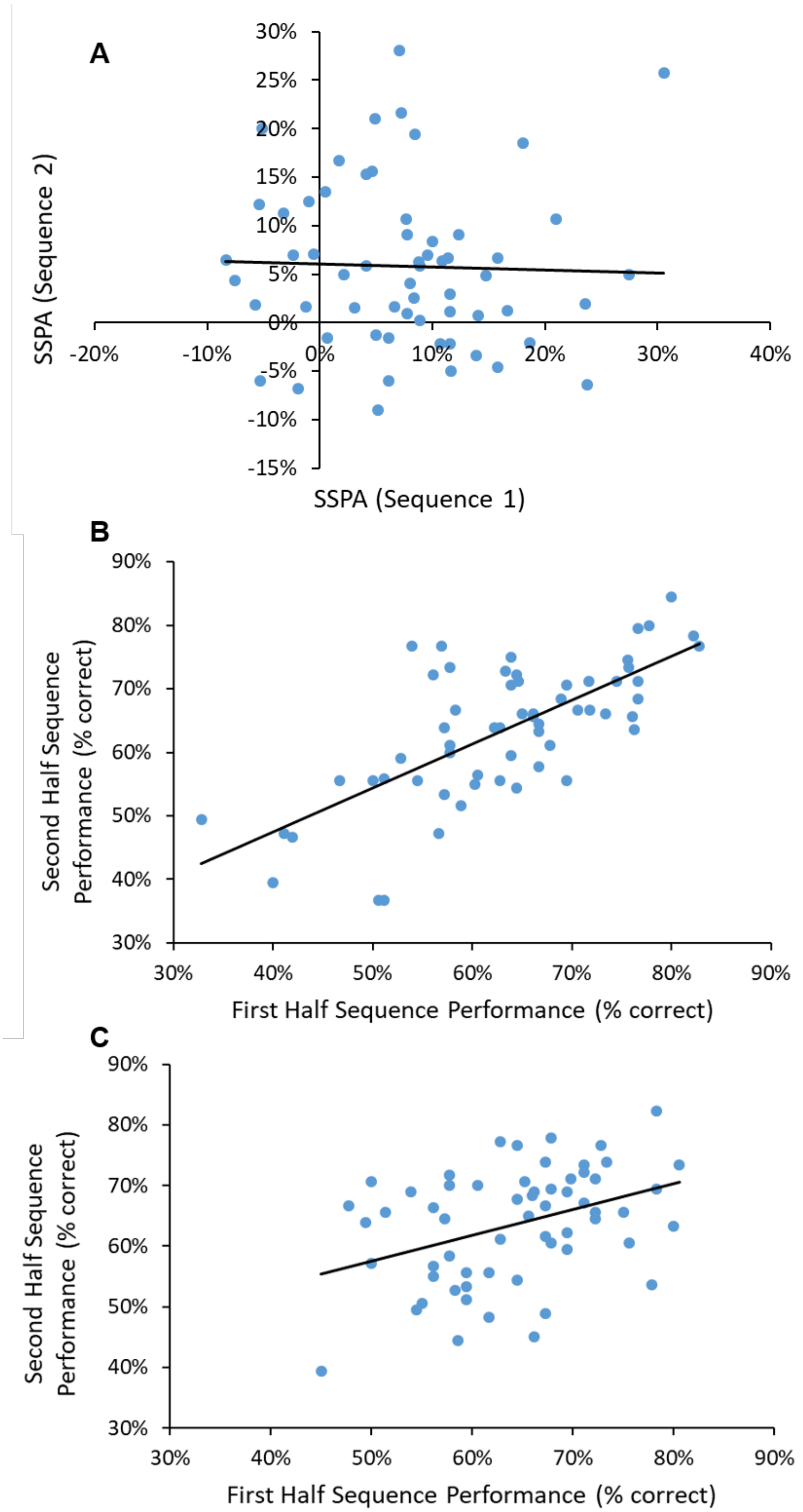

Figure 4.9. Scatterplots showing across- and within-sequence correlations in Experiment 4.2. **A)** Scatterplot of the SSPA score on the second sequence test by SSPA score on the first sequence test. **B)** Scatterplot of trained sequence performance (percent correct) on the second half of the first sequence test by trained sequence performance on the first half of the first sequence test. **C)** Scatterplot of trained sequence performance (percent correct) on the second half of the second sequence test by trained sequence performance on the first half of the second sequence test.

Discussion

Experiment 4.2 replicated the results of Experiment 4.1, with the same finding that sequence-specific learning as measured by SSPA does not correlate significantly across sequences, while general task performance as measured by test speed is highly reliable across sequences. Additionally, the correlation analyses shown in Figure 4.9 indicate that the within-sequence reliability is much stronger than the cross-sequence reliability, and that performance instability within a given sequence is unlikely to be interferring with accurately measuring individual differences in sequence learning using the SISL task.

One potential issue with quantifying individual differences in sequence learning during the SISL task may be the design of the SISL test to assess sequence knowledge. As discussed at the beginning of this chapter, the foil sequences that are compared to the training sequence at test are themselves repeating. Thus, participants are likely showing some learning of these sequences as well, which could mean that individual differences affecting learning of both the training sequence and the foils are subtracted out when calculating the SSPA used as our measure of sequence-specific learning. In addition, the speed was not reset with each new sequence training/test block pair in Experiments 4.1 and 4.2, which may have influenced the correlations I observed in the speed measure. Experiment 4.3 aimed to address these two issues.

Experiment 4.3

Experiment 4.3 addressed the issue of participants learning the test foil sequences by constructing foil sequences that equally balanced all possible trigrams from which the second-order conditional sequences used in SISL are derived. It also addressed the issue of the speed adjustments across sequence tests by resetting the speed back to 1.5s to target after each sequence training/test pair. The remainder of this experiment was a replication of Experiment 4.1.

Methods

Participants

Participants for this study were 65 undergraduate students enrolled in introductory psychology at Northwestern. Participants were given course credit for participation. After excluding participants for noncompliance as in Experiments 4.1 and 4.2, 51 participants were left for analyses.

Materials

SISL task. The structure of the SISL task in Experiment 4.3 addressed the issue of foil sequence learning at test by using non-repeating test foils that were 36 items long and contained one of each of the 36 possible trigrams[2]. Thus, the transitional probabilities were flat at the trigram level.

Because no apparent advantage was offered by using longer training and test blocks, participants completed four training and test block pairs as in Experiment 4.1. The test blocks contained 15 repetitions of the training sequence organized into 60-trial blocks (5 repetitions

[2] Because no immediate repeats (e.g., DD) are allowed in the sequences used for the SISL task, the total possible trigrams = 4 x 3 x 3 (36).

each) as before. These were randomized among two 180-trial foil blocks, which each contained 5 different 36-item sequences structured as described above. New training and foil sequences were used for each training/test block pair. In addition, the speed was reset back to 1.5s to target at the beginning of each new training/test block pair. This detail was unfortunately overlooked and not implemented in Experiments 4.1 and 4.2, but is important for an accurate assessment of individual differences in the speed performance measure.

Results

The average performance advantage for the trained sequence across both sequence tests and all participants was 8.08% (*SE* = 0.89%). A one-way repeated measures ANOVA of the SSPA scores for the four individual sequence tests indicated that there were no significant differences in learning between the sequences (Seq 1, *M* = 10.70%, *SE* = 1.67%; Seq 2, *M* =

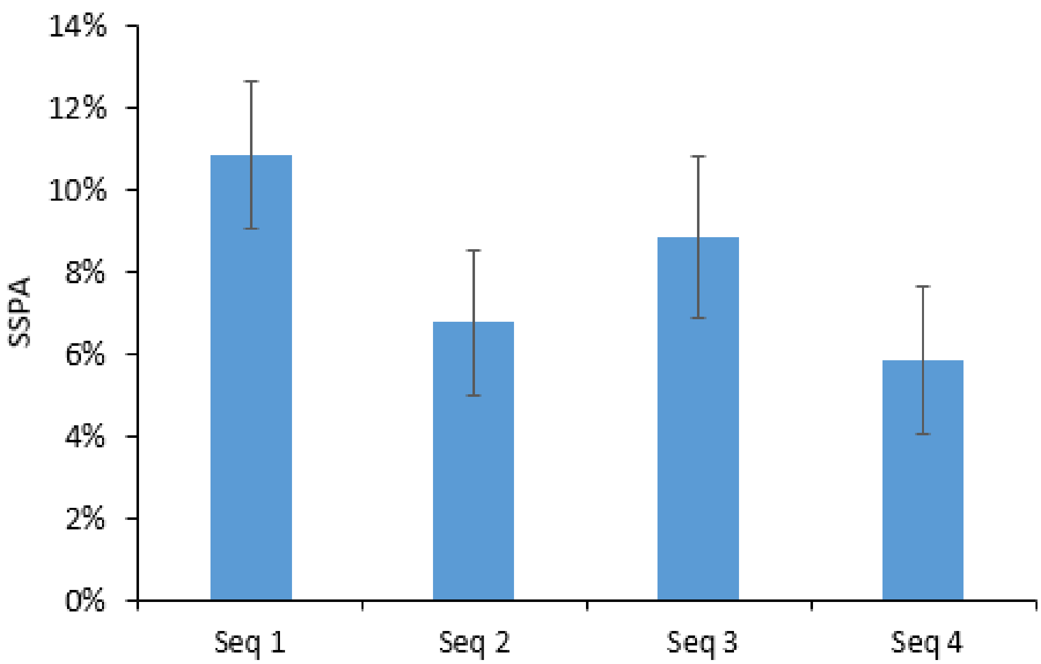

Figure 4.10. Average test SSPA for each of the four sequences in Experiment 4.3. Error bars reflect SEM.

7.34%, *SE* = 1.75%; Seq 3, *M* = 8.77%, *SE* = 1.76%; Seq 4, *M* = 5.52%, *SE* = 1.76%), $F(3,150) = 1.55$, $p = .205$ (Figure 4.10). However, in this case the linear trend across sequences nearly reached significance, $F(1,50) = 3.73$, $p = .059$.

The overall average speed at test across the four sequence tests and all participants was 0.76s (*SE* = 0.02s). A one-way repeated measures ANOVA of test speed across the four sequence tests indicated that speed did differ significantly across the four tests, $F(3,150) = 29.07$, $p < .001$. As in Experiment 4.1, the linear trend across the four sequence tests was significant ($F(1,50) = 49.88$, $p < .001$), indicating that participants were performing the task faster during each subsequent test (Figure 4.11).

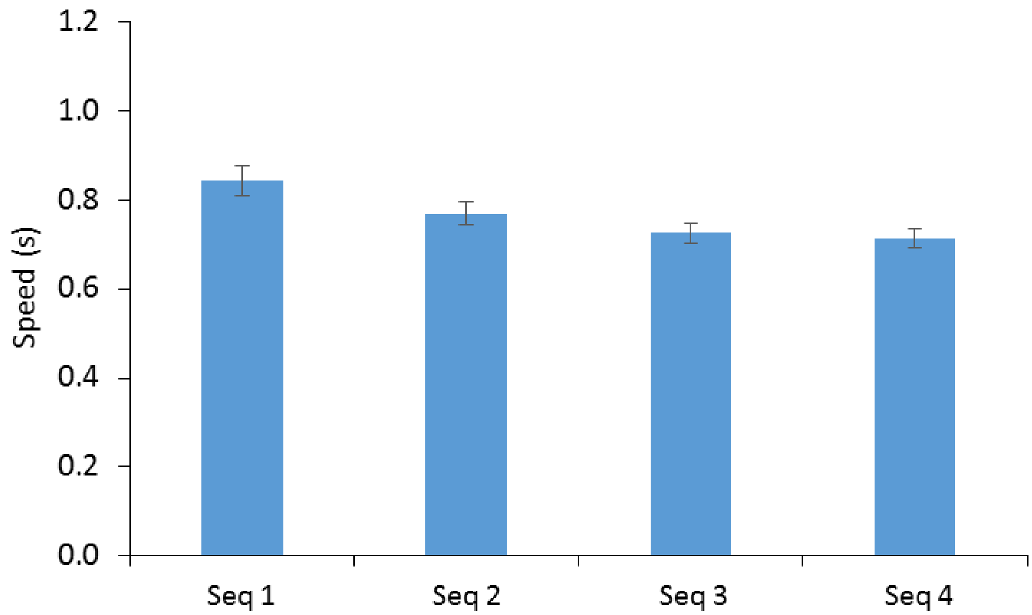

Figure 4.11. Average test speed (in seconds to target) for each sequence in Experiment 4.3. Error bars reflect SEM.

As seen in both Experiment 4.1 and Experiment 4.2, the correlations among the four sequence tests were small and nonsignificant (Table 4.3), but speed was highly correlated across all sequence tests (Table 4.4). This latter finding reinforces the conclusions drawn about test speed as a reliable individual difference measure in the prior two experiments despite the fact that speed was not reset between sequences in those experiments.

Table 4.3

Correlations between the sequence-specific performance advantage (SSPA) measure for the four sequence test blocks in Experiment 4.3.

	SSPA 1		SSPA 2		SSPA 3	
	r	*p*	*r*	*p*	*r*	*p*
SSPA 2	-0.06	.716				
SSPA 3	-0.01	.971	-0.04	.781		
SSPA 4	0.14	.346	-0.25	.094	-0.01	.949

Table 4.4

Correlations of speed between the four sequence test blocks in Experiment 4.3.

	Speed 1		Speed 2		Speed 3	
	r	*p*	*r*	*p*	*r*	*p*
Speed 2	0.84	< .001				
Speed 3	0.91	< .001	0.88	< .001		
Speed 4	0.85	< .001	0.87	< .001	0.91	< .001

The correlation between average speed across the four sequence tests and average sequence learning as measured by SSPA trended towards significance, $r(49) = -0.26$, $p = .066$ (Figure 4.12).

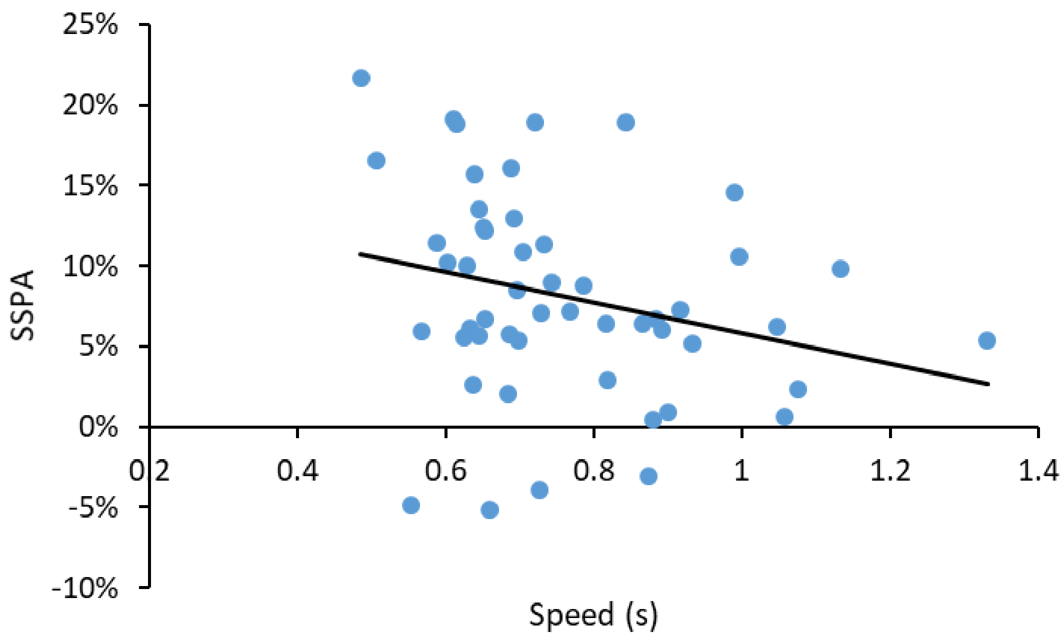

Figure 4.12. Scatterplot of average SISL SSPA score across the four sequence tests in Experiment 4.3 by average test speed across the four tests.

Discussion of Experiments 4.1, 4.2, and 4.3

From these three experiments, it appears that performance speed may be a more reliable individual difference measure than sequence-specific learning. Because speed is a more task-general performance measure, this suggests that individuals may differ in either general perceptual or motor ability, allowing those who are more skilled in these areas to perform the SISL task at an overall faster rate. Though previous literature aligns with an absence of individual differences in implicit sequence learning, it was still surprising to find a consistent pattern of near-zero correlations of individual subjects' sequence learning across multiple sequence tests. This suggests that early learning (i.e., within the first few hundred repetitions) of a new motor sequence does not exhibit stable individual differences across people.

One might argue that running this type of task online produces a noisier measure than the controlled environment of the lab and therefore reduces the possibility of observing individual differences. Nevertheless, the robustly stable individual differences observed in the test speed measure would suggest that this method does not have a marked impact on the results obtained. In addition, the SSPA learning scores for each experiment aligned relatively well with what one would expect based on the log-linear relationship between learning and sequence repetitions reported in Sanchez and Reber (2012). Furthermore, the split-half correlation analysis in Experiment 4.2 did not suggest any cause for concern with within-sequence performance reliability on the SISL task.

A more plausible alternate possibility is that the effect size for individual differences in implicit sequence learning is small, and thus a robust sample size is needed. Therefore, to be sure I was not simply underpowered to observe individual differences in sequence learning, I conducted a further large scale study aimed at greatly increasing the number of participants and introducing other measures that do have a strong individual difference component to compare with SISL.

Experiment 4.4

As discussed at the beginning of Chapter 4, one method for measuring individual differences is to look at test-retest reliability. However, not all assessments lend themselves to this type of design (e.g., if it is not possible to make multiple versions of the assessment). This is especially true in intelligence research, for example, where there is no one standard test of IQ. Therefore, researchers in this field have instead favored factor analysis methods. Factor analysis simplifies the intercorrelations between several cognitive tests into discrete factors. If several tests load onto the same factor, they are assumed to measure a common underlying construct. Thus, if the variance among individuals can consistently be accounted for by a particular factor, this provides evidence for the existence of a particular trait (represented by that factor) that reliably differs across people. Further, if a particular assessment in one domain consistently predicts variability on several assessments in another domain, this can also suggest the existence of a meaningful individual trait. To take an example from the working memory literature, Daneman and Carpenter (1980) showed that their reading span measure correlated strongly with three measures of reading comprehension, showing that individual differences in working memory capacity could meaningfully predict variation in this domain. Experiment 4.4 assessed individual differences in implicit sequence learning using both test-retest and factor analysis methods.

Methods

Participants

Two hundred and twenty subjects were recruited through Northwestern's Paid Participant Registry (56 male, $_{m}$Age = 24.25 years). Participants were paid $10 per session (sessions described in more detail below) of the four session experiment. Technical issues unfortunately resulted in 29 participants having missing data from 1 or more sessions. Additionally, an unfortunate coding error resulted in missed trials not counting as errors within the speed adjustment algorithm. Thus, the speed adjustments that should normally have occurred every 12 trials were not always correctly triggered. This led to much lower performance than usual, as misses actually counted against participants rather than leading to a slowing of the task to help improve their performance, likely leading to even more missed trials.

This therefore caused many participants (the coding issue was not corrected for the first 109 subjects) to be filtered due to a high number of missed trials and low performance; an additional 46 participants were excluded based on the typical criteria. Although several of these were likely excluded in error, it was impossible to determine which subjects were correctly excluded and which were not. Thus, the Results section discusses correlation and factor analyses with both the 145 complete subjects (220 minus the 29 with missing data and the additional 46 who did not meet exclusion criteria) as well as the full sample of 191 subjects that included participants who had been filtered according to the exclusion criteria (the 29 subjects with missing data were also excluded from this second set of analyses).

Materials

In addition to the SISL task, which was structured identically to Experiment 4.3, I created a battery of assessments using measures of working memory, fluid intelligence, personality, and processing speed. As reviewed in Chapter 3, fluid intelligence and working memory show reliable differences among individuals. Additionally, working memory has recently been considered as a potential source of individual differences in implicit sequence learning. There are several measures of both fluid intelligence and working memory with a long history of individual differences research. Two of these measures, the Operation Span task (Turner & Engle, 1989) and Raven's Progressive Matrices task (Raven, Court, & Raven, 1977), were adapted for online data collection for the purposes of this study.

Personality is another construct that has been studied in relation to implicit learning. In particular, a few studies have shown a positive relationship between openness to experience and implicit learning (Kaufman et al., 2010; Woolhouse & Bayne, 2000). These authors suggest that the potential link between openness and implicit learning is intuition; intuition seems to involve a similar reliance on unconscious knowledge as implicit learning, and individuals scoring high on scales measuring openness to experience also score high on intuition measures (McCrae, 1994). As openness to experience is one of the "big 5" personality constructs, several extensively validated measures of it existed to draw from for this study.

Finally, the cognitive abilities discussed above match closely with those studied by Kaufman et al. (2010), one of the few (perhaps the only) comprehensive studies of individual differences in implicit sequence learning (using the SRT task). Kaufman and colleagues also showed that processing speed was correlated with implicit sequence learning, suggesting that this more basic and primitive cognitive function measure is more likely to relate to implicit learning than measures of more complex cognitive mechanisms such as fluid intelligence. Thus, the measures described below were chosen for a combination of reasons: 1) well-established measures of a particular construct, particularly those with a history of use in individual differences research, 2) measures easily deployable for, or easily adapted to, online data collection, and/or 3) measures used in Kaufman et al. (2010).

Working memory measures. Participants were given three working memory assessments: operation span, list sorting, and a working memory assessment (SeVi) developed in our own lab.

***Operation span*.** The operation span (OSPAN) task (Turner & Engle, 1989) is a commonly used complex working memory span measure. In the task, participants are asked to solve a series of mathematical operations while simultaneously remembering a set of unrelated words. A typical trial consists of a question such as “Is (9/3) – 1 = 1?” followed by the word “DOG”. Participants must evaluate the truth of the math statement and indicate whether it is correct. They are then instructed to read the word “DOG” before moving on to the next operation-word pairing. After a certain number of trials (typically 2-6), participants are asked to recall the words that had been presented previously, in the order they had been presented.

All of the mathematical operations were structured as a simple multiplication or division problem, such as (3 x 4) or (8/2), followed by the subtraction or addition of a single digit integer. Half of the operations had the correct answer listed after the equal sign while the other half were incorrect. The words paired with the mathematical operations were all one syllable concrete nouns 4-6 letters long, after Turner & Engle (1989). At intervals of 2-6 trials, participants were asked to recall the words that accompanied the previous set of trials in the correct order. Participants began at a set size of two trials and moved sequentially up to a set size of six, completing three trial orders at each length before moving up to the next set size. Working memory capacity was scored as the sum of the number of words from each correctly recalled trial order (thus the maximum score possible was 60).

List sorting. The List Sorting Working Memory Test was taken from the NIH Toolbox Cognitive Function Battery (Tulsky et al., 2013), which is intended for online/computer-based use. Participants were shown pictures of animals for two seconds each and asked to recall those animals in the correct order for set sizes of 2 to 7 animals. Sets progressed serially from 2 to 7, with two trial orders at each set size. Working memory span was scored as the set size for which participants correctly recalled at least one of the two trial orders.

Sequential visuospatial (SeVi) working memory task. Previously, the SeVi task has been used as a tool for studying the effects of working memory training. The task is very similar in appearance to the SISL task, and I chose to adapt it for one of my working memory assessments for this reason. In the adapted version of the task, participants viewed circular cues scrolling down the screen towards target circles that were labeled with either a D, F, J, or K. Each trial contained two sequences, distinguished by the color of the cues (red or blue). These sequences were presented in a randomly interleaved fashion and participants were instructed to watch the cues as they fell down the screen (Figure 4.13A) and to remember the order of the red cues only. The cues took 1.5s from onset to reach the target circle and had an inter-stimulus interval of 600ms. Once all of the cues disappeared from the screen, there was a short delay (~1s) before participants were instructed to repeat back the red sequence using the keyboard or by clicking on the target circles with the mouse in the correct order (Figure 4.13B).

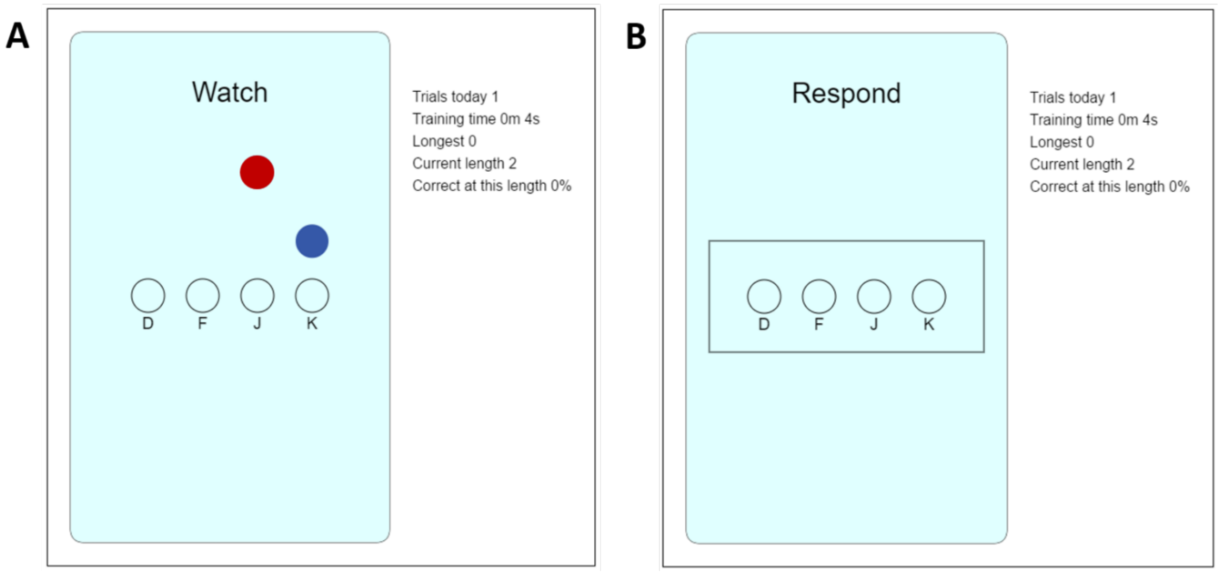

Figure 4.13. The SeVi task. **(A)** Participants are instructed to watch and remember the red sequence. **(B)** Participants attempt to repeat back the red sequence using the keyboard or the mouse.

Participants started with an initial length of two items for each sequence. If they completed two sequences in a row correctly at this length, the total length increased by two, so that the red and blue sequences were each three items long. This continued until the participant missed two sequences in a row at a given length. The task then stepped down to the previous sequence length. It continued to move between sequence lengths based on these criteria (2 correct/2 incorrect) throughout the task. Participants completed 30 trials of this task (5-10 min) and working memory capacity was scored as the longest sequence length at which the participant achieved an overall accuracy of at least 70% correct.

Personality measures. Participants were given subsets of two personality instruments to measure openness to experience: the openness subscale of the NEO-PI-R (Costa & McCrae, 1992) and the openness subscale of the Big Five Aspect Scales (BFAS; DeYoung, Quilty, Peterson, & Gray, 2014). Both scales ask participants to indicate the extent to which they agree or disagree (5-point scale) with a series of descriptive statements (e.g., “I love to reflect on things”). Individual items were scored from 1-5 based on the participants’ response (with reverse-coded items scored accordingly) and then summed across items, yielding a single “openness” score for each scale (NEO-PI-R max = 170; BFAS max = 50).

Fluid intelligence measures. Participants completed two fluid intelligence measures from the International Cognitive Ability Resource (http://icar-project.com/), a collaborative effort to produce public domain assessment tools for various cognitive measures (e.g, see Condon & Revelle, 2014), and thus easily obtained for online use.

Matrix reasoning. Similar to Raven’s Progressive Matrices (Raven et al., 1977), a commonly used measure of fluid intelligence, the Matrix Reasoning items of the ICAR are 3x3 arrays of geometric shapes with one of the nine shapes missing. Eleven of these items were presented to participants, and on each trial participants were asked to decide which of the six possible shapes presented below the array best completed the pattern.

Letter and number series. The Letter and Number Series items were nine short digit or letter sequences following a particular pattern. Similar to the Matrix Reasoning items, participants were prompted to choose the next letter or number in the sequence from six possible choices.

Processing speed measures. Participants completed two processing speed measures, modeled after Kaufman et al. (2010): the Speed of Information Processing sub-test from the British Ability Scales (Elliot, 1996) and the Digit-Symbol Substitution task from the WAIS-R (Wechsler, 1981).

Speed of information processing. For this task, participants were shown sets of five integers, each randomly chosen from the range 1-100, and were asked to select the highest number in each set. They were given 60 seconds to complete as many of the 48 items as they could. The score for this task was the number of items completed correctly after 60s.

Digit-symbol substitution. This task presented participants with a key of symbols that matched with the numbers 1-9 (Figure 4.14). Beneath the key were a series of symbols each

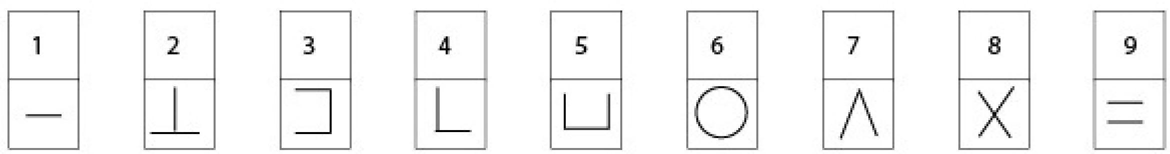

Figure 4.14. The Digit-Symbol task key.

followed by a blank box. Participants were instructed to fill in the correct number that corresponded to that symbol in the key (note that this is in contrast to how the task is normally presented, with participants being asked to draw the corresponding symbols; the task was reversed to make it easier to complete online). There were 93 items and participants were given 90s to complete as many as they could. Similar to the previous task, the score was the number completed correctly in 90s.

Procedure

Participants completed four approximately one-hour sessions. Following completion of a session, the link to the next session was emailed to participants approximately 18-24 hours later. In the first session, participants completed the Operation Span and List Sorting tasks, the two personality measures, the two fluid intelligence measures, and the two processing speed measures. These tasks were completed online using Qualtrics survey software. For the subsequent three sessions, participants completed a session of SISL training and a session of the SeVi task. Each session of SISL consisted of 8 blocks of training and testing (one block of each for four different sequences, as in Experiment 4.3), with new sequences used in each session. Each session of the SeVi task was 30 trials long as described above.

With this design, I was able to compare the reliability of individual performance on the SISL task to that of a task (SeVi) that measures a construct (working memory) well-known to behave in a trait-like manner with stable individual differences. Additionally, I was able to run a factor analysis for all seventeen measures (the eight cognitive measures, the three average SISL SSPA and test speed measures from each session of SISL, and the three sessions of SeVi) to reveal the underlying factor structure.

Results

The average SISL sequence-specific performance advantage (SSPA) across the 145 participants who were not filtered or excluded due to missing data for each sequence test in each of the three sessions is shown in Figure 4.15 and Table 4.5. A one-way repeated measures

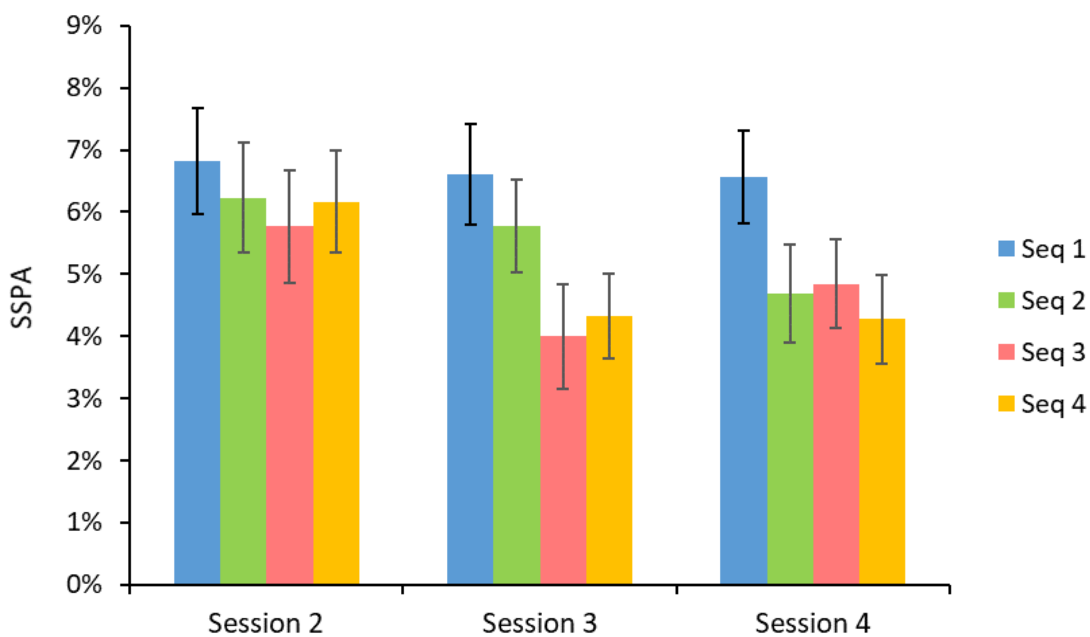

Figure 4.15. Average test SSPA for each of the four sequences across the three sessions of SISL in Experiment 4.4. Error bars reflect SEM.

ANOVA of the SSPA learning measure across the four sequence tests in each session did not show a significant linear trend for session two ($F(1,143) = 0.27$, $p = .60$), but was significant for sessions three ($F(1,142) = 5.63$, $p = .02$) and four ($F(1,144) = 4.56$, $p = .03$). The linear trend model for the repeated measures ANOVA on the overall average SSPA for each session (session 2, $M = 6.26\%$, $SE = 0.45\%$; session 3, $M = 5.19\%$, $SE = 0.38\%$; session 4, $M = 5.09\%$, $SE = 0.39\%$) was also significant ($F(1,144) = 4.14$, $p = .04$).

Table 4.5

Mean SSPA and standard error for the twelve sequence tests in Experiment 4.4.

	M	***SE***
Session 2		
Sequence 1	6.81%	0.86%
Sequence 2	6.23%	0.88%
Sequence 3	5.77%	0.90%
Sequence 4	6.17%	0.82%
Session 3		
Sequence 1	6.61%	0.81%
Sequence 2	5.78%	0.75%
Sequence 3	4.00%	0.85%
Sequence 4	4.32%	0.68%
Session 4		
Sequence 1	6.56%	0.75%
Sequence 2	4.69%	0.79%
Sequence 3	4.84%	0.72%
Sequence 4	4.28%	0.72%

The average speed at test for each of the twelve sequence tests across the three sessions of SISL is shown in Figure 4.16 and Table 4.6. The linear trend for the repeated measures ANOVA was significant across the four sequence tests in sessions two ($F(1,143) = 64.63$, $p < .001$), three ($F(1,142) = 5.17$, $p = .03$), and four ($F(1,144) = 10.23$, $p < .01$). It was also significant for the overall average test speed across the three sessions (session 2, $M = 0.96$s, $SE = 0.03$s; session 3, $M = 0.79$s, $SE = 0.02$s; session 4, $M = 0.73$s, $SE = 0.02$s), $F(1,144) = 171.42$, $p < .001$. This suggests that participants generally improved at the task across sessions.

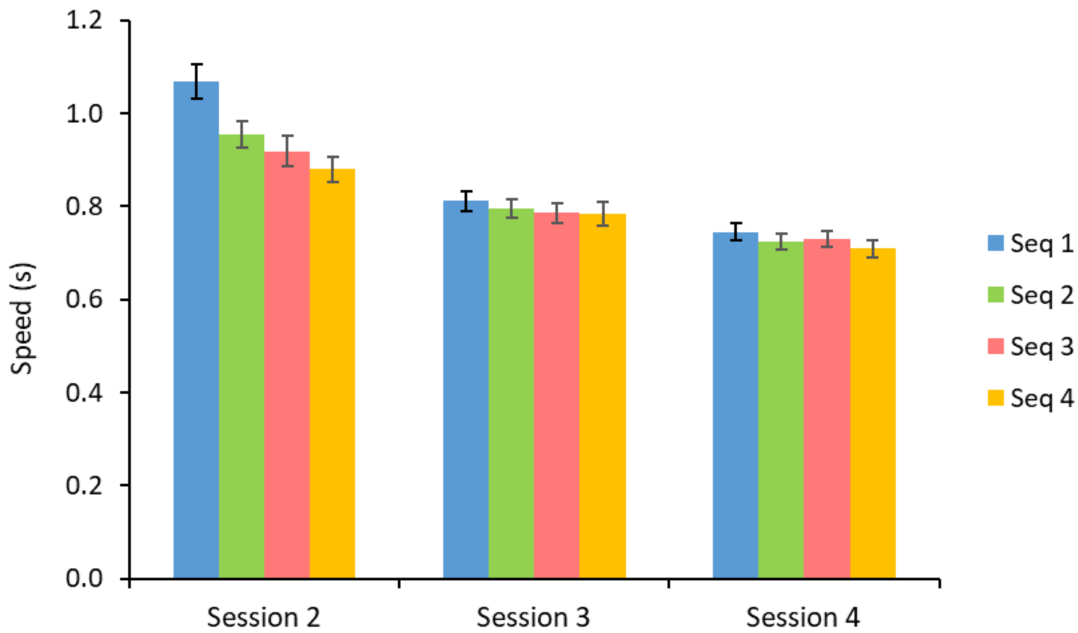

Figure 4.16. Average test speed (in seconds to target) for each of the four sequences across the three sessions of SISL in Experiment 4.4. Error bars reflect SEM.

Table 4.6

Mean speed and standard error for the twelve sequence tests in Experiment 4.4.

	M	***SE***
Session 2		
Sequence 1	1.07s	0.04s
Sequence 2	0.96s	0.03s
Sequence 3	0.92s	0.03s
Sequence 4	0.88s	0.03s
Session 3		
Sequence 1	0.81s	0.02s
Sequence 2	0.80s	0.02s
Sequence 3	0.79s	0.02s
Sequence 4	0.78s	0.03s
Session 4		
Sequence 1	0.74s	0.02s
Sequence 2	0.72s	0.02s
Sequence 3	0.73s	0.02s
Sequence 4	0.71s	0.02s

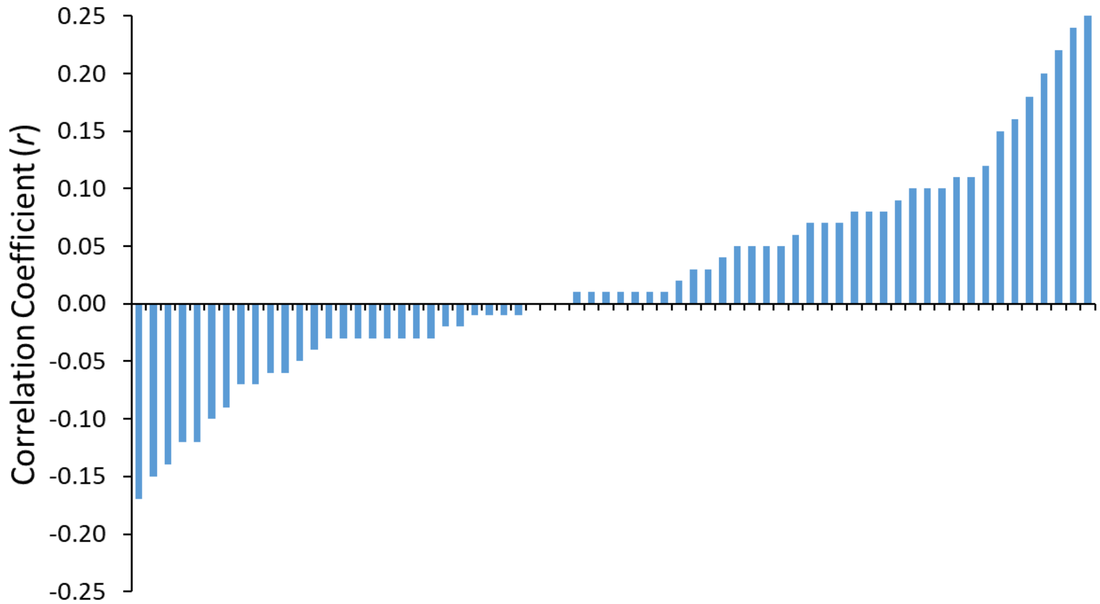

Figure 4.17. Distribution of correlation coefficients for the SSPA learning measures across sessions 2-4.

Figures 4.17 and 4.18 show the distribution of correlation coefficients derived from all pairwise correlations between the SSPA learning measures (Figure 4.17) and all pairwise comparisons between the test speed measures (Figure 4.18) across all twelve sequences from

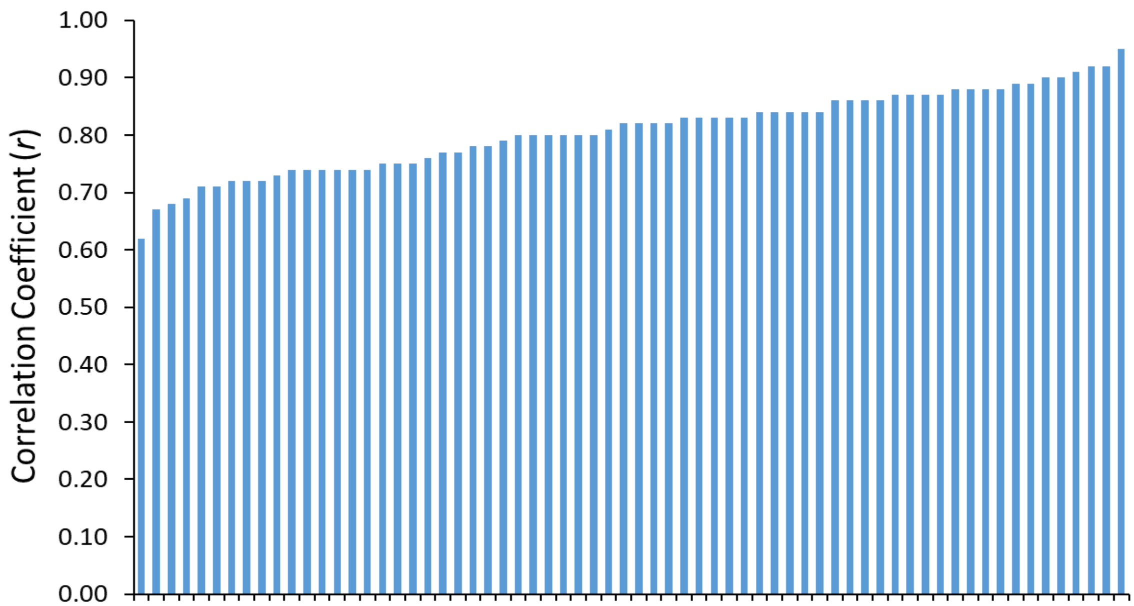

Figure 4.18. Distribution of correlation coefficients for the test speed measures across sessions 2-4.

sessions 2-4, sorted smallest to largest. The correlation coefficients for the SSPA learning measures centered around zero (average $r = 0.02$), while the correlations for test speed were all robustly above zero (average $r = 0.81$).

Table 4.7 shows the correlations among all cognitive measures completed during the first sessio n as well as the average SSPA, SISL test speed, and SeVi working memory span (using the overall averages from sessions 2-4) for the 145 subjects with complete datasets. Importantly, tasks reportedly measuring the same construct tended to have the highest correlations (OSPAN and List Sorting tasks, $r = .43$; fluid intelligence tasks, $r = .49$; processing speed tasks, $r = .57$; personality measures, $r = .81$; all p's <.001). Additionally, there were at least moderate correlations between most of the different cognitive measures, particularly the working memory and fluid intelligence measures as would be expected. The SeVi task was significantly correlated with the other working memory measures (r's = .19 - .44; p's = < .001 - .02). Each of the three sessions of SeVi were also significantly correlated with both of the fluid intelligence measures (r's = .22 - .36, all p's < .01).

Table 4.7

Correlations (r) among all measures of working memory, fluid intelligence, processing speed, personality, and the SISL task – 145 complete subjects.

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. OSPAN	-																
2. List Sorting	**.43**	-															
3. SeVi – 1	**.19**	**.30**	-														
4. SeVi – 2	**.26**	**.24**	**.30**	-													
5. SeVi – 3	**.32**	**.44**	**.49**	**.37**	-												
6. Matrices	**.27**	**.27**	**.32**	**.22**	**.36**	-											
7. Letter Number	**.49**	**.36**	**.31**	**.24**	**.36**	**.49**	-										
8. Digit-Symbol	.10	**.26**	**.20**	**.27**	.16	.14	**.25**	-									
9. SoIP	**.26**	**.27**	**.22**	**.22**	.12	.08	**.26**	**.57**	-								
10. Openness (NEO-PI-R)	**.17**	**.18**	.05	**-.17**	.03	**.19**	.06	-.03	-.04	-							
11. Openness (BFAS)	**.20**	**.23**	.03	-.15	.06	**.19**	.12	.05	.03	**.81**	-						
12. SISL SSPA–2*	.02	**.16**	.10	.04	**.24**	.07	-.03	-.01	.00	.10	.11	-					
13. SISL SSPA–3	.15	.15	.05	.03	**.17**	.13	**.18**	.00	.09	.08	.13	.03	-				
14. SISL SSPA–4	-.04	.03	.00	-.03	-.05	.09	.04	.03	-.03	.08	.11	.09	.12	-			
15. SISL Speed–2*	**-.21**	**-.22**	**-.24**	**-.28**	**-.23**	-.15	**-.28**	**-.47**	**-.35**	.03	-.02	-.15	**-.12**	-.10	-		
16. SISL Speed–3	**-.21**	**-.20**	**-.25**	**-.27**	**-.27**	-.12	**-.22**	**-.46**	**-.34**	.05	.02	-.13	**-.26**	**-.18**	**.88**	-	
17. SISL Speed–4	**-.23**	**-.20**	**-.27**	**-.31**	**-.31**	**-.18**	**-.28**	**-.78**	**-.33**	.08	.03	-.13	**-.26**	**-.22**	**.85**	**.92**	-

Table 4.7

Correlations (r) among all measures of working memory, fluid intelligence, processing speed, personality, and the SISL task – 145 complete subjects.

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
N	145	145	145	144	141	145	144	145	144	145	145	145	145	145	145	145	145
Mean	46.4	5.7	4.5	4.5	4.9	6.5	5.5	39.4	22.7	132.2	38.9	6.3%	5.2%	5.1%	0.96s	0.79s	0.73s
SEM	.99	.10	.12	.11	.12	.23	.18	.74	.44	1.48	.56	.45%	.37%	.39%	.03s	.02s	.02s

Note: Significant correlations ($p < .05$) in **bold.** Matrices = Matrix Reasoning task; Letter Number = Letter and Number Series task; SoIP = Speed of Information Processing task

* SISL SSPA and Speed were averaged across the four sequence tests within a given session; numbers after each measure reflect the session number

The SeVi task also showed significant correlations across the three sessions for which it was administered (sessions 1 and 2, $r = .30$; sessions 1 and 3, $r = .49$; sessions 2 and 3, $r = .37$, all p's $< .001$). By contrast, in line with the previous experiments, sequence-specific learning (SSPA) in SISL was not correlated across sessions (all r's $< .12$, all p's $> .15$). In addition, the SSPA scores had very few (likely spurious) correlations with the other cognitive measures. Also confirming previous results, SISL test speed was significantly correlated across sessions (sessions 1 and 2, $r = .88$; sessions 1 and 3, $r = .85$; sessions 2 and 3, $r = .92$; all p's $< .001$). Furthermore, SISL speed was significantly correlated with many of the other cognitive measures, particularly processing speed (r's = .33 - .78, all p's $< .001$).

Approximately half of the correlations between the overall average SSPA and the overall average speed for each session were significant. This, along with the moderate and occasionally significant correlations found in Experiments 4.1-4.3 invites a more precise indication of the nature of the relationship between SSPA and speed. To achieve this, the mean-centered SSPA and speed data from all four experiments were combined to look at the correlation between the two measures across all experiments. The resulting correlation was modest but significant, $r(604) = -0.20$, $p < .001$. A similar method was used for estimating the SSPA-SSPA correlations across sequence tests for all experiments, using the SSPA for the first sequence test and the average SSPA of the remaining sequence tests to account for the different number of sequence tests from experiment to experiment; this correlation was not significant, $r(604) = 0.06$, $p = .178$. While these correlations confirm the relative instability of learning across sequences, it is curious that the SSPA-speed correlation is more robust. As speed seems to be a reliable individual difference measure, the suggestion of a relationship between speed and SSPA hints at the possibility of a weak individual differences signal in SSPA. This point is returned to in the concluding chapter of this thesis (Chapter 5).

Following up on the correlational analyses, I conducted a principal components factor analysis to further explore the relationship between the cognitive and implicit learning measures (again using the overall average SSPA and speed from the three sessions). Using promax rotation, I initially obtained a five factor solution. However, only one variable loaded primarily onto the fifth factor. As this factor no longer meaningfully summarized the data with only one variable loading, therefore making it more difficult to interpret, the analysis was redone forcing the solution to four factors. The resulting factor loadings are shown in Table 4.8.

Table 4.8

Rotated factor loading matrix (loadings shown in parentheses) – 145 complete subjects.

Factor 1: Processing Speed	Factor 2: WM/gF	Factor 3: Openness	Factor 4: Implicit Learning
SISL Speed – Session 3 **(.90)**	SeVi – Session 4 **(.76)**	Openness – BFAS **(.91)**	SISL SSPA – Session 2 **(.56)**
SISL Speed – Session 4 **(.89)**	Letter and Number Series **(.69)**	Openness – NEO-PI-R **(.88)**	SISL SSPA – Session 4 **(.51)**
SISL Speed – Session 2 **(.88)**	SeVi – Session 2 **(.65)**		SISL SSPA – Session 3 **(.36)**
Digit-Symbol Substitution **(-.74[3])**	List Sorting **(.65)**		
Speed of Information Processing **(-.63)**	Matrix Reasoning **(.64)**		
	OSPAN **(.63)**		
	SeVi – Session 3 **(.55)**		

[3] Again, with speed measured as time-to-target (i.e., as the task speed increases, the value recorded for speed decreases), these negative loadings should be interpreted as associated with this factor, in the same way as the positive loadings for the other variables.

SISL test speed and the two information processing tasks loaded onto the first factor, and SeVi, the other working memory measures, and well as the two fluid intelligence measures loaded onto the second factor. The two personality measures loaded most strongly onto the third factor, while the fourth factor was described by the SISL SSPA measures from the three sessions. However, the factor loadings for the SISL SSPA measures were still relatively low compared to the other three factors.

Finally, as in Experiment 4.2, I wanted to investigate the stability of performance within a given sequence test (i.e., on the same sequence) to ensure this wasn't masking the true learning differences. Because of the shorter test blocks and the longer foil sub-blocks, it was not possible to do a true split-half correlation. Instead, I looked at the correlation between performance on the first and last repeating sequence sub-block (60 trials) within the first and last sequence tests for each of the three SISL sessions (Table 4.9). Though all correlations were moderate in strength, they were all significant and much higher than the correlations between the SSPA scores across the three sessions. As with the similar correlational analysis performed in Experiment 4.2, this indicates that within-sequence performance is more stable than across-sequence performance.

Table 4.9

Correlations between sequence performance on two sequence sub-blocks within the first and last test of each SISL session.

	Sequence Test 1		Sequence Test 4	
	r	*p*	*r*	*p*
Session 2	0.48	< .001	0.34	< .001
Session 3	0.32	< .001	0.34	< .001
Session 4	0.19	.025	0.41	< .001

The correlation matrix and factor analyses were repeated on the full sample (which included participants who had originally been filtered through the exclusion criteria described at the beginning of this chapter, but still excluded participants with missing data). As Table 4.10 shows, the pattern of correlations across all of the cognitive and implicit learning measures was very similar for this sample. The factor analysis (Table 4.11) with this sample did not fully match that of the smaller sample, but still showed that SISL test speed and processing speed loaded onto a single factor, while sequence learning as measured by SSPA did not associate very strongly on a particular factor.

Table 4.10

Correlations (r) among all measures of working memory, fluid intelligence, processing speed, personality, and the SISL task – all subjects.

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. OSPAN	-																
2. List Sorting	**.48**	-															
3. SeVi – 1	.11	**.23**	-														
4. SeVi – 2	**.21**	**.23**	**.42**	-													
5. SeVi – 3	**.24**	**.28**	**.52**	**.49**	-												
6. Matrices	**.25**	**.25**	**.38**	**.30**	**.41**	-											
7. Letter Number	**.39**	**.28**	**.33**	**.30**	**.41**	**.57**	-										
8. Digit-Symbol	.03	**.17**	**.25**	**.24**	**.17**	.22	**.29**	-									
9. SoIP	**.22**	**.18**	**.20**	**.19**	**.16**	.10	**.22**	**.60**	-								
10. Openness (NEO-PI-R)	.13	**.21**	.03	-.10	.03	**.17**	.08	.00	-.03	-							
11. Openness (BFAS)	**.18**	**.25**	.03	-.09	.02	**.16**	.07	.04	.03	**.80**	-						
12. SISL SSPA–2	.01	.12	**.15**	.04	**.17**	.12	.01	.03	.05	.07	.09	-					
13. SISL SSPA–3	**.16**	**.18**	-.01	.00	.06	.01	.02	.04	.11	.12	**.15**	-.02	-				
14. SISL SSPA–4	.01	.09	.01	.08	-.02	.09	.03	-.04	-.03	.05	.10	.06	.06	-			
15. SISL Speed–2	**-.23**	**-.27**	**-.26**	**-.26**	**-.25**	**-.24**	**-.31**	**-.44**	**-.31**	-.12	-.13	-.13	-.14	.01	-		
16. SISL Speed–3	**-.15**	**-.17**	**-.31**	**-.31**	**-.27**	**-.24**	**-.28**	**-.56**	**-.38**	-.04	.00	-.09	**-.19**	-.09	**.81**	-	
17. SISL Speed–4	**-.18**	**-.17**	**-.31**	**-.33**	**-.31**	**-.24**	**-.26**	**-.49**	**-.36**	.00	.02	-.11	**-.23**	**-.20**	**.72**	**.86**	-

Table 4.10

Correlations (r) among all measures of working memory, fluid intelligence, processing speed, personality, and the SISL task – all subjects.

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
N	191	191	191	191	191	191	191	191	191	191	191	191	191	191	191	191	191
Mean	46.1	5.6	4.3	4.4	4.6	5.9	5.04	37.9	22.4	132.4	39.2	5.9%	5.3%	5.4%	1.07s	.87s	.79s
SEM	.88	.09	.12	.10	.12	.20	.18	.71	.38	1.29	.50	.44%	.35%	.41%	.05s	.03s	.02s

Note: Significant correlations ($p < .05$) in **bold.** Matrices = Matrix Reasoning task; Letter Number = Letter and Number Series task; SoIP = Speed of Information Processing task

Table 4.11

Rotated factor loading matrix (loadings shown in parentheses) – all subjects.

Factor 1: Processing Speed	Factor 2: WM/gF	Factor 3: Openness	Factor 4: Implicit Learning
SISL Speed – Session 3 **(-.90)**	SeVi – Session 4 **(.78)**	Openness – BFAS **(.84)**	OSPAN **(.60)**
SISL Speed – Session 4 **(-.90)**	Letter and Number Series **(.70)**	Openness – NEO-PI-R **(.81)**	SISL SSPA – Session 2 **(-.49)**
SISL Speed – Session 2 **(-.84)**	Matrix Reasoning **(.69)**	List Sorting **(.54)**	SISL SSPA – Session 4 **(-.35)**
Digit-Symbol Substitution **(.71)**	SeVi – Session 2 **(.67)**	SISL SSPA – Session 3 **(.36)**	
Speed of Information Processing **(.62)**	SeVi – Session 3 **(.65)**		

Discussion

Experiment 4.4 generally confirmed the pattern of results observed in Experiments 4.1-4.3. In contrast to both a working memory task (SeVi) and SISL test speed, sequence-specific learning in SISL did not show robust test-retest reliability. With a much larger sample size, I was also able to conduct a factor analysis using SeVi, SISL, and a set of tasks measuring working memory, processing speed, openness to experience, and fluid intelligence, the first three of which have previously been investigated as potential sources of individual differences in implicit sequence learning (e.g., Kaufman et al., 2010). Both average SISL speed and SeVi again stood apart from sequence-specific learning in that they each loaded onto a common factor along with a subset of the other cognitive measures. On the one hand, this suggests that the performance speed component of skill learning does exhibit stable individual differences, while extraction of the specific sequence pattern during initial learning of a new sequence is much less stable across individuals. Nevertheless, the fact that sequence-specific learning across the three sessions loaded onto a single factor suggests at least some underlying stability in this measure. Thus, individual differences in implicit sequence learning may be present but subtle. This point, along with other possible sources of individual differences in skill learning, is further considered in the following, and final, chapter.

Chapter 5: Summary and Future Directions

In contrast to explicit learning, many researchers have operated on the commonly held assumption that implicit sequence learning ability shows little variation across individuals. This assertion is supported by one of two arguments, both of which have their own points of weakness. Some maintain an evolutionary argument, claiming that because the implicit learning system is evolutionarily older than the explicit system, one should expect lower between-subject variability. However, imaging studies have shown that implicit learning processes involve not only older structures such as the basal ganglia, but areas of the more newly formed neocortex as well (Gobel et al., 2011). Thus, arguing for a lack of individual differences in implicit learning from an evolutionary standpoint does not provide strong support for such a claim.

Others use the argument that implicit learning is an automatic process that occurs incidentally and should therefore operate independently of other cognitive processes. However, this has proven challenging to show experimentally using dual-task protocols, with specific characteristics and timing of the secondary task having a significant influence on whether impaired or intact implicit learning is observed (Schumacher & Schwarb, 2009). Furthermore, studies of state effects on learning provide additional evidence that implicit sequence learning is not an entirely automatic process. Both mental fatigue (induced through an ego depletion task; Thompson et al., 2014) and avoid motivation (Chon et al., 2017) have been shown to influence the degree of learning observed in an implicit sequence learning task (SISL). Coupled with the fact that individual differences in implicit learning have rarely been systematically studied, I saw providing a quantifiable measure of such differences as an important addition to the body of research on implicit learning.

The relatively flawed arguments historically used to support the claim that implicit learning ability should not differ across individuals, plus my own intuition, led me to expect to find at least modest evidence that people do in fact vary not only in explicit learning but implicit learning as well. Anyone who considers examples of people they have encountered who seem to be “naturals” at real-world skills such as music or sports would most likely easily concede that certain individuals must be naturally “better” at skill learning. As an important component of skill learning, one might thus expect that implicit learning ability should also differ across individuals. However, the first three experiments described in Chapter 4 suggested that only certain components of learning exhibited stable individual differences. In particular, performance speed was robustly correlated across different sequence tests. While this certainly represents an important component of overall skill learning, it is not specific to the individual sequence that participants are expected to extract. Learning on a given sequence in the SISL task was almost completely unrelated to learning of a subsequent sequence. This suggests that initial learning of a new sequence (i.e., within the first 50 or so repetitions of practice) does not differ in a trait-like manner across individuals.

This pattern was again observed in Experiment 4.4 with a multi-day experimental protocol. Compared to both speed at test and the SeVi working memory measure, sequence learning on the SISL task was much less reliable across sessions. Furthermore, sequence learning did not correlate consistently with any other measures employed in that experiment, while performance speed correlated with many of these measures. Finally, a factor analysis revealed a common factor underlying both processing speed measures and test performance speed on SISL. Thus, general task performance as measured by speed did robustly emerge as an individual trait, but sequence-specific learning, surprisingly, did not.

This result is particularly interesting in light of real-world evidence that innate talent does play a role in attaining expertise in a skill. In particular, evidence for this comes from both the motor learning literature (Ackerman and Cianciolo, 2000; Engel et al., 2013; Golenia et al., 2014; Wu et al., 2014) and the studies of Fernand Gobet discussed in Chapter 1 (Campitelli & Gobet, 2011; Hambrick et al., 2014). A certain number of hours of practice—even deliberate practice, as Ericsson has suggested is necessary for achieving expertise—do not guarantee a certain level of skill. This makes intuitive sense when one considers the absurdity of assuming anyone could become an Olympic-level athlete or world-class musician. However, the results of my experiments are not necessarily inconsistent with the notion of innate talent. Experiment 4.4 showed that a common factor does underlie sequence learning in SISL, though it should be noted that this factor had among the weakest loadings of the four factors. But this doesn't imply that innate talent is nonexistent; rather, weak evidence of stable individual differences in learning of a new sequence suggests that individual differences in skill learning (i.e., talent) arise from something other than core sequence learning (i.e., pattern extraction) ability. Thus, the research described in the previous chapter makes an important contribution to our understanding of skill learning.

Furthermore, it raises the question of how to more accurately define differences in innate talent, rather than suggesting that this concept be disregarded entirely. First, perhaps individual differences only manifest themselves when comparing experts to novices. If so, I should not necessarily have expected to see them emerge with a relatively small sample size of mostly young adults (when considering the smaller subgroups of the population I would have had to target to ensure enough variability in expertise) or over such a short training period (roughly 3 hours). Targeted recruitment of experts (e.g., musical experts, as we have observed on an anecdotal basis that musicians tend to perform better on SISL) would be a valuable area for future research. Individual differences in implicit learning ability may be subtle enough that they only emerge after extensive hours of practice. Even a slight learning advantage, while perhaps not observable on the smaller scale of my experiments, could lead to faster skill development when compounded over thousands of hours.

Or perhaps initial learning might proceed similarly across individuals, but realization of expert status requires something extra beyond basic pattern extraction ability. One possibility is that pure physiological differences account for much of the variability in real-world skill expertise. For example, in the world of sports, individuals with specific physical characteristics (e.g., height, weight) tend to excel in specific positions within a given sport. In music, more difficult pieces are often characterized by complex rhythmic structures and faster transitions between notes or chords; it is conceivable that individual differences in musical ability arise simply from individual differences in motor skill afforded by a specific physiological profile. Additionally, the importance of speed would be more consistent with my findings that overall task performance ability, as measured by speed of responding, is a robust individual difference measure in SISL. Perhaps this component of skill learning plays a greater role in determining individual ability or talent when it comes to real-world skills.

Alternatively, evidence from the reinforcement learning literature suggests a possible genetic component to skill learning. In a typical reinforcement learning paradigm, participants view pairs of neutral stimuli and must learn to choose one and avoid the other in each pair based on probabilistic feedback. Participants are then tested with novel stimulus pairs to determine how well they generalize the information learned during training. Frank, Moustafa, Haughey, Curran, and Hutchinson (2007) and Collins and Frank (2012) have demonstrated a relationship between the Val158Met polymorphism in the *COMT* gene, working memory capacity, and dopaminergic function in predicting participants' performance on a probabilistic reinforcement learning task. Because dopamine likely plays an important role in skill learning as well (Gobel et al., 2013; Siegert et al., 2006), genetics may play a part in giving rise to individual differences. Again, targeted sampling may be necessary to test this idea, given that the various polymorphisms are not equally distributed across the population.

A further possibility is that individual differences in explicit learning may have greater impact on attainment of complex real-world skills than on learning in laboratory tasks designed to tap only implicit processes. Indeed, most skilled performance likely draws on both explicit and implicit knowledge. A prominent example of this again relates to musical ability. Researchers as well as musicians themselves will often speak of musical training in a way that suggests the importance of both explicit and implicit knowledge. Achieving increased accuracy through repeated practice as well as acquiring knowledge about rules governing musical structure are likely supported by implicit mechanisms (Rohrmeier & Rebuschat, 2012; Tillmann, Bharucha, & Bigand, 2000), but studying written music to learn a piece by memory is a more explicit process. This explicit knowledge of a piece is particularly important for recovering from a mistake or fumbled note—in other words, when implicit knowledge fails. It is also important when changing the context of performance, such as when transposing music to another instrument or key (Colwell, 2006). Therefore, while I did not find strong evidence for individual differences in implicit learning, individual differences in real-world skills may arise more from individual differences in explicit learning ability than implicit learning ability.

Finally, a deeper understanding of the specific characteristics of the SISL task itself represents an additional important area of future study. Measurement error is of course a component of any experimental task, and the relatively unexplored potential sources of error in the SISL task may present a caveat to any conclusions that can be drawn about individual differences. While learning within a sequence was shown to be much more reliable than learning across sequences, suggesting that the learning measure itself is relatively stable and reliable, two additional questions that have not been systematically answered are worth considering: 1) Are particular sequences learned faster than others? and 2) How does speed relate to performance? For each participant, one of the 256 possible 12-item sequences is randomly chosen as the trained repeating sequence. We assume that each of these sequences are of equal difficulty to learn, but perhaps this is not the case. With thousands of prior participants in dozens of studies that have used the SISL task, it would be possible to mine this data to look for evidence that a particular sequence (or set of sequences) is learned faster than others. It would be important to know if some sequences are easier to learn, as this could present an additional source of measurement error when attempting to study individual differences in sequence learning on SISL.

Second, the relationship between speed and performance on SISL remains relatively unknown. The cross-experiment correlation analysis showed that these measures are modestly but significantly correlated. However, it would be interesting and worthwhile to characterize this relationship more definitively. Because I have treated speed and sequence-specific learning (SSPA) as separate performance measures throughout this dissertation, more carefully characterizing the relationship between the two could lead to a reconsideration of my conclusions about the results presented in the previous chapter. Perhaps the way learning is measured using the SSPA subtraction score is subtly influenced by speed. To investigate this idea further, one could imagine presenting participants with non-repeating sequences while randomly varying the speed of the task (as opposed to tying speed changes to overall participant performance). This would allow for a more systematic method of observing how accuracy changes as a function of speed.

Barring these further investigations, however, the experiments presented in this dissertation raise important questions about the nature of expertise. Arguing whether certain individuals are more adept at implicit learning is overly simplistic. Many factors likely contribute to the attainment of expertise in complex real-world skills. My work has provided robust evidence that at the level of pattern extraction processes underlying performance on an implicit sequence learning task, individuals do not differ. This component of skill learning does not behave in a trait-like manner similar to well-studied constructs such as working memory or fluid intelligence. Rather, all individuals have an equal capacity to learn.

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