DISSERTATION

CONTROLLED AND AUTOMATIC PROCESSING IN IMPLICIT LEARNING

Submitted by

Heather Marie Skeba Mong

Department of Psychology

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Doctoral Committee:

Advisor: Carol Seger

Ed DeLosh
Vicki Volbrecht
Bruce Draper

ABSTRACT

CONTROLLED AND AUTOMATIC PROCESSING IN IMPLICIT LEARNING

This dissertation proposes a new approach for measuring the cognitive outcomes of learning from implicit tasks: measure the controlled and automatic processes at use by participants after training, and focus on how controllable the acquired knowledge is under different learning conditions as measured through a process-dissociation procedure. This avoids the uncertainty of any explicit knowledge test's ability to exhaustively measure the contents of consciousness, and provides a different way to view the cognitive changes due to implicit task training. This dissertation includes three experiments using two different implicit learning tasks (serial response reaction time [SRTT] and contextual cuing) to test how controllable the knowledge gained from these tasks is. The first two experiments used the SRTT, in which participants have to make the appropriate corresponding spatial response when presented with a visual stimulus in one of four locations. The trained information is a repeating 12-item response series, which participants are not typically told is repeating. These experiments found use of both controlled and automatic processes by participants. When participants were cued that a sequence was repeating (Experiment 2), there was significantly less use of controlled processes than when participants were not cued into the sequence repetition, suggesting a shift away from controlled processes when explicitly learning the repeating information. The third experiment used the contextual cuing visual search task, which requires participants to rapidly locate a target (T) in a field of distracters (L). Participants become faster at locating the target within repeating spatial configurations across training. Experiment 3 also found use of both controlled and automatic processes after training. However, cuing the repetition did not change either controlled or automatic process estimates, suggesting that control over acquired knowledge is not affected by intent to learn. Altogether, the process dissociation approach

provides process estimates congruent with existing theoretical explanations of the two implicit learning tasks, and are a useful addition to the techniques available to study implicit learning.

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Attention: A complex cognitive component with many aspects that allows for focusing mental effort and processes. The alerting subsystem of attention is a basic form that is used primarily in vigilance or sustained tasks. The orienting subsystem is used when picking one possible stimulus out of many. The executive subsystem holds active mental information together, is used when working towards a goal (including error detection and monitoring current goal state), and includes selective and focused attention constructs.

Automatic processes: Cognitive processes that are not strictly limited by attentional resources, not open to conscious awareness, are used without intent, slower to acquire, and rigid once learned.

Conscious(ness): Mental state of being aware of the contents of the mind.

Controlled processes: Cognitive processes that require attentional resources, open to conscious awareness, and are used with intent.

Explicit learning: Learning of information that is intentional by the participant. The information to be learned is directly presented in training.

Implicit learning: Learning of information that is done without the awareness of the participant. The information to be learned is covertly presented in training, with the surface task having a purpose not directly related to the trained information.

Recall memory test: Memory test following training that requires the participant to retrieve the target information from memory. A correct response is providing the target information on the test.

Recognition memory test: Memory test following training that requires the participant to compare information presented in the test with the contents of memory. A correct response is accurately identifying the memory test's probe as being presented during training or not.

Training: Period of time that the experimental learning conditions are carried out.

Unconscious: Mental state of not being aware of the contents of the mind, *also known as non-conscious.*

Chapter 1

Introduction

A major focus of research on implicit learning concerns the conscious experience or awareness of what is learned. However, the implicit learning field is divided on how essential conscious awareness is for learning to occur, if conscious awareness is a cause or effect of learning, and if learning can occur without conscious awareness. I propose that one way to further understand learning from implicit tasks is to adopt a dual-process approach [1, 2], and investigate the controlled and automatic processes supporting performance on the tasks. This proposition comes from my view that the understanding of consciousness is not yet at a point that it can be objectively and reliably measured. Adapting the process-dissociation (PD) procedure from implicit memory [3, 4] allows for estimation of the relative contribution of automatic and controlled processes in task performance under different implicit and explicit learning conditions.

This dissertation provides support for adopting a dual-process approach to the study of implicit learning. After first showing the feasibility of implementing PD in one implicit learning task (serial reaction time task, SRTT, Experiment 1), learning and process estimates were measured for two implicit learning tasks (SRTT in Experiment 2, and contextual cuing in Experiment 3) under concurrent implicit and explicit learning directions. These two tasks were chosen because they are affected differently by manipulations of learning instructions – when participants are told that there is repeating information SRTT responses tend to get faster [e.g., 5], but contextual cuing response times do not improve [6]. The automatic and controlled process estimates following this repetition-knowledge manipulation can be compared between tasks.

The Introduction will first define the terminology used in this dissertation before reviewing the distinctions between implicit and explicit learning, introduce and review PD, and provide information regarding the implicit learning tasks and manipulations used in this dissertation.

Implicit Learning

People's ability to learn and use information without being conscious of it has long been of interest to psychologists [e.g., 7–9]. Reber was the first to label it as "implicit learning" [10], and the field has increased in complexity and research interest since then. A current general definition of implicit learning is learning new information without being told to, with participants often lacking awareness of what was learned [11–15]. It is important to note that the two components of this definition are not necessarily linked to each other, but do seem to be important parts of implicit learning. However, beyond this simplistic statement that sets implicit learning apart from explicit learning[1], the field is rife with debate about different aspects of implicit learning: how does the learning occur, how is it represented, is the learning necessarily conscious or non-conscious, plus many other more nuanced discussions. Furthermore, many of these different aspects are frequently included in the implicit learning definition as necessary features [e.g., 11, 13]. This results in some tasks having some implicit features while not possessing others (e.g., non-intentional learning of a repeating sequence, but developing conscious awareness of what was learned). As such, it may be useful to focus on one feature that can bridge the different aspects of implicit learning. One factor that may help bring together defining

[1] This definition would suggest that explicit learning is acquired intentionally, which does match with the different forms of explicit learning (e.g., learning word pairs as done in [16]; or different forms of educational content, [17]).

characteristics for the different implicit learning tasks and awareness trends is the extent to which participants can control what they have learned.

Before discussing the proposed dual-process approach for investigating outcomes of implicit learning, the measures of awareness and issues associated with conscious awareness are explored with greater depth.

Awareness of Learned Information

The categories of awareness measures will be briefly introduced before discussing the overarching issues for measuring awareness.

Categories of Awareness Measures

There are five main categories of awareness measures. First is the self-report of explicit knowledge [11, 14, 18], in which the participant is directly asked if they had any knowledge of the manipulation of interest. This test is the easiest to administer, but it is also the least likely to be sensitive to the information used during the task [14, 15]. It is only sensitive to information participants can articulate about what they have learned at the time of the self-report test. These tests are often in the form of a yes/no response when asked if they had noticed the repeating information [e.g.. 6, 19, 20]. This results in a binary measure of self-reported awareness. However, self-reports can miss aspects of conscious experience that are less readily described verbally [15, 21]. In sum, self-reports provide a rough but potentially incomplete approximation of what knowledge is consciously accessible to participants [e.g., 22].

Second is a recognition test [11, 14, 23]. Participants are tested to see if they can explicitly recognize the information they were exposed to during the experiment. While this test examines the same information participants were exposed to during the experiment, it has been argued that recognition tests are pushing participants to use the information in a different way [15], and as such will be insensitive to whatever consciously accessible knowledge participants were actually using during the experiment.

Furthermore, both conscious and non-conscious knowledge types may be used to answer all questions. For example, if a participant does not consciously know if an item was encountered during the experiment, they may rely on their ‘gut feeling’, which seems to be supported by non-conscious knowledge [24]. This response that is not based on conscious knowledge would be correct, and consequentially assumed to be due to conscious knowledge.

Third is a generation test, in which participants are asked to produce part of the repeated information they had been exposed to during the experiment [e.g., 6, 25–27]. This test more closely matches the training conditions, but participants still have to access the trained knowledge in a different way, and as such any lack of consciously accessible knowledge in the generation task could be due to the test missing critical aspects of the available knowledge. This awareness measure also suffers from consciousness purity issues, in that both non-conscious and conscious knowledge can be used at any point during the test. As with the recognition test, in the absence of consciously knowing what they are generating, they can use their ‘hunch’ of what might be right. If the participant is able to generate parts of the repeating information, under the criteria of the test, this would be assumed to have come from conscious knowledge, even though the participant was responding based on non-conscious knowledge.

Fourth involves the participant making confidence ratings about their performance on one of the other tests (such as the generation or recognition test) [18]. The logic behind confidence ratings is that if participants are confident they are correct, that indicates they have conscious awareness of something they learned during the experiment. If participants are not confident, they may be relying on information that is not fully conscious, such as a feeling of familiarity or a hunch. This form of test requires the participant to make a metacognitive assessment of where the information supporting their decision is coming from. Similar to the other tests, confidence ratings can also be missing some of the explicit information used by participants during the experiment since they measure the participant's confidence rather than the knowledge acquired.

Issues for Measuring Awareness

One focal point of debate in implicit learning research is the extent to which people are conscious of what they have learned [6, 11–15, 24, 28]. Consciousness is a tricky concept; it would be hard to deny that there is some subjective state associated with being aware of the current surroundings and mental events [29, 30], but exhaustively measuring a participant's mental contents is likely an unattainable goal [14, 15]. The largest issues for measuring consciousness are:

1. *What measures should be used?* There are many possible measures that each have strengths and weaknesses (as previously discussed), and some measures are easier to implement in certain tasks than others. Another problem is that slightly modifying an awareness measure can lead to drastically different awareness results (e.g., [6] versus [26]).

2. *How do participants transition from being unaware to aware of what they have learned, and how gradual is this transition?* This is tied to the nature of conscious awareness, and how it changes over time. A lot of implicit learning research has attempted to demonstrate that participants are either aware [14, 15, 26, 31–35] or unaware [6, 19, 20, 36–40] of what was learned. The division between aware and unaware mental states is unclear because participants can gradually develop awareness across the time course of learning [25, 26, 41–45], and therefore being aware or unaware of the learning contents are not dichotomous states of awareness [46–52]. Furthermore, why is the transition from unaware to aware of learning not a universal finding, either between experimenters or between participants? The participants' control over acquired knowledge may provide a predictive measure that could help resolve this issue [cp. 53].

3. *Is awareness a causal force or a by-product of learning and cognition?* It has been argued that awareness must precede learning [e.g., 26]. However, it has also been argued that awareness does not develop from implicit tasks [e.g., 6, 19, 54]. The case has also been made that awareness can develop during learning, but is not required [e.g., 41].

4. *Is the learned information consciously accessible?* This issue is contentious [11–15]. Some have argued that implicit learning tasks result in consciously accessible knowledge in all participants who learn the repeating information, [15, 26, 32–35, 55], while others have argued that the acquired knowledge remains non-conscious in at least a subset of learners, [6, 36, 37, 39].

Part of the problem at the heart of this debate is that there are still no fully objective measures of conscious awareness. Shanks and St. John (1994) argued that awareness measures should be both valid and exhaustive [but see 56–63]. The measure must be valid in that it is really capturing what is responsible for differences in performance [cp. 60, 64] . This is hard to guarantee since it is possible the existing measures are merely reflecting aspects that are correlated with changes in performance, but missing the key factor or construct actually responsible for performance. The measure must be exhaustive by fully and accurately representing the entire contents of a participant's conscious awareness. This is also hard to guarantee as the measure may not fully engage the participant's ability to demonstrate their conscious awareness of what they had learned.

A further problem with using conscious awareness as the criteria for how learned information is represented is that some parts of the knowledge may be consciously accessible while other aspects are not [46–49]. Many tests of awareness focus on the participant being able to identify or verbally articulate the repeated information [e.g., 19], while ignoring other aspects of conscious experience, such as familiarity with the information [e.g., 65]. It is incorrect to then conclude that all knowledge is consciously accessible or not from these tests, as they are not fully representing the participant's conscious awareness. Additionally, any available knowledge (conscious or non-conscious) will probably be used to some extent on tests of conscious awareness, so treating the test performance as evidence of only conscious or non-conscious awareness is also flawed [66–68].

Role of Task Directions

Incidental learning refers to unplanned and non-intended learning that occurs while doing other activities [21, 69, 70]. Implicit learning could be classified as a special case of incidental learning, because incidental learning involves learning environmental regularities without the intent to learn them, which is usually true for implicit learning tasks as well [13]. The two terms are sometimes used interchangeably [e.g., 43]. However, incidental learning does not entail additional assumptions about what is learned as in implicit learning (e.g., awareness of what was learned, processes associated with learning); rather, incidental learning tends to be a shorthand description for the type of directions given to participants to guide their learning strategy [e.g., 21]. As such, it is not surprising that incidental learning continues to be invoked when discussing implicit learning research.

Implicit learning tasks customarily utilize incidental, or implicit, instructions rather than explicit instructions[2]. Explicit instructions directly tell participants to learn the information, but implicit instructions tell participants to perform the surface task and provide no information about the underlying repeating information (e.g., 'respond to the target's location as quick as possible' in SRTT, [74]; 'find the target in a field of distracters' in contextual cuing, [19, 36]).

Explicit learning instructions (i.e., directions specifically telling the participant to learn the repeating information) have sometimes been used in different implicit learning

[2]This distinction is somewhat different for implicit and explicit memory tasks [71, 72]. A key difference between implicit and explicit memory tests is whether the person is instructed to use words encountered during the experiment on the test (explicit), or use the first word that comes to mind to answer the question (implicit; [73]). This is similar to the direct and indirect test distinction on page 14.

tasks in order to examine whether the participants strategy changes the quantity or quality of learning. Explicit directions to learn the repeating sequence in SRTT tends to result in faster responses compared to random responding ([27, 45, 75, 76], but see [77]). However, explicit directions to learn the repeating visual arrays in contextual cuing have not resulted in reduced search times [6]. Explicit directions to learn the underlying grammar in the artificial grammar task tends to hurt learning ([78, 79]; but see [80]). The failure or success of participants learning the repeating information seems to be contingent on the complexity of the information [24]: if the information is simple enough to verbalize or hold in working memory, there will likely be some benefit from explicit directions that lead the participant to figure out the repeating information; but if the information is too complicated to figure out or keep online in working memory, there will probably either be no benefit or a cost to explicit directions.

The previously described experiments used between-participants comparisons of implicit and explicit learning directions. Willingham and colleagues developed an experiment that combined the two kinds of directions [5]. In this SRTT experiment, participants were trained on two types of repeating sequences: (1) a repeating sequence that participants were aware was repeating and which used a red object as the target; and (2) a repeating sequence that participants were told was random, and which used a black object as the target. During an additional period of testing following training, there was an additional series of trials in four conditions: (1) the same cued repeating sequence, still with the red cue; (2) the cued repeating sequence, shown with the not-cued black object; (3) the not-cued repeating sequence, shown with the not-cued black object; and (4) random not-cued sequences. Response times were fastest for the cued sequence, next fastest for both the never-cued and cued sequence shown with the black object, and finally slowest for the random sequences. Integrating the different direction types into one within-participant manipulation allowed for a more direct comparison of the effects of the implicit and explicit learning directions, as each participant’s reaction times or accuracy can be measured under the different learning conditions. The second and third experiments of this dissertation have adopted this manipulation in conjunction with a process-dissociation recognition test (see page 14) to compare the participants' control over acquired knowledge under the different cue/direction conditions.

Information Processing

The two-process theory of attention ([1, 2]; but see [81]) states that there are two main types of information processing. One type are controlled processes: they require attentional resources, tend to be accessible by conscious awareness, and are intentionally used. The other type are automatic processes. These are less limited by attentional resources, are not open to conscious awareness, are not intentionally used, take extensive exposure to learn, and are rigid once learned.

Both automatic and controlled processes are likely recruited during explicit and implicit learning tasks [3, 25, 47, 48, 82, 83]. This means that implicit learning tasks will not just involve automatic processes, nor would explicit learning tasks only involve controlled processes. That being said, automatic processes require more training to develop than controlled processes [2], so one would expect automatic contributions to implicit learning tasks to increase with training.

There does seem to be a link between states of conscious awareness and type of processing. Controlled processes tend to be accessible by conscious awareness, while automatic processes are not [1–3, 84–90]. However, just because controlled processes are available to conscious awareness does not then necessitate that the information gained is fully aware. For example, participants in an artificial grammar experiment can control when they apply information previously learned, but still cannot fully verbalize what they have learned [91]. Awareness of an automatic process can occur through observing the outcomes of the process or in noticing the interference between the automatic and controlled processes [e.g., 92]. Since the link between processes and conscious awareness is not direct, the processes cannot serve as a proxy for conscious awareness.

The original distinctions between automatic and controlled processes have been criticized over time. There is evidence that automatic processes are sensitive to available cognitive resources [93–95], as well as being controllable if attention is focused to relevant portions of the automatic processing [96–101]. Logan [102] argues that the difference between automatic and non-automatic processes is the amount of exposure. Participants can either search through the contents of their memory, which is slow and effortful, or access the solution via direct memory retrieval, which is faster and easier. In other words, participants in a controlled stage have to solve the 'problem' each time; in an automatic stage attained after more practice, they only have to find the solution in memory. Logan also proposes that <u>all</u> information is encoded and retrieved as long as it is attended.

Tzelgov [100, 101, 103, 104] expanded on Logan's automaticity theory. Tzelgov argues that a critical difference between automatic and controlled processes is whether or not the process is being monitored: automatic processes are not intentionally used to serve goal-directed behavior nor are the consequences of the automatic processes evaluated for that goal, whereas monitored processes are used in accord with the current goal, and progress towards that goal is actively monitored [104]. By his definition, monitoring a process requires conscious awareness of it. Tzelgov explains that automatic processes are faster than the monitored processes because the outcome of the process is directly activated (as in Logan's idea of direct memory retrieval), whereas monitored processes have additional steps for accessing the outcome of the process and in updating the goal state.

By using process-dissociation (see the process-dissociation section on page 14), it is possible to measure relative amounts of control over knowledge between different manipulations. It is also possible to determine if the automatic process estimates change with the different learning direction or time manipulations. The second and third experiments in this dissertation manipulate repetition-knowledge directions given to participants (i.e., that a cued sequence is repeating, or a visual configuration of elements is repeating) in two implicit learning tasks to determine if the process estimates can account for any performance differences resulting from the different task directions. If strategic control is beneficial for a certain implicit learning task, cuing participants in to the repeating elements of the task should improve performance as well as boost controlled processing; but if strategic control is not crucial for the task, then cuing participants in to the repetition should not improve performance (and may possibly even impair performance) and should not increase effective controlled processing.

Attention in Implicit Learning

Before discussing the role of attention in implicit learning, the different aspects of attention and their relevance to implicit learning are defined. Raz and Buhle [105] provide a useful framework for the different subsystems of attention, drawing from the work of Posner and Boies [106]. The three attentional subsystems are alerting, orienting, and executive. They are theorized to be functionally and anatomically separate, with imaging data supporting this view [107–109]. In this framework, the alerting subsystem is the foundation of the other subsystems and is associated with vigilance or sustained attention tasks. The alerting subsystem is likely necessary for implicit learning, but to no greater extent than for other cognitive processes. The orienting subsystem is responsible for selecting one stimulus out of many possible stimuli, and is frequently measured with cued-location reaction times. It is thought that the cue helps orient the attentional and sensory system to where the stimulus will occur, especially since an invalid cue typically shows a cost in reaction time. This subsystem may be involved in some forms of implicit learning (e.g., contextual cuing); however, it probably is not the sole level of attention required for learning. Finally, the executive attention subsystem includes the separate selective and focused attention constructs, which Raz and Buhle [105] characterize as a conflict monitoring and resolution system. Memory researchers propose that executive attention is the cognitive component that holds the active mental information together [110–114].

There is mixed evidence for how necessary executive attention is in implicit learning [11, 13]. It has been argued that this type of attention is not required for implicit learning ([75, 115, 116] [3]; also see [117]). Jimenez and Mendez [118] claim that implicit learning is independent of attentional load, but can only associate items concurrently held in working memory. Similarly, Jiang and Leung [119] have speculated that attention is needed, but only for binding the items currently in attention [similar to 120–122]. Finally, some researchers claim that attention is needed for implicit learning overall, and that when attention is divided or reduced for the learning task, so are the benefits of learning [74, 123–134]. Therefore, it does seem that some attention to the information being learned is necessary; but the extent to which performance is harmed by refocusing attention elsewhere varies by task: tasks that require minimal attention (such as sequence learning) will not suffer the same decrements as tasks that load heavily on attention (like contextual cuing). This is further expanded on page 19.

For the SRTT and contextual cuing tasks employed in this dissertation, executive attention is theorized to be required to link or bind the concurrent pieces of information together. This fits with both a dual-process approach for investigating learning following training on implicit tasks as well as past implicit learning findings [e.g., 128]. However, attention will not be directly manipulated in these experiments, beyond the likely connection between intent and attention.

[3]Nonattentional learning theories suggest that there is another distinction in learning that is contingent on whether or not manipulating attention impacts performance. The attentional and nonattentional systems are proposed to be independent and operate in isolation. The attentional system is better equipped for more complicated relations between items but is tied to attentional resources; while the nonattentional system better handles simple relations in the severe lack of attentional resources [115]. The experiments in the dissertation are operating within the attentional implicit learning system as the associations are non-trivial and the tasks are performed alone.

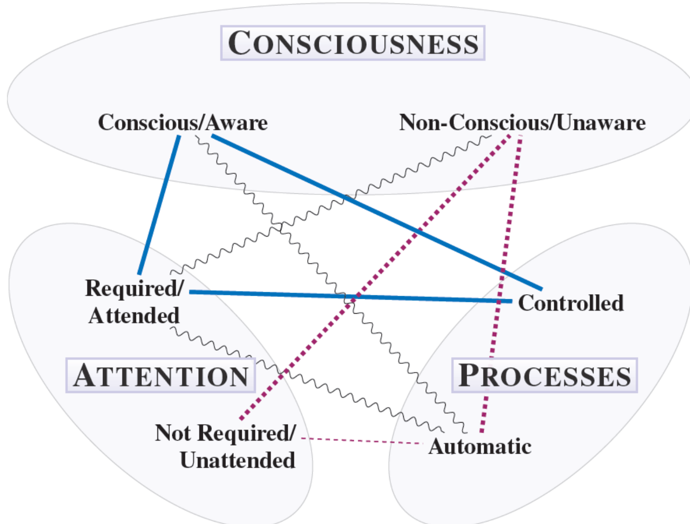

Figure 1.1. Representation of how consciousness, attention, and cognitive processes interrelate. The solid blue line indicates the linkages reported for aware states of consciousness, the dashed purple line indicates the observed relations for unaware states of consciousness, and the wavy black line represents links that do not fall under the other two main relationships. The lighter weight line between attention–not required/unattended and processes–automatic indicate that this relationship is not as well understood as the other links.

Interrelations Between Consciousness, Attention, and Automatic and Controlled Processes

There are many interrelations between consciousness, attention, and automatic and controlled processes, but direct links are not clear. The view assumed in this dissertation is shown in Figure 1.1. There are two primary interrelations associated with the two main categories of awareness states: the aware conscious state (indicated with solid blue), and the unaware non-conscious state (indicated with the dashed purple). Items entering awareness tend to be attended [75, 131, 135–137], and will tend to undergo controlled processing [87, 88, 138–142]. Furthermore, information in the focus of attention will probably undergo controlled processing [3, 143]. Information that does not reach conscious awareness is probably not attended to [46, 124, 136, 144–146], and will primarily be processed automatically [25, 39, 84, 88, 138–140, 147]. The thin dashed line indicates the less clear relationship between automatic processing and attentional demands [1, 3, 118, 143].

However, as indicated by the wavy lines, other linkages exist. Information that is attended does not have to reach conscious awareness [19, 144, 148–151], and can be processed automatically [3, 152]. Also, information that has been processed automatically can later reach conscious awareness [84].

Process-Dissociation

As described previously, an issue for many conscious awareness tests, especially generation and some recognition tests, is that non-conscious information can also be used during the test, which then inflates the measure of what is consciously accessible. This contamination issue has been grappled with in different ways.

One major approach has been to contrast direct tests, in which participants are told to apply their knowledge, and indirect tests, which do not ask them to do so, or even ask them to deliberately not apply their knowledge. This approach equates conscious knowledge with what is under controlled processing, and unconscious knowledge with what is automatically processed. An early attempt [68] at solving the process purity issue in the realm of non-conscious perception was to compare how sensitive participants were to the stimuli when tested directly or indirectly. Direct tests asked participants to attempt a perceptual discrimination. Indirect tests asked participants to perform a different task which could be influenced by the percept indirectly. For this method to be valid, the direct test must be more sensitive to conscious percepts (or knowledge) than the indirect test. The underlying logic is that if reactions are faster or more accurate on the indirect test, then non-conscious knowledge is used. However, Jacoby [3, 4] argued that neither of these tests are “process pure”, and that both conscious and non-conscious knowledge are likely used during both direct and indirect tests.

The process-dissociation (PD) procedure is an implicit memory training and testing technique [3] that assumes process impurity and instead sets conscious and unconscious knowledge against each other. This approach again assumes that conscious knowledge is controlled, and unconscious knowledge is automatically processed. The procedure is accomplished by having one situation in which both automatic and controlled processes yield a correct response (Inclusion condition), and another situation in which the controlled processes support a correct response but automatic processes do not (Exclusion condition). One example is the false fame effect [153]. Participants read a list of non-famous names, either with full or divided attention. They were later asked to judge how famous names were in a new set of names, which consisted of the previously read non-famous names, new non-famous names, and famous names. Automatic and controlled processes could support performance on the new non-famous names and famous names, but controlled processes were in opposition with the automatic processes for the previously read non-famous names, as they had been given a familiarity boost by the prior reading. As the authors predicted, the divided attention participants were more likely than the full attention group to falsely identify the old non-famous names as famous as they did not have sufficient control over the previously acquired knowledge. PD has been a useful tool for implicit memory research [154].

The derivation of controlled and automatic process estimates from identification rates on the Inclusion and Exclusion tests begins with how the processes support decisions on each test. Correct identification on the Inclusion test can come from both controlled and automatic processes (in the absence of controlled, hence the $(1 - Controlled)$ multiplier):

$$Inclusion = Controlled + Automatic \times (1 - Controlled). \tag{1.1}$$

Correct identifications on the Exclusion test can only be made when the automatic familiarity with items is overridden by controlled recollection of the item. Exclusion errors occur when automatic process function in the absence of controlled processes, this is represented as

$$Exclusion = Automatic \times (1 - Controlled). \tag{1.2}$$

The rates at which participants identify the to-be-included or -excluded information in the previous formulas can be combined to arrive at the process estimates. The controlled process estimate is found by subtracting the Exclusion test's false alarm rate from the Inclusion test's correct identification rate:

$$Controlled = Inclusion - Exclusion. \tag{1.3}$$

The automatic process estimate is the incorrect inclusion rate of previously trained items from the Exclusion test divided by what is not part of the controlled process estimate:

$$Automatic = \frac{Exclusion}{1 - Controlled}. \tag{1.4}$$

Using PD to calculate the automatic and controlled process estimates avoids the process purity assumption, i.e. that the processing supporting performance on any particular task is only controlled or only automatic.

PD can reveal information about the extent to which participants have control over knowledge gained from the experiment. Inclusion test responses can be supported by both controlled and automatic knowledge. On the other hand, 'correct' Exclusion test responses must come from controlled knowledge. If a participant has perfect control over the knowledge gained from training, they will always be able to exclude the necessary items, essentially precluding any input from the automatic processes. This will result in a high (approaching 1.0) controlled process estimate and very low (approaching 0.0) automatic process estimate. However, if a participant has poor control over the knowledge gained from training, it will be reflected by the automatic processes playing a greater role in supporting test decisions. Under Exclusion directions, weaker control over the knowledge will allow the automatic processes to support a false decision. This will then increase the false alarm rate on the exclusion test as well as possibly decrease the hit rate on the Inclusion test. Consequently, the controlled process estimate will be lower and the automatic process estimate will be higher than for the perfect discriminator.

One key assumption of PD is that the controlled and automatic processes are independent [3]. Curran and Hintzman [155] argued that if instead the two process types are correlated (i.e., high controlled process estimates associated with high automatic process estimates), it will produce what appears to be a dissociation between controlled and automatic processes, when it is really just reflecting a difference in response bias between participants (i.e., some participants consistently reject items, other participants consistently include items). Jacoby [156] responded by producing artificial data that suggested that Curran and Hintzman were unable to distinguish between an actual independence violation or an aggregation error. Furthermore, Curran and Hintzman's knowledge test directions violated PD requirements. To prevent violating the independence assumption, Jacoby [4] argued researchers should do the following: (1) Exclusion directions to participants must specify that they should only exclude items when they have full recollections for the memory, and (2) incorrect Inclusion rates to the novel items must be equivalent for Inclusion and Exclusion conditions.

Buchner, Erdfelder, and Vaterrodt-Plünnecke [157] argued that the differences in base-rates of guessing between direction types should be included in the process-estimate calculations. Guessing base-rates are an index for what a participant's particular bias is in responding either 'old' or 'new', and are derived from their likelihood of calling the novel items 'old'. By including random items in both Inclusion and Exclusion direction types, it is possible to determine if participants are responding to items in the two direction type tests differently, or if they are actually evaluating the items through controlled (Exclusion) and automatic (Inclusion) based memory processes. The authors were concerned that differences in guessing were possibly altering one (or both) process estimates. Unfortunately, the resulting modified PD procedure that factored in guessing had the effect of separating guessing out into an independent form of memory not influenced by automatic processes. Yonelinas and Jacoby [158] countered this by showing that guessing only invalidates the process estimates if the base rates of guessing differed between the Inclusion and Exclusion tests. Jacoby [4] further claimed that the correction for guessing does not provide correct process estimates if the base guessing rates are different between tests. Consequently, base rates of guessing should be reported and compared for all included experiments to ensure assumptions of PD are not being violated.

Current Experiments

The goal of the dissertation is to show that performance differences from training on implicit learning tasks can be characterized using a cognitive processes perspective, and that it is worthwhile to address implicit learning using a different approach. I advocate using PD as a method to allow for the comparison of the processes supporting knowledge gained from training. To allow for the necessary comparisons in PD, I include an experimental technique (adapted from [5]) that presents participants with concurrent explicit and implicit directions for different subsets of stimuli. In addition to process-estimate comparisons, performance differences from the explicit and implicit learning conditions are compared with respect to the differences in theorized learning processes.

The included experiments probe the relationship between automatic and controlled processes and performance on implicit learning tasks. These experiments move beyond relying on self-reports of awareness to instead ask if participants have control over application of the knowledge they gained during training. Furthermore, these experiments focus on the relationships between task performance and the relative process estimates under different types of learning directions (i.e., implicit learning directions with no mention of repetition, or explicit learning directions with direct mention of the repeating nature of stimuli).

Implicit Learning Tasks

Experiments 1 and 2 used the serial reaction time task (SRTT), and Experiment 3 used the contextual cuing task. Experiment 1 followed a typical SRTT paradigm, with consistent repeated exposure to one trained sequence interspersed with rare exposure to a novel sequence; Experiments 2 and 3 used the novel knowledge-repetition manipulation (similar to [5]). SRTT and contextual cuing were chosen because participants' performance in the tasks are differentially affected by explicit directions indicating to the subjects that stimuli will be repeating: reaction times are faster compared to random responding after explicit directions in SRTT, but contextual cuing reaction time differences between participants with the repetition knowledge and without have not been found. By utilizing two implicit learning tasks with different effects of overt repetition knowledge, it is possible to compare the process estimates in an attempt to further understand the changes associated with explicit and implicit learning.

Serial Reaction Time Task

One prominent task used in implicit learning research is the serial reaction time task [SRTT, for a review, see 41]. A typical set-up for the SRTT is a display with four possible target locations arranged along a horizontal line, and some method of responding (i.e., effectors, usually individual fingers on one hand), resulting in four possible response locations. A trial begins when the target appears, and ends when the participant responds at the appropriate response location. The target then appears in a new location, and this process is repeated. SRTT experiments tend to involve hundreds of trials. Unbeknownst to participants, there is an embedded repeating response sequence that leads them to make the same series of responses through the course of the experiment. As experience with the sequence increases, the time required to make responses decreases overall, and to a greater degree for the sequence trials than for random trails. Standard SRTT is an incidental learning task as participants are not told to learn the repeating series of response locations. Furthermore, improvements in reaction time are found for participants who are unaware of what they have learned, suggesting the learning has occurred in the absence of awareness [as reviewed in 41]. Thus SRTT meets the criteria for implicit learning.

One important manipulation is the instructions given to participants about the nature of the task. By default, participants are not informed of the repeating nature of the sequence, or that there is a sequence at all [41]. However, a few studies have instructed some participants that there is a repeating sequence, and it would benefit their performance to learn it [5, 76, 77, 159–162]. These experiments have tended to find a benefit for being instructed about the presence of the sequence repetition [5, 76, 159].

PD has also been used with SRTT [25, 47, 48, 82, 163, 164]. However, these studies have analyzed only the basic Inclusion and Exclusion test results, making inferences from differences in performance by Inclusion and Exclusion directions about awareness states [i.e., conscious or nonconscious; 47] or type of knowledge gained by the participants [i.e., implicit or explicit; e.g., 25, 48, 164]. They did not calculate the automatic and controlled process estimates, as will be done in Experiments 1 and 2.

Contextual Cuing

The contextual cuing effect is the decrease in reaction time for repeated spatial configurations in a visual search task [19]. This learning seems to be unconscious and not verbalizable ([19]; but see [26]), robust to interference or noise in the display [165], sensitive to the training context [166], dependent on attending predictive information [119, 127, 130], retained for at least a week [6, 38], and seems to generalize to real world scenes [167, 168]. It has been suggested that participants abstract the spatial configuration of the locations of target and distracters, which then helps attention to shift faster to the target [for a review, see 36].

An explicit instruction manipulation was conducted by Chun and Jiang [6], wherein learning of the spatial context was compared between participants who were given explicit instructions to try and learn the repeating arrays in a visual search task and those who just performed the visual search task. It was thought that if some aspect of the task could benefit from explicit learning of the arrays, performance would improve after explicit instruction. If, however, the information was either too difficult to learn explicitly, or if the most efficient way to learn this information was the gradual implicit abstraction of the regularities, there should be no difference in performance between the two groups, or even a performance deficit in the explicit instruction group. Chun and Jiang [6] found that even with the explicit instruction, participants performed no better than their implicit counterparts, suggesting that this type of learning can occur without being given knowledge about the environmental regularities. Before this work, no PD manipulations had been conducted with contextual cuing, so it is not yet clear what to predict for process estimates [6, 26].

Similarities and Dissimilarities Between SRTT and Contextual Cuing

There are several useful similarities between SRTT and contextual cuing when compared against other implicit learning tasks. SRTT and contextual cuing are both non-symbolic tasks; the stimuli do not have to be ‘read’ in order to perform the task. This is different than other tasks that use symbols, such as artificial grammar learning or the Hebb digits [13]. This reduces the possibility that differences in process estimates or trends in performance are due to the extra cognitive processing needed for comprehending the stimuli. Both tasks require a response on the basis of a simple stimulus feature; either indicating the spatial location of the target in SRTT, or responding based on the direction of the target in contextual cuing. Therefore, somewhat comparable task demands are being placed on the participant; e.g., participants are not having to categorize in one task but not the other or solve problems in one experiment but simply respond to stimulus locations in the other. Furthermore, the executive attentional load in these two tasks is relatively low compared to other implicit learning tasks. The visual search task is somewhat more engaging than identifying which of the possible locations the target has moved to. However, both SRTT and contextual cuing have lower executive attentional demands than complex system tasks or verbally repeating strings of numbers in the Hebb digits task. The similarities between SRTT and contextual cuing make the pair a good place to start identifying differences between the different implicit learning tasks, and the cognitive processes engaged by each.

Contextual cuing is different from the serial reaction time task (SRTT) in several ways. First, contextual cuing is at its heart a visual search task while SRTT is a choice reaction time task. As such, the two tasks have different specific task demands. For example, the response for contextual cuing is to indicate the direction of the target, which involves finding the target, figuring out which way it is pointing, then translating that into an appropriate response. For SRTT, there are discrete possible target locations (typically four) and corresponding possible responses. When the target appears, the participant just needs to map the stimulus location to the response location. The second difference is that contextual cuing has strong visual and attentional components whereas SRTT has a strong motor component with less involvement of selective attention. Finding a target in a cluttered field of very similar distracters is more difficult and attentionally demanding than identifying the location of a single target. It was recently demonstrated [169] that the two tasks, when set up properly and performed concurrently, will not interfere with each other, suggesting that there are not many shared central cognitive resources. The third difference is that contextual cuing does not have a built-in temporal component but SRTT does. The trial-to-trial relationship between possible configurations and target locations is not controlled in contextual cuing; the only control is in ensuring there is roughly uniform and equivalent exposure to the repeating configurations. In SRTT experiments, the trial-to-trial relationship is what is being repeated and trained. The final difference is that explicit knowledge of the repetition can be beneficial in SRTT [5] but does not seem to have an effect in contextual cuing [6]. With these differences, particularly in the varied demands on attention and differential outcomes from explicit learning directions, there should be differing uses of controlled and automatic processes between the two tasks. Controlled processes will likely play a greater role throughout the contextual cuing visual search task itself, but less of a role in how the participant is willfully deploying their attention under explicit learning directions [120, 170, 171] than in SRTT.

The Experiments

Experiment 1 establishes that PD can be used in an implicit learning task to measure the cognitive processes used by participants. Previous experiments have used PD in SRTT, but have stopped short of calculating the process estimates [25, 47, 172], instead relying on differences in test performance to indicate differences in available knowledge. The training followed the normal paradigm of SRTT, with learning being indexed from the reaction time difference between the trained sequence and a novel sequence, and was done to provide a solid amount of experience with the two trained sequences before the ending recognition-PD test. The first experiment demonstrates that the process estimates can be calculated from the PD recognition tests without violating assumptions of PD [4].

Willingham and colleagues' technique [5] was adopted in the second and third experiments. This 'repetition-knowledge', or instruction manipulation has worked previously in SRTT ([5]; see page 8 for a brief description), and was utilized in Experiment 2. This instruction manipulation has not previously been used in contextual cuing experiments, so Experiment 3 allowed for the first direct comparison of explicit and implicit instruction on contextual cuing search performance.

Experiment 3 also looked at how learning in contextual cuing changed across time, as well as how the automatic and controlled process estimates changed with the differing lengths of training. It was also possible to test Smyth and Shanks' [26] claim that contextual cuing learning is driven by explicit knowledge that becomes measurable when training length is increased [but see 6]. Additionally, based on Logan's framework [102], automatic processes should increase with greater exposure to the stimuli, and at a certain point the attentional resources could support the addition of controlled processes possibly supporting the formation of awareness. Smyth and Shanks' [26] account predicted that significant changes in performance would only occur when controlled processes were strong enough to be able to sufficiently support behavior, also with explicit knowledge linked to the controlled processes. So in one account, controlled processes would largely follow learning of the repeated configurations, but in the other, controlled processes are necessary for learning.

Chapter 2

Experiment 1: Serial Reaction Time Task with a Process-Dissociation Recognition Test [1]

This experiment expanded on the research by Destrebecqz and Cleeremans [25] in deriving process estimates for trained sequences. Destrebecqz and Cleeremans' participants were trained on a single sequence under two timing conditions. The condition with a 250 ms pause between responding and the next sitmulus has been associated with bolstering explicit awareness and knowledge of the sequence. The other condition did not have a pause between responding and start of the next trial. After training on the sequences, participants were asked to generate a sequence under two instructional forms. The Inclusion instructions had participants try to generate the trained sequence, and the Exclusion instructions had participants try to generate anything that was not the trained sequence. The logic was that if participants had control over the trained sequence knowledge, they should have minimal intrusions of that information in the Exclusion test. However, if this information was out of their control, there would be significant intrusions of the trained sequence in the Exclusion generation. By examining the generation proportions under the two instruction sets, Destrebecqz and Cleeremans concluded that

[1] This experiment in this chapter has been accepted for publication at *Advances in Cognitive Psychology*

participants who were in the pause condition had the ability to control the knowledge gained from sequence training, whereas participants in the condition that did not allow for explicit knowledge to develop did not have control over the knowledge gained.

The current experiment was conducted to determine if the controlled and automatic processing estimates could be derived rather than inferring awareness states from Inclusion and Exclusion test scores, as well as to determine what experimental set-up would facilitate the PD calculations. This allows the discussion of implicit learning to move beyond the knowledge gained through training to a deeper level of the processes supporting the knowledge. Examining the control participants have over knowledge acquired through training can provide new insights into what is changing with learning that may not be possible by inferring awareness states. The current experiment can also improve the understanding of what changes with training in sequence learning by allowing the comparison of a participant's self-reported awareness of learning and their control over the acquired knowledge.

In the present study, different sequences were employed in the two distinct halves of the training. The Inclusion test instructions for a subsequent recognition test asked participants to respond "old" if the presented sequence was from either half of the training phase, and thus, knowledge of either sequence would lead to a correct response; this could result from the influence of either controlled or automatic processing. For the Exclusion task instructions, participants responded "old" only if the sequence was from one half of the training phase. Thus accurate responding in the Exclusion condition requires that participants identified the sequence as encountered before and from the correct half (e.g., was it from the second half of training?). Consequently, to the extent that controlled processing fails, but automatic processing influences performance, participants will make errors on the Exclusion test.

Similar to the memory experiments [3, 173], the current experiment required participants to discriminate which half of the experiment an item (i.e., sequence) appeared for the Exclusion directions. If participants have control over the sequence knowledge they were trained on, they should be able to successfully make this discrimination. If participants do not have adequate control over this knowledge, then they will be unable to exclude the directed trained sequence as they will be relying on the general familiarity for both sequences in responding. This will lead to a higher automatic processing estimate, and a low or non-existent controlled processing estimate. [2] For a participant to have a controlled process estimate in this experiment, the participant needs to have access to each of the two sequences that were trained. If they are only able to recognize that the sequence had been experienced before, but not which half, their control over the knowledge for that sequence is incomplete [2]. In this case, their judgment will be based on the automatic processes supporting familiarity.

There have been concerns about the possibility that participants could have awareness of the learned information, but not have access to when it was learned. One valuable perspective on this issue comes from Yonelinas and Jacoby [174]. This 'partial recollection' of the learned information should result in the automatic estimates looking like controlled estimates. This is because the partial recollections would result in those items being treated as familiar rather than actually recollected, thus bleeding the partially recollected items into the automatic process estimate. The authors then concluded that this must be infrequent compared to the full recollection rates, and was not a great concern.[3]

In the acquisition phase of implicit learning experiments, participants are usually only exposed to one repeating sequence [74] or set of repeating information (e.g., the repeating visual search arrays of contextual cuing, [19]). Adding a temporal component to testing after non-intentional learning allows for a different criterion of what knowledge is accessible to the participant, as well as a finer grain of analysis of what knowledge is

[2]It is possible that participants will lack sufficient control to reliably discriminate temporal half [15]. However, even if this is the case, since PD allows for the calculation of relative use of the two processes, the process estimates will reflect use of controlled processing if participants are able to discriminate temporal half at least some of the time.

[3]This admittedly comes from a field other than sequence learning. However, Yonelinas and Jacoby [174] argued that their results should generalize to other forms of memory.

measurable during testing. Importantly the introduction of a second sequence within the SRTT paradigm can lead to some temporary short-term interference during its initial acquisition, but it does not impair learning of either sequence [see 175].

It has been proposed that the SRTT, and implicit learning research in general, can benefit from shifting to thinking of the underlying processes for non-intentional learning [e.g., 103, 176–178]. One conceptualization of an automatic process assumes that the process is capable of occurring without conscious control and without intention ([179, 180]; but see [34]). However, all participants will employ both automatic and controlled processes during learning and at test [72]. Thus, this study will determine if the standard version of PD can be implemented within the SRTT paradigm, and based on that investigate the relative influence these two processes have on SRTT.

The current experiment was conducted to determine if the controlled and automatic processing estimates could be derived rather than inferring awareness states from Inclusion and Exclusion test scores, as well as what experimental set-up would facilitate the PD calculations. This will allow the discussion of implicit learning to move beyond studying the knowledge gained through training to a deeper level of the processes supporting the knowledge. Examining the control participants have over the knowledge acquired through training can provide new insights into what is changing with learning that may not be possible simply by inferring awareness states. The current experiment can also improve the understanding of what changes with training in sequence learning by allowing the comparison of a participant's self-reported awareness of learning and their overt control over the acquired knowledge.

Different knowledge tests were used following standard training on two separate sequences. In the current experiment, after training, a self-report knowledge test was administered, in which participants were asked if they noticed any repeating information. Next they were given a recognition PD test wherein they had to rely on the knowledge gained during training to be able to appropriately include or exclude the presented sequences. A recognition PD test was used rather than a generation test for several reasons.[4] First, a recognition test forces participants to enter the trained sequences, whereas for a generation test it would be possible for participants to never produce the trained sequences. Guaranteeing that participants are re-entering the sequences then allows for a more valid comparison of the participants' controlled and automatic processes for the trained sequences. That being said, there should not be drastic differences between ending memory tests within a modality [23]. Furthermore, both controlled and automatic processes are expected to be used at the memory test as these are posited to support most, if not all, decisions [3, 87, 141].

While there will likely be differences in process estimates between participants, the question remains whether predominant automatic processing can drive enhanced performance with the SRTT. If automatic processes are sufficient for SRTT, participants who did not show evidence of significant controlled processing at test should still have the speeded serial reaction times after acquisition of the trained sequence. Finally, it was expected that overall there would be both controlled and automatic processing estimates; i.e., both processes support the speeded responses on trained sequences.

Method

Participants

Forty-six Colorado State University students participated in exchange for partial course credit. All participants had normal or corrected-to-normal vision.

[4]It is possible that the recognition PD test will underestimate the controlled process estimate. However, the process estimates are relative estimates of the two process types, so if the controlled process estimate is underestimated the automatic process estimate will be overestimated. But because the two process estimates are mathematically linked, it is incorrect to directly compare the two process estimates. To spoil the results, a controlled process estimate was found, so the concern that a false rejection of controlled processes occurring is unwarranted.

Table 2.1. Sequences participants were trained on, transferred to during training, and exposed to during the recognition test. The leftmost response position is designated by 1, and the rightmost is designated by 4.

Sequence Type	
Training	Transfer
1 4 3 1 2 4 2 3 4 1 3 2	2 3 1 3 4 2 1 4 3 2 4 1
1 2 3 1 4 2 1 3 4 3 2 4	4 2 3 4 1 2 4 3 2 1 3 1

Materials

All stimuli were shown and data were collected in E-Prime [181]. The SRTT display consisted of a white background with four black square outlines evenly spaced in a row along the center of the display. These four black square outlines essentially served as the place holders for where the target could appear on any trial. Each square was 5 cm along a side, the black outline was .2 cm thick, and the squares were filled with white. The green target was 3.8 cm in diameter. It appeared in the center of the appropriate square for each trial.

In total, four ambiguous [124], second order conditional sequences [182] were used in this experiment. All sequences had equivalent response frequencies. The two training sequences were presented to all participants, but presented in a counterbalanced order. Participants were trained on the sequences shown in the training column of Table 2.1. Learning of the practiced sequences was assessed through the introduction of new sequences at the eighth block during each training half, known as the transfer sequences. These sequences were chosen because they had minimal overlap in item response chunks. Importantly, the two training sequences had no overlapping item response chunks longer than 2 responses.

Procedure

Responses were made with the 'v', 'b', 'n', and 'm' keys, which corresponded to the four display locations from left to right. Participants were instructed to respond as quickly and as accurately as they could. Each trial started when the target appeared in one of the four possible locations and ended when participants made the correct response. After the correct response was made, the target appeared with no delay at the next location. Participants were given four practice trials before starting the experiment.

There were two phases of training blocks, each phase featured practice with a different 12-item sequence as described above. Each phase had nine blocks of 100 trials each. The first four trials of each block were pseudo-randomly generated and not part of the sequence. Therefore, there were 900 trials per half, of those 864 were sequenced trials. There was a mandatory 10 s break between each block, after which participants were free to rest further if they chose. The eighth block switched participants to a non-trained sequence, which was different for the two halves. The ninth block returned participants to the repeated sequence for that section of the experiment. Thus, participants responded to 1800 stimuli between the two lists, of which 1728 followed one of the two practiced sequences. In between the two sets, there was a 3 minute distracter task.

After participants completed both training sets, their knowledge of the sequences was assessed using two measures. The first was a simple self-report, in which participants were asked, "Did you notice anything repeating? If yes, describe what you noticed. If not, type no to move on." This was done before the recognition test so the recognition test items did not impact self-reported knowledge. Participants were not explicitly asked to input the trained sequences at this point, only asked to describe what patterns they had noticed, if any.

Next participants completed the recognition PD procedure. Participants were informed of the presence of repeating sequences of responses, and that they would now be asked to recognize them. Participants were first told they would be entering part of a sequence (nine items) and then to respond based on the instructions for that section. The two instruction sets (Inclusion and Exclusion) were in separate, counterbalanced blocks. Each recognition block started with instructions only for that block. The Inclusion instructions told participants to call a sequence fragment ‘old’ if it was from either half of the training period. The Exclusion instructions were to call a sequence fragment ‘old’ only if it was from a certain half of the training set, with half (i.e., first or second) specified by the directions. The half which participants had to exclude was counterbalanced for which training sequence was viewed first, as well as if the first sequence or second sequence was to be excluded, thus leading to a total of four counterbalanced conditions. Unbeknownst to participants, sequences were taken from both sets as well as random sequence fragments. There were 12 trials of each sequence type per instruction set, leading to 96 total trials in the recognition test.

Measures

The reaction time for a correct response for all training trials was recorded. The mean reaction time for each block by list was calculated for each participant. Participants responses to the recognition test were recorded and likelihood of calling an item old was calculated for the different sequence types.

Results

Training Performance

The reaction times from training were submitted to a 2 (training sequence) x 2 (half of training) x 9 (block) x 4 (counterbalance condition) repeated-measures MANOVA. The main effect of block, F(8,35) = 6.90, $p < .05$, $\eta_p^2 = .61$, suggests that participants’ performance changed with practice, as shown in Figure 2.1. There was not a difference by experimental half, F(1,42) = .64, $p > .05$, $\eta_p^2 = .02$. There was also not a

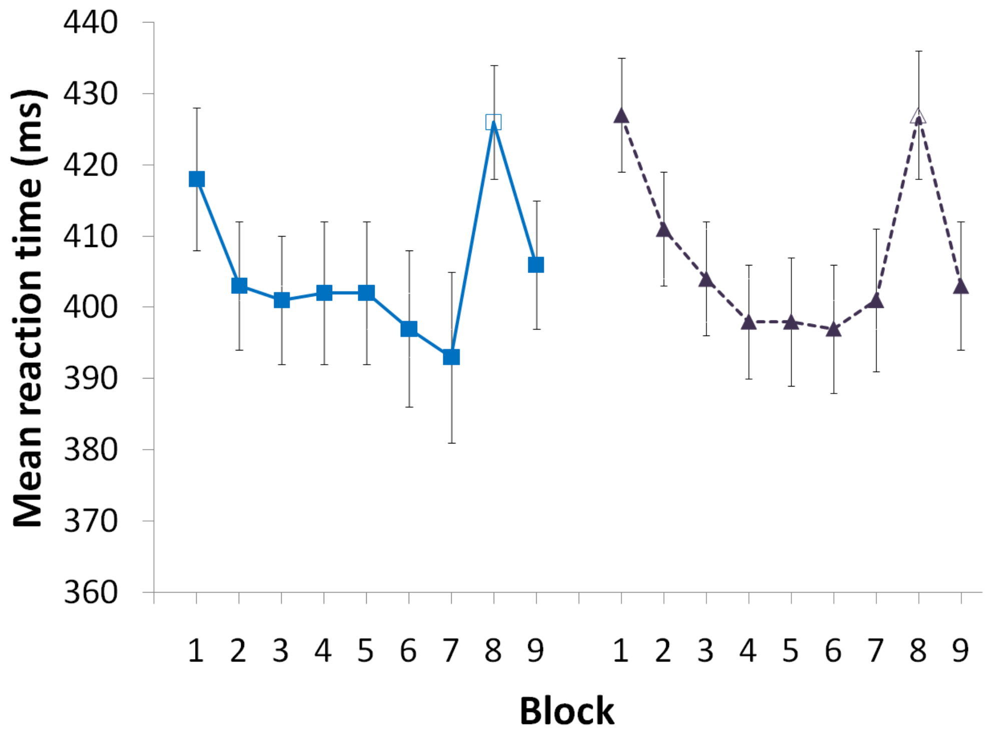

Figure 2.1. Mean response times in the SRTT by training block and sequence. Closed symbols represent blocks with the trained sequence, and open symbols represent the transfer to a novel sequence. Error bars represent one standard error.

difference between the counterbalance conditions in training performance, F(3,42) = 1.81, $p >$ .05, $\eta_p^2 =$ .11.

To test whether participants learned both of the trained sequences, and whether learning was at comparable levels, the mean response times for the transfer sequences introduced at the end of training were compared against the mean response times of the surrounding trained sequence blocks in a repeated-measures MANOVA. There was a significant difference between the block types, F(1,45) = 35.61, $p <$ .05, $\eta_p^2 =$ .44, with participants responding slower on the transfer block. This slower response time on the novel sequence indicates that participants were responding faster on the trained sequences because they had learned them, not because they became more proficient at responding in the task. There was no difference between the response times for the two experimental halves, F(1,45) = .11, $p >$ .05, $\eta_p^2 =$ .003, nor an interaction between the block type and experimental half (mean response time by block type and half in ms: transfer-sequence 1 = 422, trained-sequence 1 = 395, transfer-sequence 2 = 422, trained-sequence 2 = 399), F(1,45) = .51, $p >$ .05, $\eta_p^2 =$ .01.

Self-Report

Participants were asked at the end of training if they noticed anything repeating during the experiment and to provide information on what they noticed. Thirty-one of the 46 participants reported some level of awareness of the repetition. The remaining 15 non-aware participants showed a significant cost when the trained sequence (mean for the two surrounding trained sequence blocks = 401 ms) was replaced with a novel sequence (mean = 412 ms), t(14) = 2.78, $p <$.05, Cohen's d = 1.05. This finding is congruent with previous suggestions that those participants whose self-reports reflect little awareness of any repeating information in the experiment are nonetheless able to learn the sequences (although as discussed previously, this does not necessarily translate to evidence of purely implicit learning). A first conclusion that can be drawn is that awareness is not necessary

Table 2.2. Mean probability of responding "old" to a sequence fragment on the recognition test by sequence type and instruction form.

	Sequence Type		
	Sequence 1	Sequence 2	Random
Inclusion	.46	.45	.32
Exclusion	.28	.33	.24

for sequence learning, which replicates previous sequence learning findings for the necessity of awareness [41].

Recognition Test

For the recognition test, participants were asked to respond to a series of nine locations, as during training, and then indicate if the sequence was old or new according to the type of instructions. Under Inclusion instructions, participants were to call a sequence fragment old if they had encountered it during the experiment at any point. The Exclusion instructions were to call a sequence fragment old only if it was from the second half of the experiment. The likelihood participants called each item type "old" was calculated under both forms of instruction, and is shown in Table 2.2. In order to calculate PD estimates, response bias should be roughly equivalent for the Inclusion and Exclusion tests [4][5]. Response bias was examined by comparing the false alarm rate to the new random sequences, which did not differ for the Inclusion and Exclusion tests, $t(45) = 2.0$, $p > .05$. There was also not a difference between counterbalance conditions in recognition responses, $F(3,42) = .16$, $p > .05$, $\eta_p^2 = .01$, and as such will not be discussed further.

As per the process-dissociation procedure, the controlled and automatic processing estimates were calculated using the formulas presented in the Introduction for the

[5] These proportions should not be confused with accuracy. These are the proportion of how often each item type was identified as "old". The concept of a base error rate derived from accuracy is not as important for PD as the participants' base rate of incorrectly identifying novel information as having been encountered before. If the false alarm rates differ between the Inclusion and Exclusion tests for these novel items, it would indicate that participants are using different strategies between tests. If this were true, it would be inappropriate to calculate process estimates.

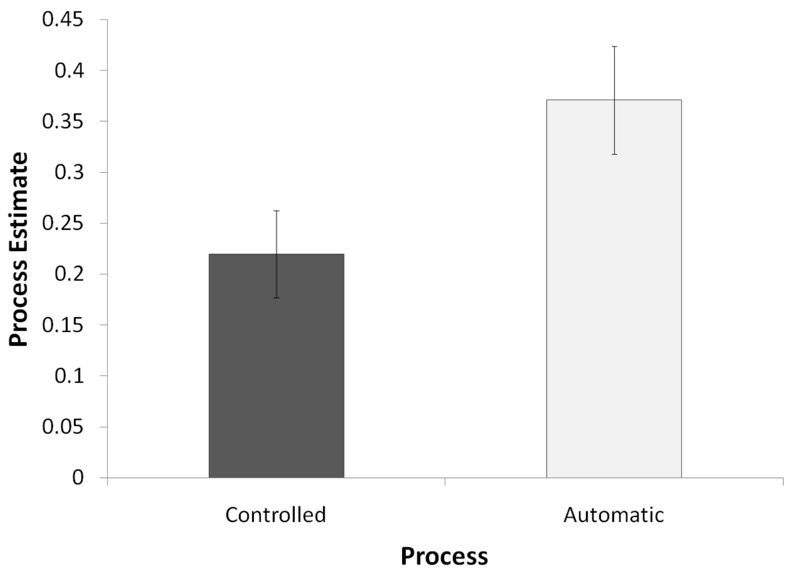

Figure 2.2. Controlled and automatic process estimates for the recognition test. Error bars represent one standard error.

to-be-excluded sequence. These rates can only be calculated for the to-be-excluded sequence because this is the only sequence in which there can be failures of controlled processes allowing the trained automatic processes to influence responses. The process estimates were submitted to separate t-tests to examine whether they were greater than zero. Both the controlled processing estimate (.22), $t(45) = 5.12$, $p < .025$, Cohen's $d = 1.09$, and automatic processing estimate (.37), $t(45) = 7.02$, $p < .025$, Cohen's $d = 1.50$, were greater than zero, as shown in Figure 2.2.

Participants were separated into those who had greater than zero controlled processing estimates ($N = 30$ of 46, mean controlled processing estimate = .31), and those who did not (mean controlled processing estimate = 0). This is similar to separating participants on the basis of self-reported awareness of what had been repeating. If learning of the sequence can be supported only by automatic processes, then the participants who do not demonstrate significant controlled processes at retrieval should nonetheless have a significant cost in switching from the trained sequences. The 16 participants who demonstrated no significant evidence of controlled processing showed evidence of

Table 2.3. Training reaction times for self-reported aware and non-aware participants, and participants who did or did not demonstrate use of controlled processing on the PD test. All reaction times are in ms, and standard deviations are given in parentheses.

		Reaction Time	
		Trained	Transfer
Self-Report	Non-Aware	401 (48)	412 (48)
	Aware	394 (66)	427 (49)
Test Processing	Only A	388 (46)	410 (46)
	C and A	401 (67)	429 (49)

learning the sequences. They had a significant cost of transferring to a novel sequence (410 ms) from the trained sequence (388 ms), $t(15) = 4.33$, $p < .05$, Cohen's $d = 1.58$, consistent with the notion that the sequence could be performed without using controlled processes at test. Training reaction times for participants who failed to demonstrate controlled processing at test, as well as participants who used controlled processing, are shown in Table 2.3. A second conclusion from this experiment is that control over acquired knowledge is not necessary to receive the reaction time benefit.

To test for a difference between self-report aware and non-aware participants in their ability to control the acquired knowledge, the controlled process estimates were compared between self-reported aware and non-aware participants in a t-test. There was not a significant difference in controlled process estimates for the non-aware ($M = .18$) and aware ($M = .22$) participants, $t(44) = .63$, $p > .05$, Cohen's $d = .21$. This does not support the idea that being aware of what was learned springs from having control over what was learned, but rather suggests that general feelings of awareness of having learned something does not accurately reflect having greater overall controlled processing. This could also be due to an underestimation of the 'true' controlled processing occurring in participants, but this would need to be verified by tests with greater sensitivity to processing.

Table 2.4. Correlations between the transfer cost during training, self-reported awareness, and process estimates. A star indicates significance at the $p = .05$ level.

	Transfer Cost	Self-Reported Awareness	Process Estimate Automatic	Controlled
Transfer Cost	——			
Self-Report	*.37**	——		
Automatic	-.01	-.07	——	
Controlled	.06	.05	-.18	——

The automatic process estimates were also compared for aware and non-aware participants. There was not a difference in automatic process use on the PD recognition test, $t(44) = .62$, $p > .05$, Cohen's $d = .19$. This does not support the idea that there was different automatic process use by the aware and non-aware participants. This lack of difference is in line with the stance that sequence learning is an implicit process, as the automatic processes supporting the RT sequence advantage should be gained independent of the participant's awareness.

Correlations were computed between the transfer cost during training, the self-report measure of awareness, and controlled and automatic process estimates to test for further relations between the different factors. As shown in Table 2.4, the only significant correlation was between the training transfer cost and self-reported awareness. This small correlation suggests that participants who reported awareness tended to have greater transfer costs. To probe this issue in a more meaningful way, future experiments should use self-report measures that allow for a greater continuum of awareness states. There were no significant correlations between the self-report measure of awareness and the process estimates.

Discussion

The current study replicated the well-established finding that participants learn a repeated sequence of items within the SRTT paradigm, with shorter latencies in the trained sequences than the novel sequences presented near the end of each training segment. The process estimate data provide evidence consistent with the presence of automatic processes. However, while the results support a role for automatic processing, the recognition test also shows an influence of controlled processing that highlights the presence of both types of processes in this task.

Implementing the process-dissociation (PD) procedure in sequence learning has allowed for a new and different way of examining the behavioral consequences of training participants on repeating sequences. The ability to get through 1600 trials in one hour makes it possible to meet the necessary PD assumptions since it allows for a temporal comparison of when the different sequences were encountered. By including two trained sequences in addition to the new and random test sequences, participants could make exclusion errors thought to be driven by automatic processes [3, 4]. Importantly, the trained sequences were not so distinctive that participants showed perfect recognition. In situations in which participants are able to recognize all the learned elements as old, an absence of necessary errors renders the PD procedure inappropriate to use.

The current experiment featured the presence of two learned sequences that needed to be discriminated from each other. This rules out the possibility that participants used perceptual and motor fluency during the recognition test to influence their classification of sequences [see, 183]. While a more fluid execution of a sequence might provide opportunities to distinguish an old sequence from a new one, regardless of whether controlled processes were operating, it would not provide a basis to determine when within the experiment the sequence had been practiced. Previous sequence learning research using the PD procedure has sought ways to circumvent this issue, for example through generation of sequences rather than responses to them [25], or the addition of other measures [184]. However, the design employed here requires minimal variation from the originally developed SRTT method, and hence offers some advantages over previous instantiations of the PD procedure within sequence learning. For instance, the inclusion of the temporal discrimination at test allows for responses to be made on more than just motor fluency.

The Role of Awareness

One advantage in investigating implicit learning from an information processing approach is that while knowledge is hard to satisfactorily and exhaustively measure, the underlying processes are more readily testable. In addition to having measures that are more objective than self-report tests, shifting to a processing view of implicit learning also allows for more direct explanations of how the performance changes during and after training. Instead of inferring how the implicit and explicit-knowledge types are thought to influence performance, the PD procedure assesses automatic and controlled processes that support performance. The conditions for how these processes develop and when they tend to be employed can be further investigated using this technique.

Some theoretical accounts of sequence learning [e.g., 147] marginalize the issue of awareness. Awareness may not be a necessary characteristic of any of the processes or systems involved in sequence learning [41]. Conceptualizing performance within implicit learning tasks in terms of the underlying processes, and in particular automatic processing as identified through the PD procedure, provides a means to move beyond debates about the awareness and implicit versus explicit knowledge. Moreover, the mere ability to impose controlled processing within a task need not indicate that the relevant knowledge for task performance is ‘explicit’. Examples from motor skill performance show that automatic processes can even be disrupted, and performance degraded, if superseded by conscious monitoring [e.g., 185].

Participants who lacked controlled processes at test still had a response time benefit during training. This finding indicates that use of controlled processes are not necessary. This is in line with definitions of implicit learning that specify that learning can occur without awareness or intent [e.g., 13, 186]. However, it is possible that even the PD test used in this experiment was insensitive in determining what controlled knowledge those participants possessed [15]. Given the nature and assumptions of PD [3, 4, 174], this seems unlikely. This also again illustrates the utility of moving to a processing account of what changes after training on an implicit learning task. By focusing on the measurable differences in processing, we are no longer reliant on the introspective feelings of awareness as a primary index of how participants are performing the task.

Future Directions

One question for future research is whether recognition tests of the type employed here, and generation tests used in other sequence learning studies [e.g., 25], are tapping the same underlying processes. In one sense this issue can be related to Shanks and St. Johns [15] information criterion: whether information used within the test is tapping the information involved during the execution of the actual task. As shown with perceptual priming [e.g., 23], comparing different tests can help inform theory of the underlying processes or testing strategies by looking for similarities and differences in the tests leading to differences in performance. It may also offer insights into any strategic differences between participants on different forms of tests.

While it may seem that previous experiments using generation and recognition tests for SRTT [e.g., 34] present contradictory findings, closer examination reveals that the results are in agreement. Shanks and Johnstone trained participants on similar sequences to the ones used in the current experiment, then administered either a free-generation test or a recognition test. Their results from both recognition and free-generation tests showed that participants had some explicit knowledge of what had been learned. In the current experiment, we probed the broad category of explicit knowledge further by using the PD procedure to tease apart the processes supporting the apparent explicit knowledge at test. We chose to implement only a recognition test to insure that participants were being re-exposed to the trained sequences during test, thus forcing them to discriminate between them in their decisions. Due to the nature of the generation test, this re-exposure is not possible.

Another issue for future research is if the temporal discrimination used in this experiment led to an underestimation of the controlled processing estimate since there may be control over the sequence knowledge itself independent of which half the sequence was occurred in. It is possible that this may an infrequent occurrence (as concluded by [174]), or could warrant further methods to allow for valid PD comparisons.

The results of the correlations between transfer cost, self-reported awareness, and process estimates also suggests further experiments probing these relationships. It is possible that the two-alternative measure for self-reported awareness helped inflate the correlation with transfer cost. Future experiments should employ a self-reported awareness measure with more responses to test if the correlation still holds with transfer costs.

Conclusions

Leveraging insights from implicit memory research can provide a framework for progress on implicit learning. The process-dissociation procedure may help implicit learning research move away from arguing over the semantics of what is meant by implicit or explicit and back into the interesting nature of learning processes by providing a way to measure the likely underlying processes. This experiment demonstrated one possible method of using the process estimates to measure the relative contributions of automatic and controlled processes, and use the process estimates to then try to account for differences in training performance. Future improvements, such as non-temporal discriminations, are still possible with the reported technique. SRTT seems to rely on both automatic and controlled processing.

Chapter 3

Experiment 2: Serial Reaction Time Task with Knowledge Manipulation and Process-Dissociation Test

While the previous experiment demonstrated the use of both automatic and controlled processes during the recognition test by participants, it did not include a direct manipulation to differentially affect automatic and controlled processes. The current experiment predicted that manipulating the instructions regarding the sequence repetition would change the controlled but not the automatic process estimate. This is possible since PD allows for a comparison of differing conditions on each process [3]. In most implicit learning research, the awareness level of the repeating information has not been directly manipulated. A consequence of this is that the source of awareness is uncontrolled, and aware and unaware participants may differ in multiple ways. Explicitly instructing participants about the stimulus repetition reduces the uncertainty about what gave rise to the awareness of the repeating information.

As reviewed in the Introduction (see page 9), controlled processes are used intentionally and in a controlled manner, whereas automatic processes occur without the intent or control of the person [1, 2, 84]. Controlled processes are almost certainly used during explicit learning conditions and probably to a far lesser extent in implicit learning situations. Consequently, if participants are learning the same type of information (e.g., sequences) under explicit and implicit conditions, controlled processes should play a larger role under the explicit, intentional learning condition. In other words, in a learning task, with all other factors being equal, the directions will shift the relative use of controlled and automatic processes, with greater controlled processes following explicit learning directions and more use of automatic processes following implicit learning directions.

In previous experiments, participants were told prior to training that there would be a repeating sequence, and it would be beneficial to learn it [27, 75]. In these experiments, being informed about the presence of the repetition led to faster response times when compared to random sequences. These experiments do not inform about the effects on controlled and automatic process use under the implicit or explicit learning conditions.

The current experiment is modelled after a previous sequence learning experiment [5] that compared performance on sequences that were cued as repeating and those that were not. One repeated sequence appeared with a red target, and prior to training participants were told the red denoted the sequence was repeating. Another repeated sequence appeared with a black target, referred to as the not-cued sequence. However, participants were not informed about the presence of a sequence in the black target trials and were led to believe that all of these trials would be random. In the second half of the experiment, the cued sequence from the first half appeared both as a cued sequence (with a red target) and a non-cued sequence (with a black target). It was found that reaction times were fastest for the previously cued sequence presented with cues, followed by the previously cued sequence presented without cues and the not-cued sequence (which did not differ from each other), followed by the random trials.

Current Experiment

By combining Willingham and colleagues' [5] sequence manipulation with Experiment 1's test methodology, it was possible to compute automatic and controlled process estimates for the different cue conditions (i.e., cued or not-cued). The sequence conditions for this experiment were: only cued, which only appeared in one half of training and was cued as repeating; only not-cued, which also only appeared in one half of training and was not cued as repeating; the switch sequence, which switched cue status halfway (the order of which was counterbalanced between participants; i.e., cued–not-cued or not-cued–cued), but was presented through all of training; and novel random sequences. As shown in Table 3.2, the switch sequence was presented in both halves of training to boost familiarity for PD.[1] This is the critical sequence in calculating process estimates. At the halfway point in training, the switch sequence changed cue type, either from cued to not-cued or not-cued to cued. Consequently, the order for the two repeating sequence conditions encountered in only one half of training was linked to the switch sequence's cue order. Therefore, if the switch sequence began cued, the solely not-cued sequence was presented in the first half; likewise, if the switch sequence began not-cued, the solely cued sequence was used in the first half of training. Random trials were encountered throughout both halves of training.

Is explicit knowledge of sequence repetition beneficial early in training?

The effect of having knowledge of sequence repetition was compared for the cued and non-cued sequences in the first half. If knowledge of the repetition is beneficial to the task early on [e.g., 50], the reaction times should be faster earlier for the cued sequences than the non-cued sequences (the non-cued sequences should still be faster than the random responding). But if having knowledge is detrimental to learning, possibly through

[1] The necessity of boosting the familiarity and automatic processing of this sequence does have the downside of possibly reducing the interpretability of the PD results, since the switch sequence was both cued and not-cued. However, without this familiarity boost, the results of the PD recognition test are less meaningful as less can be said about differences in process estimates, as was the case in Experiment 1.

use of inefficient strategies, the reaction times for cued sequences should be slower than non-cued [e.g., 24, 79].

What is the effect of switching cue types on one trained sequence?

In order to properly control for order-effects of the different sequences, the order of sequences was counterbalanced between participants (as is shown in Table 3.2). For one group, the first half of the experiment involved a non-cued repeating sequence and the sequence that was trained throughout being shown with the cue (i.e., switch–cued sequence). The second half of training had a new cued repeating sequence and the same sequence from the first half which had previously been shown with the cue, then presented without the cue (i.e., switch–not-cued). The other counterbalance group had the cued-only sequence appear in the first half of training along with the sequence trained through both halves being shown without the cue first (i.e., switch –not-cued). The second half of training for this group had a new non-cued sequence and the same non-cued sequence from the first half shown with a cue (i.e., switch - cued).

It is possible that the order of exposure from cued to not-cued or not-cued to cued affected learning of the sequence. Transitioning from cued to not-cued could result in participants noticing the not-cued repetition in the second half, as they would have just finished training with it as the cued sequence. The reaction times for the trained sequence during both halves of training were compared between counterbalanced groups under the cue conditions to test if the switch order affected results. The two switch order groups (i.e., cued–not-cued [C-NC] or not-cued–cued [NC-C]) was compared for differences in reaction times for the switch sequence. If having knowledge of the sequence repetition led to faster responding [5], reaction times should be faster overall when that sequence was cued, regardless of which half of training it appeared. However, if there is an interaction with the switch sequence's order such that there was faster not-cued responding when it was encountered after cued training, it would suggest that there was a benefit to having sequence repetition knowledge.

Sequence learning in the absence of controlled processes?

It was also predicted that there would be differences between participants for the process estimates, as there is variability in ability to control attention and retrieval processes [87, 187]. However, participants who failed to show evidence of controlled processing during the PD recognition tests are predicted to still show faster reaction times for trained sequences in comparison to random trials. This was predicted because of findings from participants who failed to develop awareness of the covert sequence repetition. This group still showed faster responses with the repeated sequences than the random sequences (for a review, see [41]).

Controlled processes helping sequence learning?

The contribution of controlled processes to task performance was assessed through correlations between the controlled process estimates with the reaction time differences (random responding minus cued or not-cued reaction times). A significant positive correlation would indicate that controlled processes benefit sequence learning, and a negative correlation would indicate a response time cost associated with greater controlled processes.

Method

Participants

Fifty-four Colorado State University students participated in this experiment and were randomly assigned to the two order conditions. All were pre-screened for normal or corrected-to-normal acuity and color vision with a quick test of both prior to the start of the experiment. This pre-screening required participants to discriminate between letters in red and black ink.

Table 3.1. Sequences participants were trained on. The leftmost response position is designated by 1, and the rightmost response position is designated by 4. The role of each sequence (i.e., switch, cued, or not-cued) was counterbalanced between participants.[1]

Sequence
1 4 3 1 2 4 2 3 4 1 3 2
1 2 3 1 4 2 1 3 4 3 2 4
2 3 1 3 4 2 1 4 3 2 4 1

Materials and Design

The same basic stimuli were used as in Experiment 1 and data were again collected in E-Prime [181]. The SRTT display had the same basic configuration. The target was the same size, but was either black or red, determined by the trial condition. Three ambiguous sequences [124] were repeated throughout training. The second order conditional sequences (i.e., the current item is based on the $n - 1$ and $n - 2$ items) for this experiment were selected based on their minimal chunk overlap, and are shown in Table 3.1[2]. The random sequences used throughout training and at test were generated in accord with Willingham et al. (2002). These sequences were 12 items long, each position was equally frequent in the sequence, repetitions of one response were forbidden, and trills (e.g., 3434) were not allowed.

The flow of the experiment is shown in Table 3.2. Participants were first given 50 random practice trials to get comfortable with the task and reduce task-dependent learning in the experimental data. After the practice trials, the experiment commenced. From this design, it was possible to compare overall sequence learning between the two halves, overall learning between the cued and not-cued sequences, differences between the two cued sequence forms, differences between the two not cued sequence forms, and all

[2]It has been noted that there is overlap between the second and third sequences, and was noticed after data collection was completed. Results and interpretations thus include analyses determining the extent to which the overlap issue impacted results.

against random key pressing. As shown in Table 3.2, three sequences were learned in two switch sequence order counterbalanced conditions.

Procedure

Responses were made with the 'v', 'b', 'n', and 'm' keys, which corresponded to the four display locations from left to right. Participants were instructed to respond as quickly and accurately as they could. They were further instructed to learn the repeating sequence which was indicated by the red target. Participants were also told that the repeating sequence would start at a random point in the sequence each time. Each trial started when the target appeared in one of the four possible locations and ended when participants made a correct response. After the correct response was made, the target appeared at the next location. Participants were given 50 practice trials before starting the experimental trials.

There were two halves of training blocks. One sequence in each half had a red target and participants were informed that the sequence repeated through that half of training (cued; C). The other repeating sequence had a black target and participants were not informed of its repetition (not-cued; NC). Both halves had a total of six blocks, and 1440 trials each. Blocks of each half had two runs per sequence-type (cued, not-cued, and random), with a run consisting of two complete sequence repetitions (i.e., 24 trials). At the start of each run, there was a fixation for 500 ms, then 1 s without the fixation before the appearance of the first target. In between the two sets, there was a three minute distracter task consisting of two digit addition and subtraction problems.

After participants completed both training halves, their knowledge of the sequences was assessed with the PD recognition test. The order of the cued and not-cued tests was counterbalanced. For the cued PD recognition test, participants were told they would first enter part of a sequence (nine items) and then make a decision based on the instructions for that section. The two instruction sets (Inclusion and Exclusion) were in

Table 3.2. The design of the experiment. Three sequences were learned during the experiment. For one counterbalance group, Sequence A was shown during both halves of the experiment with a change in cue halfway through (collectively known as switch sequences), Sequence B was only shown in the first half with the black-target (i.e., not-cued), and Sequence C was only shown in the second half with the red-target (i.e., cued). For the other counterbalance group, Sequence A was still shown during both halves of the experiment with a change in cue status halfway, Sequence B was shown only in the second half with the black-target, and Sequence C was shown in the first half with the red-target.

Counterbalance Groups

Time ⟶

Practice	Cued–Not-Cued Sequence – Experiment Half: First half	Second half	PD Tests: order of tests counterbalanced: Cued	Not-Cued
Random	Sequence A: Cued (Switch-C) Sequence B: Not-Cued (NC) ——— Random	Sequence A: Not-Cued (Switch-NC) ——— Sequence C: Cued (C) Random	Inclusion: A, C correct Random incorrect Exclusion: C correct Random, A incorrect	Inclusion: A, B correct Random incorrect Exclusion: B correct Random, B incorrect

Practice	Not-Cued–Cued Sequence – Experiment Half: First half	Second half	PD Tests: order of tests counterbalanced: Cued	Not-Cued
Random	Sequence A: Not-Cued (Switch-NC) ——— Sequence C: Cued (C) Random	Sequence A: Cued (Switch-C) Sequence B: Not-Cued (NC) ——— Random	Inclusion: A, C correct Random incorrect Exclusion: C correct Random, A incorrect	Inclusion: A, B correct Random incorrect Exclusion: B correct Random, B incorrect

separate, counterbalanced blocks. Each recognition block started with instructions only for that block. The Inclusion instructions were to call a sequence fragment old if it was cued in either half of the training period. The Exclusion instructions were to call a sequence fragment old only if it was cued in the second training set for C-NC, or in the first training set for NC-C (i.e., before or after the distracter). Sequences were taken from the switch sequence (C-NC or NC-C) in addition to the trained C and NC sequences, and random sequence fragments. There were six sequence fragments for the switch, C, and NC sequences along with six novel random sequences for the Inclusion instructions. For the Exclusion portion of the cued test, there were six different sequence fragments for all sequence types.

For the not-cued PD recognition test, participants were informed of the presence of repeating sequences of responses in the black target trials, and that they would now be asked to recognize them. They again did this under Inclusion and Exclusion instructions, and received those test directions before starting the block. The instructions for this portion were altered so that participants were instructed to call an item ‘old’ only if it was presented with the black target. As with the cued Inclusion test, there were six sequence fragments for the switch, C, and NC sequences, and random sequences. For the Exclusion portion, participants were instructed to only call items originally presented with black targets before the distracter as ‘old’ for C-NC, or after the distracter for NC-C. There were six different sequence fragments for all sequence types.

Measures

The reaction time for all training trials was recorded. The median reaction time for each sequence repetition or group of 12 random trials was calculated for each participant (consistent with [5]). The mean of these medians (MMRT) was then calculated for cued, non-cued, and random sequences. A second metric, transfer cost, was also calculated. The transfer cost is the trained sequence MMRT subtracted from the random MMRT, and reflects how much faster or slower the responses were for a given repeated sequence type.

Results

All planned pairwise comparisons were run with a Bonferroni adjustment for multiple comparisons[3] unless otherwise noted.

Training Performance[4]

Overall Performance

In a manner similar to the previous research [5], the MMRTs were compared in a repeated-measures MANOVA with sequence type (random, NC, C, switch-NC, and switch-C; within) and block (1-6; within) as the factors.

The difference between sequence types are shown in Figure 3.1. There was a significant difference in MMRT overall between the sequences, F(4,50) = 18.72, $p <$ .05, $\eta_p^2 =$ .60. To determine which sequence types differed significantly from each other, the sequence types were contrasted with planned pairwise comparisons. The random trials (M = 417.20 ms) were significantly slower (all $p <$ .05) than all trained sequences. The switch-C sequence was also significantly faster than the NC sequence ($p <$ .05). All other differences were not significant ($p >$ .05).

There was also a main effect of block (MMRT by block in ms: 1 = 402.10, 2 = 406.94, 3 = 409.85, 4 = 408.20, 5 = 401.50, 6 = 397.27), F(5,49) = 8.14, $p <$ .05, $\eta_p^2 =$ .60. To determine which blocks differed from each other, pairwise comparisons with a Bonferroni adjustment were run. Block 3 was significantly different from blocks 5 and 6, ($p <$ .05); and block 4 was significantly different from block 6, ($p <$ .05). There

[3]The Bonferroni adjustment for multiple comparisons allows for comparison of the adjusted LSD probability against a set Type I error level ($\alpha =$ 05). The Bonferroni adjusted probability is found by multiplying the LSD probability by the number of post hoc comparisons.

[4]Appendix A addresses the influence of sequence overlap on the training performance. Overall, the sequence overlap does not seem to have drastically impacted the results.

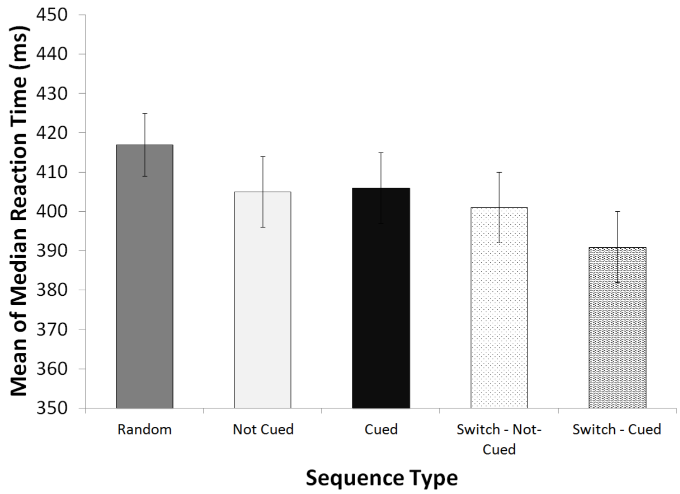

Figure 3.1. Mean of median reaction times for the different sequence types collapsed across block and experimental half. Error bars represent one standard error.

was also an interaction between sequence type and block, F(20,34) = 6.32, $p < .05$, $\eta_p^2 = .79$ as shown in Figure 3.2.

The finding that all trained sequences had significantly faster MMRTs than random sequences suggests that all trained sequences were learned. The significantly faster performance of switch-C in comparison with NC suggests that having knowledge of the sequence repetition affected learning, possibly by changing how a participant was doing the task.

Is Explicit Knowledge of the Sequence Repetition Beneficial Early in Training?

If having knowledge of the sequence repetition is beneficial [e.g., 50], there should be an early RT advantage for the C sequence compared against the NC sequence. To make the comparison easier, only the transfer RTs were compared. A new repeated-measures MANOVA was run with the factors of cue type (NC or C; within) and block (1-6; within), and the mean transfer costs are shown in Figure 3.3. This repeated-measures MANOVA did not show an overall difference for the cue type, F(1,53) = .08, $p > .05$, $\eta_p^2 = .001$. There was a main effect of block, F(5,49) = 14.16, $p < .05$, $\eta_p^2 = .59$.

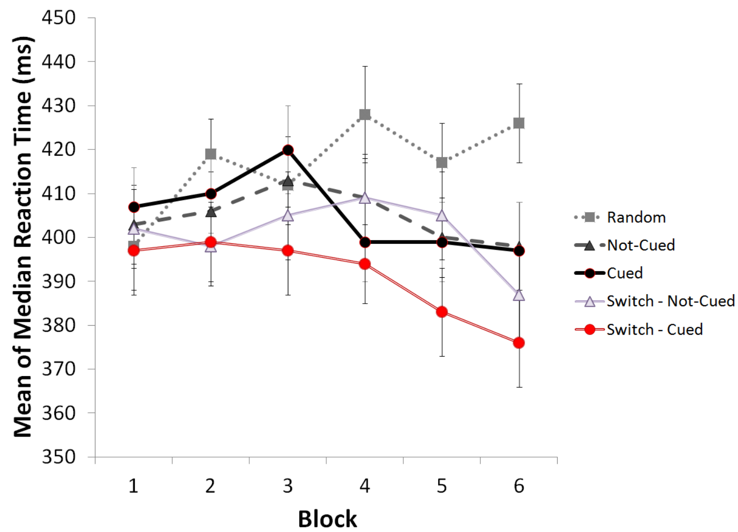

Figure 3.2. Mean of median reaction times for the different sequence types collapsed by block. Random sequences had significantly longer reaction times than any of the trained sequences. There was also a main effect of block, and a block x sequence interaction. Error bars represent one standard error.

Pairwise comparisons[5] revealed that block 1 had a significantly poorer transfer cost (M = -31 ms) than blocks 2 (M = -3.5 ms), 4 (M = 10.07 ms), 5 (M = 5.05 ms), and 6 (M = 25.62 ms). Block 2 also had a significantly poorer transfer cost than block 6. Block 3 (M = -16.45 ms) also had a significantly poorer transfer cost than blocks 4, 5, and 6. Further comparisons were not significant ($p > .05$). The general trend of the early blocks being significantly different from the later blocks suggests that learning of the repeating sequences had occurred by the fourth or fifth training block.

Cue type interacted with block, F(5,49) = 5.80, $p < .05$, $\eta_p^2 = .37$, indicating that the two cue types differentially changed over time. The interaction appears to have been driven by the C sequences having longer RTs than NC sequences for the first three blocks, then this pattern reversed in the second three blocks such that C sequences had faster RTs than NC sequences.

Given the reversal between early and late blocks for NC and C sequences in Figure 3.3, transfer mean of median RTs were collapsed by block into early (blocks 1

[5] All significant pairwise differences: $p < .05$.

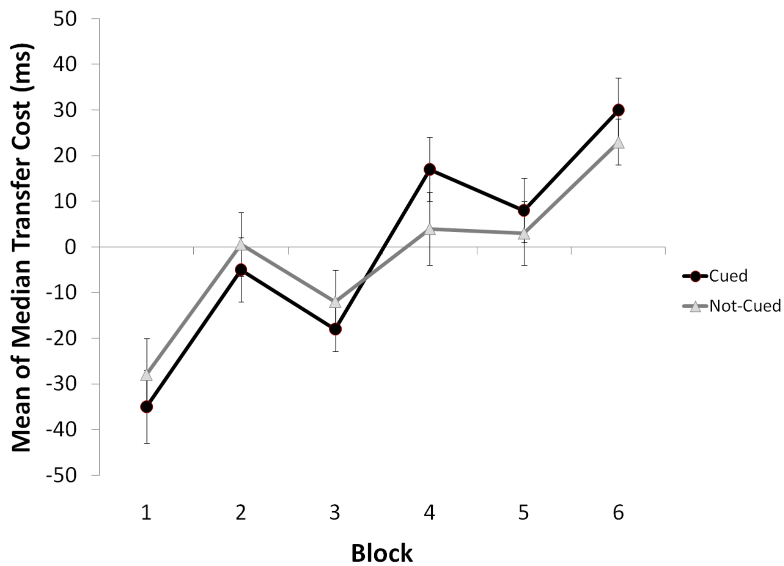

Figure 3.3. Mean transfer cost in the first half of training by block and cue condition. The cued sequence is represented by the black circles and line, and the not-cued sequence by the open triangles with gray line. Overall there was no difference between cue conditions; however, cue condition did interact with block. Error bars represent one standard error.

through 3) and late (blocks 4 through 6) training blocks for the two cue types. There was no difference between cue types (mean transfer by cue type in ms: NC = 2.2, C = 1.4), F(1,53) = .08, $p >$ .05, $\eta_p^2 =$ .001 as determined by a repeated-measures MANOVA. There was a significant interaction between early (M = -17.2 ms) and late (M = 13.6 ms) training and cue type, F(1,53) = 27.22, $p <$ .05, $\eta_p^2 =$ .34. The interaction is such that early in training, the NC sequence had a greater transfer cost (M = -14.1 ms) than the C sequence (M = -20.2 ms), t(53) = -2.48, $p <$.04[6], Cohen's d = .49. But late in training, the pattern reverses so that C sequences had a greater transfer cost (M = 17.4 ms) than NC (M = 9.8 ms), t(53) = 2.17, $p <$.04[6], Cohen's d = .43. This suggests that there was an early cost in trying to learn the cued-repeating sequence, but after the sequence was learned, participants responded faster to it than the not-cued repeating sequence.

[6]Bonferroni correction for multiple correlated comparisons

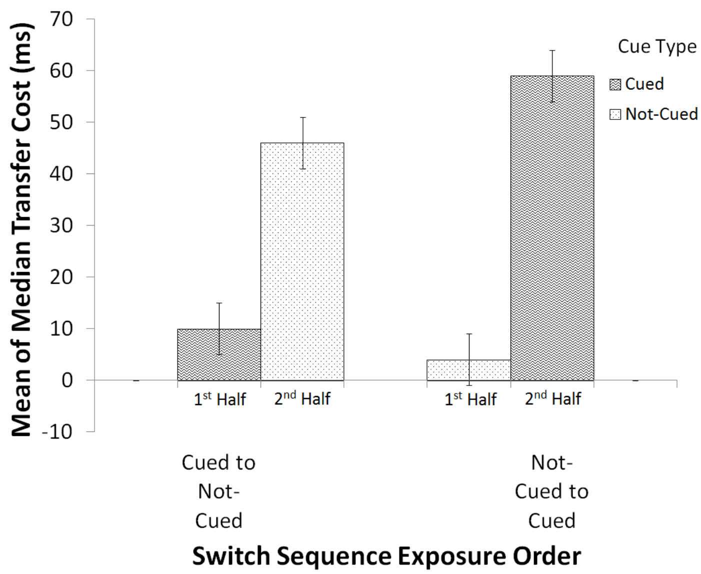

Figure 3.4. Mean transfer cost by the order participants were exposed to the cue conditions by the cue type. Error bars represent one standard error.

Effect of Switching Cue Types

Having knowledge of the sequence repetition should lead to faster RTs when the switch sequence is cued, regardless of which half the cued portion appears in [5]. An interaction with the order the switch sequence was viewed (i.e., not-cued to cued or cued to not-cued) would indicate that the mere presence of the cue was insufficient for improved learning, and that amount of exposure to the sequence was also important. The transfer RTs for the switch sequences were entered into a repeated-measures MANOVA with the factors of cue type (C and NC; within) and order the switch sequence was encountered (C-NC or NC-C; between). As shown in Figure 3.4, there were non-significant effects of cue type, F(1,52) = 3.27, $p > .05$, $\eta_p^2 = .06$, and exposure order, F(1,52) = .31, $p > .05$, $\eta_p^2 = .006$, but a significant interaction between cue type and exposure order, F(1,52) = 71.47, $p < .05$, $\eta_p^2 = .58$, with larger transfer costs occurring in the second half of the experiment for both C-NC (M = 46 ms) and NC-C (M = 59 ms) groups.

The transfer means were close to zero for both switch sequence exposure order groups in the first half. These means were submitted to t-tests to determine if they were significantly above zero (i.e., responding significantly faster to the switch than the random sequence). If the value is above zero, that provides evidence that overall participants learned the repeating sequence, albeit to a limited degree. If the value is not significantly different from zero, overall participants did not learn the repeating sequence. The C sequence for the C-NC group had transfer RTs (M = 11 ms) significantly above zero, $t(26) = 2.38$, $p < .025$[7], Cohen's $d = .67$; while the NC sequence for the NC-C group did not have transfer RTs (M = 4 ms) significantly above zero, $t(26) = .72$, $p > .025$[7], Cohen's $d = .2$.

These results suggest that exposure to the sequence was more important than whether or not the participant was cued that the sequence was repeating. However, the larger transfer RT for the switch sequence when cued in the second half of training suggests that the cue provided some benefit beyond mere exposure.

Recognition Test[8]

For the PD recognition tests, participants were instructed to indicate if they had encountered the sequence before (i.e., 'old') or if it was new under two different sets of instructions. This was done for switch, cued, and non-cued sequences under Inclusion (call a sequence 'old' if they had entered the sequence under the current cue type) and Exclusion (call a sequence 'old' only if they encountered it under the current cue type in a certain half) test directions. The switch sequence was the critical sequence for PD.

Participants' mean probability of calling a sequence 'old' is shown in Table 3.3. To ensure that any differences observed between tests are not due to differences in strategy [4], a repeated-measures ANOVA was run with the mean probability of calling the random sequence fragments 'old' for the different test cue and test direction types. There were no significant differences in the identification of random sequences for the two blocks of tests

[7] Bonferroni correction for multiple comparisons

[8] Appendix A addresses the influence of sequence overlap on the PD recognition test performance. Overall, the sequence overlap did not affect results in this section.

Table 3.3. Mean probability of responding 'old' to a sequence on the recognition test by cue type (red-target sequences, i.e. cued, or black-target sequences, i.e., not-cued) and sequence type (switch, cued, not-cued, or random). The random rates are compared on page 57 to check for any systematic response biases in responding. The switch sequence rates were used to calculate the automatic and controlled process estimates, and are included in Figure 3.5.

Cued Recognition Test

	Switch	Cued	Not-Cued	Random
Inclusion	.55	.53	.54	.38
Exclusion	.47	.43	.38	.33

Not-Cued Recognition Test

	Switch	Cued	Not-Cued	Random
Inclusion	.57	.51	.51	.40
Exclusion	.39	.38	.34	.34

(i.e., cued or not-cued), F(1,53) = .35, $p > .05$, $\eta_p^2 = .007$, between the two types of test directions (i.e., Inclusion or Exclusion), F(1,53) = 2.81, $p > .05$, $\eta_p^2 = .05$, and no interaction, F(1,53) = .19, $p > .05$, $\eta_p^2 = .004$. Therefore,there is not sufficient evidence to conclude that participants had different response biases in the two PD recognition tests.

The split-half reliability between PD recognition tests was calculated to determine if participants were answering questions comparably at different times in the test [e.g., 188][9]. There were strong correlations for the cued - Exclusion, r(52) = .77, $p <$.05, Cohen's d = 1.71, cued - Inclusion, r(52) = .71, $p <$.05, Cohen's d = 1.42, not-cued - Exclusion, r(52) = .78, $p <$.05, Cohen's d = 1.74, and not-cued Inclusion tests, r(52) = .76, $p <$.05, Cohen's d = 1.65. Thus it is unlikely participants were answering unreliably.

The process estimates for each cue type for the switch sequences were calculated from the formulas given on page 16, and are shown in Figure 3.5. There was not a difference in automatic process estimates between cued (M = .55) and not-cued (M = .50) recognition tests, t(53) = 1.04, $p >$.05, Cohen's d = .17. However, greater use of

[9]Each portion of the test was split into two halves, with an equal number of each sequence type appearing in each half. These two halves were then correlated with each other.

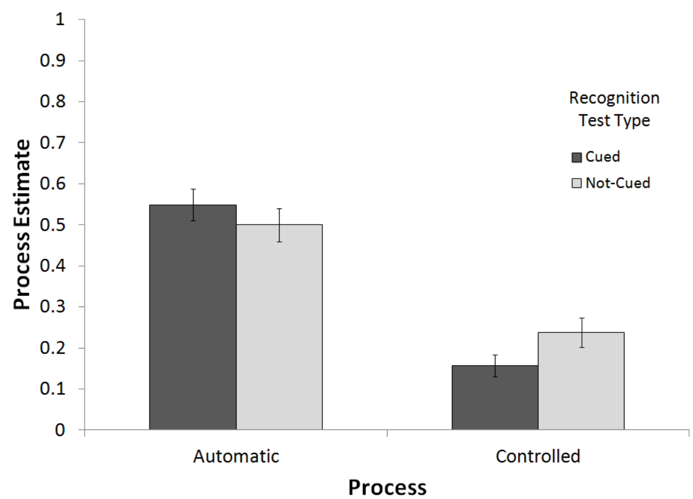

Figure 3.5. Mean process estimates for cued and not-cued recognition tests for the switch sequence. There was not a difference between automatic process estimates; however, there was significantly more use of controlled processes in the not-cued recognition test than cued. Error bars represent one standard error.

controlled processes was found for the not-cued (M = .24) over the cued (M = .16) recognition tests, $t(53) = 2.15$, $p <.05$, Cohen's d = .35[10][11].

The absence of a difference between automatic process estimates is not surprising [5, 27, 41], as it has been suggested that repeating sequences in SRTT can be learned via intentional and automatic processes in parallel [27].

Sequence Learning in the Absence of Controlled Processes

Since the repeating sequences in SRTT are thought to be capable of being learned incidentally and via automatic processes [41], participants who failed to show evidence of controlled processing during the PD recognition tests should still have some RT benefit for the trained sequences that may be due to automatic processing. To qualify as failing to show use of controlled processing on a recognition test, the participant must have a zero

[10] As included in Appendix A, there were non-significant differences between the counterbalance groups (and therefore the degree of overlap between sequences) for proportion 'old' responses and process estimates. As such, it is unlikely this is due to overlap between sequences.

[11] An additional repeated-measures MANOVA was run to see if the switch sequence order impacted the controlled process estimate with factors of cue type (cued or not-cued; within) and exposure order (C-NC or NC-C; between). Exposure order did not interact with recognition cue type, $F(1,52) = 2.83$, $p > .05$, $\eta_p^2 = .05$; nor was there a main effect of exposure order, $F(1,52) = 1.77$, $p > .05$, $\eta_p^2 = .03$. Therefore, exposure order did not seem to influence the controlled process estimates.

controlled process estimate on the recognition test. Of the 54 participants, 18 participants had greater than zero controlled process estimates for both PD recognition tests, 11 showed no use of controlled processing on either test, 15 had greater than zero controlled process estimate for the not-cued but not the cued PD recognition test, and 10 had greater than zero controlled process estimate for only the cued PD recognition test.

Not-Cued PD Recognition Test

The MMRTs for the participants who failed to show use of controlled processing on the not-cued sequence recognition test ($N = 21$) were entered into a repeated-measures MANOVA with sequence type (random, NC, C, switch-NC, and switch-C; within) and exposure order to the switch sequence (C-NC or NC-C; between) as the factors. There was a difference between sequence types, $F(4,16) = 35.85$, $p < .05$, $\eta_p^2 = .90$. This was driven by the random sequence having significantly longer reaction times than the NC and switch-C sequences (mean of median RT by sequence type in ms: random = 420, NC = 388, C = 402, switch-NC = 401, switch-C = 377; all other comparisons $p > .05$), as shown by planned pairwise comparisons. This suggests that these participants learned some of the trained sequences.

The exposure order did not differentially affect the not-cued recognition test (MMRT by order in ms: C-NC = 409, NC-C = 386), $F(1,19) = .42$, $p > .05$, $\eta_p^2 = .02$; but order did interact with sequence type, $F(4,16) = 5.75$, $p < .05$, $\eta_p^2 = .59$. However, none of the paired differences comparing the two order conditions for each sequence type were significant (all $p > .01$[12]).

Cued PD Recognition Test

The MMRTs for participants who failed to show use of controlled processing on the cued sequence recognition test ($N = 26$) were entered into a new repeated-measures MANOVA, again using sequence type (random, NC, C, switch-NC, and switch-C; within) and exposure order to the switch sequence (C-NC or NC-C; between) as the factors. This

[12]Bonferroni correction for multiple comparisons

also showed a difference in RT between sequence types, $F(4,21) = 29.30$, $p < .05$, $\eta_p^2 = .85$. The pairwise comparisons showed that all trained sequences were faster than the random sequence (mean of median RT by sequence type in ms: random = 422, NC = 297.03, C = 402, switch-NC = 399.10, switch-C = 382.03). There were no detectable differences between the trained repeating sequences (all $p > .05$).

There was no main effect of exposure order on the cued recognition test (mean of median RT by order in ms: C-NC = 419, NC-C = 381), $F(1,24) = 1.86$, $p > .05$, $\eta_p^2 = .07$, but there was an interaction between exposure order and sequence type, $F(4,86) = 11.44$, $p < .05$, $\eta_p^2 = .32$. There was a difference in RT between C-NC (M = 428 ms) and NC-C (M = 336 ms) participants for the switch-C sequence, $t(24) = 3.084$, $p <.01$[13], Cohen's $d = .9$, with a faster RT for the NC-C group (all other comparisons: $p > .01$[12]).

Overall the analyses comparing participants with no controlled processing on the cued PD recognition test led to similar results for these on the non-cued PD recognition test. However, there were some salient differences. First, non-controlled processors in the cued recognition test had significantly faster than random RTs for all trained sequences; non-controlled processors from the not-cued recognition test only achieved this for the NC and switch-C sequences. The lack of difference for training RT in the not-cued recognition test's zero controlled process estimate participants for the switch-NC and C sequences could indicate a difference in strategies used by the participants that ultimately interfered with their sequence learning. Second, the difference between C-NC and NC-C participants who did not show use of controlled processes on the cued recognition test on switch-C RT (with NC-C responding faster than C-NC) suggests that cued performance relying only on automatic processes benefits from prior not-cued exposure to the sequence.

[13]Bonferroni correction for multiple comparisons

Controlled Processes Helping Sequence Learning?

The controlled and automatic process estimates were correlated with the training sequence transfer costs, and are shown in Table 3.4. The only process estimate to correlate with any of the training measures was the controlled process estimate from the not-cued recognition test. It positively correlated with the switch-NC transfer RTs, meaning that larger transfer RTs were related to higher controlled process estimates. Said another way, participants with greater controlled process estimates on the not-cued recognition test also had larger transfer RTs for the switch-NC trials. This controlled process estimate also negatively correlated with the NC and switch-C sequences. Therefore, greater transfer RTs were observed for these two sequence types with lower controlled process estimates. The difference in the direction of the relationship between the switch sequence cue conditions suggests that the controlled processes were not as beneficial for the switch sequence when it was cued. That the controlled process estimate was negatively related to the NC sequence RTs further supports this possibility.

This suggests that overt knowledge of the sequence repetition can hurt performance on the SRTT, as was shown in the analysis examining only the first half of training. The negative correlation between the not-cued controlled process estimate and NC transfer RT could reflect a RT cost associated with knowing the sequence. Since a higher controlled process estimate is only possible if the sequence is memorable and can be correctly included and excluded, it is possible that developing controlled processes results in slower responding than just allowing the automatic motor responses to happen [e.g., 1, 2, 84, 180]. A possible explanation of this is participants may be deliberately encoding the cued sequence of responses, and in doing so are making slower responses.

Discussion

Differences in RT performance on the SRTT suggest that all the trained sequences were learned as reaction times were faster on the repeating sequences than random

Table 3.4. Correlations of the process estimates with the transfer scores from training, with transfer being derived from the trained sequence mean of median RT subtracted from the random sequence mean of median RT. A negative correlation indicates less transfer with higher process estimates, as found for the not-cued controlled process estimate and not-cued and switch - cued sequence types. The starred correlations were significant at the $p = .05$ level.

Process Estimate		Training Sequence			
		Not-Cued	Cued	Switch - Not-Cued	Switch - Cued
Cued	Controlled	-.16	.04	.05	-.15
	Automatic	.03	.18	.13	.03
Not-Cued	Controlled	*-.34**	.24	*.34**	*-.31**
	Automatic	.09	.04	.14	.12

responding. Both automatic and controlled processes were inferred to have been used by participants during sequence learning. Furthermore, participants who did not show evidence of controlled processes at test were still able to respond faster to the repeating sequences than random sequences, suggesting that controlled processes are not necessary to learn the sequences [25, 189].

There seems to be an early cost associated with having sequence repetition knowledge [50], but after early training (i.e., first three blocks) there is a reaction time advantage for the cued sequence as shown in the analysis comparing cued to not-cued sequence transfer RTs for the first half of training. This reversal in RT reflects the shift away from controlled processing [190, 191] when considered in conjunction with the controlled process estimates. Early in training with the sequences, faster performance occurs for repetitions the participant is not trying to learn; with greater exposure and presumably after the cued sequence has been thoroughly ‘learned’, responses are even faster for the cued sequence than the not-cued sequence. If this experiment were run with an additional factor that varied amount of training, it would be possible to examine the relative use of controlled processes for cued and not-cued sequence repetitions.

This change from early to late training RT for the cued and not-cued sequences with the associated controlled process difference further emphasizes the utility of examining the automatic and controlled processing estimates rather than awareness associated with learning. In a more applied context that maps onto the current results, Masters [192] manipulated how much attention participants were paying to their golf stroke. When the participant's attention was drawn to their form and technique, their performance suffered. They were almost certainly aware they were playing golf in all cases, though. Likewise, participants in the current experiment were hopefully aware the red-target sequence was repeating, but their awareness of that repetition does not necessarily mean they will respond differently, especially if they have shifted towards automatic responding. In other words, their awareness of the repetition is not tied to their performance.

Something to explicitly note from the PD test is that the switch sequence was the key piece of information to be excluded for the cued and not-cued tests. Consequently, the controlled process estimate difference between the cued and not-cued tests reflects a difference in how the switch sequence was processed with or without cuing to its repetition during training. The lower controlled process estimate for the cued recognition test indicates that participants were less able to exclude the switch sequence on that test. This also fits with the possibility that participants were shifting to greater use of automatic processes for the cued sequence.

The proposed shift in processes can also account for the switch-sequence exposure order interaction. For the C-NC group, they likely had sufficient time in the cued part of training to have their performance shift from being supported by controlled to automatic processes; during the second part of training it is possible participants' performance continued to be supported by these automatic processes, or they realized the previously cued sequence was now appearing without cues and were still aware of the repetition [14, 15]. Likewise, the NC-C group probably learned the not-cued repetition in the first half, but not to the same extent as that half's cued sequence; however, in the second half when the switch sequence was now cued, what they had learned of that repetition likely transferred to the new conditions, given the large transfer cost. The current design does not allow for more to be said on whether successful transfer was contingent on the participant's awareness of the repetition continuing between halves, but future experiments could test this by using manipulations that have been shown to reduce awareness, such as using a minimal response-stimulus interval [25]. This pattern of results is similar to those found in previous artificial grammar research, as well [50]. In that experiment, better grammar learning was found for participants who started with explicit directions followed with implicit, than for participants who started with implicit directions followed by explicit.

The available data from the original repetition-knowledge experiment [5] only includes a grand mean of medians for each sequence type, and a comment that learning did not change during the test phase. Willingham did not have a 'pure' cued sequence as in the current experiment (i.e., only presented with the repetition cue), but only a sequence that was cued during training then presented at test with and without the repetition cue. Both Willingham's and the current experiment had significantly faster RTs for the repeated sequences. Both experiments also had significantly faster RTs for the switch - cued sequence than the never-cued repeating sequence. Therefore, the only difference the current experiment failed to replicate was the difference between switch - cued and switch - not-cued sequences, which could be due to a methodological difference. The original experiment gave participants 24 training runs with the switch sequence in its cued state before presenting it in both cued and not-cued forms at test for an additional eight runs per cue type. The current experiment did not give participants this isolated training. It is possible that with this extra pre-training for the switch sequence, the same pattern of differences would have emerged.

There is also a difference in the nature of the trained sequences between this experiment and Willingham's [5]. All sequences for Willingham's experiment followed the criteria that the random sequences did in this experiment (i.e., 12 items long, each position was equally represented, there were no immediate repetitions of one response, and trills were not allowed). The trained sequences in the current experiment had the additional constraint of being second-order conditional, such that the preceding two responses must be known to make the next response. Since additional information is not given about Willingham's sequences, it is unknown how these differences in sequence structure may have affected the results.

One possible additional characteristic that differed between the random sequences and trained sequences are the number of reversals present in the sequences [48, 182, 193]. A reversal is when the $n-1$ item in the sequence is the same as the $n+1$. Of the trained sequences in Table 3.1, the first sequence does not have any reversals while the second and third each have one. The 'random' sequences were generated according to the criteria given in the previous knowledge manipulation study [5]. Since trills (e.g., 4242) were not allowed (242 or 424 were included), many reversals were also excluded. This means that two of the trained sequences each had one more reversal than the other trained sequence or the random sequences. At this point it is hard to rule out that the different reversal frequency may have altered performance, but it is unlikely. As described in Appendix A, there were very few significant differences between the different counterbalance sequence-identity conditions, which implies that if there was a difference due to the different reversal frequency, it was not large.

Chapter 4

Experiment 3: Contextual Cuing with Knowledge and Amount of Exposure Manipulations and a Process-Dissociation Test

The previous experiments demonstrated that controlled and automatic processes are measurable in the SRTT (Experiment 1) and that a change in learning directions that instructs participants to try and learn the repeating information can change the process estimates (Experiment 2). The current experiment posits that differences in controlled processes resulting from differing task learning directions do not necessarily entail differences in task performance. It also examines changes in the relative use of each process type with greater exposure.

This experiment uses a different implicit learning task (contextual cuing) that has not shown the same benefits from explicit learning directions as in the SRTT [6]. Since explicit repetition knowledge does not seem to be useful for improving response times on repeated configurations, it was predicted that there would be no task performance differences between explicit and implicit learning directions. However, greater controlled processes would be used for the cued trials as participants would likely be engaged in secondary strategies such as hypothesis testing or memory encoding not directly relevant to the visual search task.

Contextual cuing is a visual search task in which participants are exposed without their knowledge to repeating configurations of target and distracters, resulting in a reduced search time [19]. The visual search task is typically done with arrays similar to the ones shown in Figure 4.1. The object is to find the target (in this case, the T) as quickly as possible in each array. The cuing is achieved through repeated (i.e., 10 or more trials) exposure to the same configuration of target and distracters, and results in an observed decrease in the amount of time it takes to find the target. Each row in Figure 4.1 shows a separate repeating configuration of elements. The location of the target and distracters for each context are repeated, but the identities (i.e., color and orientation), are random. This learning seems to fall within the definition of implicit used in this dissertation (page 2), as participants learn this information without being directly instructed to, and lack awareness of what they have learned ([19]; but see [26]). Further support for contextual cuing as an implicit learning task comes from other hallmarks of implicit learning: learning is robust to interference or noise in the display [165], sensitive to the training context [166], dependent on attending to predictive information [119, 127, 130], retained for at least a week [6, 38], and generalizes to real world scenes [167, 168].

Most of the contextual cuing literature has focused on the conditions under which learning occurs [36, 128], rather than examining the type of the knowledge (be it implicit or explicit, automatic or controlled) acquired during learning. One exception is a study that focused on giving participants ample time to demonstrate explicit knowledge [26]. In this experiment, the normal contextual cuing learning benefit was observed. However, by significantly increasing the number of explicit knowledge test trials, they were able to find better generation and recognition rates for training configurations than untrained. Smyth and Shanks [26] argued this modification allowed them to finally have sufficient sensitivity to explicit knowledge held by the participants. However, it is possible that performance on the generation and recognition tests relied on implicit knowledge as well as explicit knowledge [3]. Furthermore, studying awareness focuses on the verbalizable

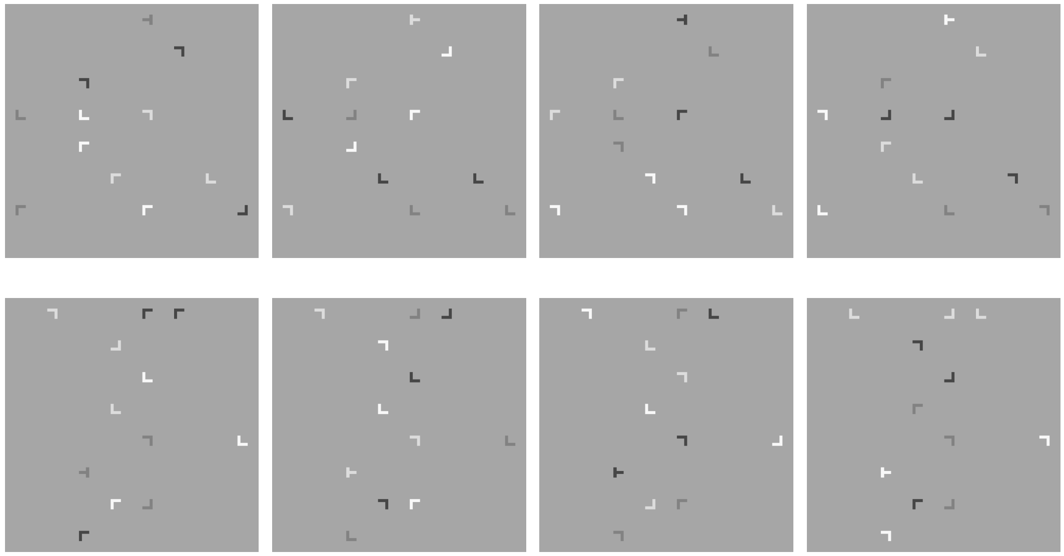

Figure 4.1. Example of visual search arrays frequently used in contextual cuing experiments. The target T is surrounded by 11 L distracters. When the configuration is repeated in subsequent blocks, the identity (i.e., color and orientation) of the objects will change, but the spatial arrangement will remain. Each row has a separate repeating configuration.

characteristics of what had been acquired by the end of training, rather than examining controlled and automatic processes. Finally, awareness measured after extensive training does not mean that behavioral changes during acquisition were necessarily dependent on explicit knowledge.

Chun and Jiang [6] gave participants explicit instructions to learn the repeating configurations rather than waiting for participants to develop explicit knowledge on their own (as in [26]). Even armed with knowledge of repeating configurations of target and distracters, participants were unable to use this knowledge to increase the contextual cuing benefit. Further, participants did not demonstrate explicit knowledge of which configurations were actually repeated during training. However, explicit knowledge was tested with a generation task in which participants were instructed to indicate the quadrant in an array full of distracters where the target would appear, which is a different task than simply finding the target (see the criterion introduction on page 6; [15]).

Current Experiment

Is explicit knowledge of the array repetition beneficial?

If explicit repetition knowledge is necessary for obtaining the contextual cuing benefit [26], greater contextual cuing should be seen for the explicitly cued arrays. However, if the repetition can be learned without having knowledge of the repetition [e.g., 19, 128], there should be a similar reduction in response times for both the cued and non-cued arrays. In both cases, the non-cued and cued arrays should yield faster reaction times than the novel configurations. Related to this, if explicit knowledge of the array repetition is beneficial for learning the repeating context, the cued configurations should be learned faster than the non-cued configurations, resulting in reaction time differences between repeated and novel configurations earlier in training.

It has also been proposed that explicit repetition knowledge is detrimental to configuration learning [128]. If so, reaction times for the cued configurations should be slower than the non-cued configurations. This could also retard the ability of participants to learn the cued configurations, which would mean it would take longer for participants to learn the cued configurations than the non-cued.

What is the effect of switching cue types on trained configurations?

As in Experiment 2, the consequence of switching cue type in the middle of the experiment was examined. If having explicit repetition knowledge was beneficial for contextual cuing [26], response times should be faster overall when the arrays are cued. If an interaction is found between switch condition and cue type, it would suggest that the repetition knowledge cuing was more beneficial if it occurred at a particular time.

Process estimates for the different switch orders can be directly compared. If the shift of the arrays from cued to not-cued decreased controlled process estimates, it would suggest that participants were unable to continue the same control over the knowledge gained in the first half. But if the shift to non-cued arrays did not alter process estimates, it would be highly suggestive that participants had gained controlled knowledge of the repeating arrays.

Use of automatic and controlled processes in contextual cuing

As previously stated, automatic and controlled processes have not been investigated in contextual cuing learning. If learning of the repeating spatial configurations is purely implicit, PD recognition tests of the processes should result in a strong automatic component with no controlled component (see *Information Processing* on page 9). If learning is purely explicit [26], PD recognition tests should reveal a large controlled component and a negligible automatic component. If both automatic and controlled processes are used [e.g., 3], both should be present in the PD recognition test. An additional goal of this experiment is to overtly manipulate the amount of training and to evaluate how controlled and automatic processes are affected.

While awareness of the sequence has been overtly manipulated via explicit instructions in a previous study [6], the effects on controlled and automatic processes have not been examined. This experiment uses the same type of repetition knowledge manipulation as in Experiment 2 for the SRTT. Participants were told that some cued configurations would repeat during the experiment, but were not cued for all the repetitions. Explicit knowledge has been found to be less beneficial for the contextual cuing task [50, 128], so it was expected that the awareness manipulation would have different effects on performance and processing estimates in contextual cuing than seen in Experiment 2.

Smyth and Shanks [26] argued that Chun and others [6, 19, 20, 128, 165, 194] failed to find evidence of explicit knowledge because they gave participants an insufficient amount of exposure at test to be able to demonstrate explicit awareness. However, if the focus is on the underlying processes, more exposure should allow for a greater number of instances to be stored, thus reducing the time needed to retrieve the target location from memory ([102]; also see page 10 of this thesis). This should lead to an increase in the automatic process estimate with greater exposure.

This leads to two possible outcomes with more exposure to the repeating configurations. If Smyth and Shanks [26] are correct, with more exposure to the repetition, participants should have more explicit knowledge and awareness of what is repeating; thus, they would be using more controlled processes since controlled processes are only accessible to awareness [1, 2, 84]. The other possibility is that with greater exposure to the repetition, participants have more instances stored in memory of the different repeating configurations, leading to both faster response times, as automatic processes are faster than controlled, and more evidence of automatic processes, as these automatic processes will be unimpeded by the controlled processes on the PD test. Further, under an information processing framework [1, 2, 102], controlled processes could also[1] come into use later during learning as attentional resources are freed with the greater use of automatic processes for the task, which would then allow for the formation of awareness.

Controlled processes helping contextual cuing?

The contribution of controlled processes to contextual cuing task performance was tested by correlating the controlled process estimate with the mean response time difference from random arrays to trained arrays for the two cue and three training length conditions. A significant correlation between controlled process estimates and size of the contextual cuing benefit would indicate that controlled processes are serving a useful function in the task. However, an interaction with the training length would indicate that this is not consistent across different amounts of training.

The contextual cuing effect in the absence of controlled processes?

Differences between participants for the process estimates were expected. However, participants who failed to show evidence of controlled processing during the PD

[1] Controlled processes will have to be used early in training to help perform the visual search task and facilitate learning of the arrays. This hypothesis suggests that with greater training, executive attention resources will become available for controlled processes to use in other visual search task irrelevant ways.

recognition tests (i.e., have a controlled process estimate of zero) should still show faster response times for trained arrays, supporting the claim that contextual cuing was learned 'implicitly' [6, 19, 20].

Method

Participants

Ninety Colorado State University students participated in this experiment and were randomly assigned into one of the six order x exposure groups. All were pre-screened for normal or corrected-to-normal acuity and color vision using a task that required participants to discriminate between letters in red and black ink.

Materials and Design

This experiment was run with E-Prime 2.0 [181]. Stimuli were pre-generated with Matlab (see Appendix B). The stimuli consisted of 12 objects: 11 were distracters (L) and one was the target (T). Each object subtended 1.5°, and the full array subtended 36°. The configuration of objects was random, such that there were three objects per quadrant. The gray array's items and background only varied by brightness. The red array included an overlay of a red tint on all values, both background and objects. Within each repeated configuration, the random object identities (i.e., gray value and orientation) were determined randomly, however the objects and target occurred in the same location on each trial using that configuration, as shown in Figure 4.1.

For each trial, the participant needed to indicate quickly and accurately which direction the target T was pointing. The T could point to the left (⊢) or right (⊣). Responses were made with the arrow keys. All objects were presented against a solid grey or slightly red background.

The basic structure of the experiment was the same for all participants (see Table 4.1), but the number of trials differed by exposure condition: the minimum exposure

Table 4.1. The design of the training portion of the experiment. Prior to training, all participants did 20 practice visual search trials. After training, all participants were given the PD recognition test. For training, three sets of arrays were learned during the experiment. Set A was shown during both halves of the experiment with a switch in cue halfway through (cued to non-cued: C-NC, or non-cued to cued: NC-C), Set B was only shown in the half when the switch condition was cued with the gray scale arrays (i.e., not cued, NC), and Set C was only shown in the half when the switch condition was not cued with the red tinted arrays (i.e., cued, C).

Order Condition

Experiment Half	
First half	Second half
Set A: Cued (C-NC: cued)	Set A: Not Cued (C-NC: not cued)
Set B: Not Cued (NC)	———
———	Set C: Cued (C)

Experiment Half	
First half	Second half
Set A: Not Cued (NC-C: not cued)	Set A: Cued (NC-C: cued)
———	Set B: Not Cued (NC)
Set C: Cued (C)	———

condition (short) had six blocks of training in each half of the experiment, the standard exposure condition (medium) had 18 blocks of training in each half of the experiment, and the maximum exposure condition (long) had 30 blocks of training per half. There were 30 trials per block. There was one repeated array set with 10 configurations seen in both halves (switch: C-NC or NC-C). There was another array set of 10 configurations repeated in each half of the experiment. In one half, these configurations were cued (C), and in the other half, a separate repeated configuration array set was not-cued (NC). The other 10 configurations in each block were randomly generated. The order of stimuli was random in each block.

Amounts of training had not previously been systematically manipulated in contextual cuing expeirments. Smyth and Shanks [26] argued that researchers should increase the number of trials at test, but not during training. Learning of the spatial configurations seems to occur between the sixth block (144 trials, [19]) and the thirteenth block (312 trials, [26]); however, we do not know anything of the changes in controlled or automatic processing occurring during the early or later parts of learning.

The current experiment manipulated the amount of exposure to the repeated configurations during training to measure the relative contributions of automatic and controlled processes at different phases of learning. Some participants received a minimal amount of training, others received a standard amount of training, and the final group of participants were over-trained on the repeated configurations. The minimal amount of training was set at six blocks (with 30 trials in each) per half for this experiment, as this seems to be when a difference begins to emerge between the repeating and novel configurations [6, 19, 26]. The standard amount of exposure consisted of 18 training blocks (with 30 trials in each block) per half as this tends to be around when the performance difference between configuration conditions stabilizes [6, 19, 26, 166]. Finally, the maximum exposure amount was 30 training blocks per half (again with 30 trials in each block); the maximum number of blocks for many contextual cuing experiments tends to be in the 24 to 30 range, and additional response time benefits tend to not be observed at this point in training [6, 19, 20, 128, 166–168, 195].

Procedure

At the start of the experiment, the participant received instructions about the visual search task including that the target T would appear at an orientation which they would then need to indicate with the arrow keys. Two examples followed the explanation, and if the participant had no questions they completed 20 practice trials before starting the experimental trials. As with Experiment 2, participants were informed that some of the visual arrays would repeat during the experiment, and it would be in their best interest to try and learn the configurations. They were told further that these repeated arrays would be signalled with a red tint to the visual search array. For all trials, participants were instructed to find the target T in the field of distracter Ls, and indicate which way it was pointing, either to the right with the right arrow key, or to the left with the left arrow key.

Each trial started with a white O appearing in the center of the screen on a gray background for 1 s, which was then followed by the visual search array. Participants had an unlimited amount of time to respond, and errors were indicated by a beep. Between each set of visual search trials, participants were given a mandatory 10 s break. After the 10 s, participants could rest further if they wanted, or continue with the next set of trials. Between the first and second sets, there was a three minute distracter task consisting of two digit addition and subtraction problems.

After completing the visual search task, participants started the PD recognition tests. The order of the cued and not-cued versions of PD recognition testing was counterbalanced between participants. For the cued PD recognition test, participants were told they would view visual search arrays, and they would need to respond if they had viewed the array during the experiment under two sets of instructions. Under Inclusion instructions, they were instructed to call an array 'old' if the array had been viewed during the experiment with a red-tint. There were 30 configurations for switch, C, and NC arrays as well as 30 novel arrays. Under Exclusion instructions, participants were to call an array 'old' only if they viewed it with a red-tint in a specified half determined by order-counterbalance condition: for the C-NC order, the cued arrays to call 'old' were shown after the distracter task, and for the NC-C order, the cued arrays to call 'old' were shown before the distracter task. There were 30 arrays for all conditions, and order of the direction blocks was counterbalanced.

The non-cued PD recognition test asked participants to call an array 'old' if they viewed it with a gray tint at any point during the experiment (under Inclusion directions), and to call an array 'old' if they viewed it with a gray tint during a specific half of the experiment (under Exclusion directions; C-NC condition were to call items before the distracter 'old', NC-C condition were to call items after the distracter 'old'). The order of these test directions was counterbalanced. Participants were again told that there were new items in the tests. The tests followed the same format as the cued recognition PD tests, including number of trials per trial type.

Results

The reaction time for all training trials was recorded. The mean reaction time for each block by array type was also calculated for each participant. The block RTs were collapsed into epochs, each consisting of three blocks. Transfer RTs were used in later analyses to show benefits or costs associated with the different training conditions compared to random arrays. These were calculated by subtracting the trained array from random array RTs.

All planned pairwise comparisons were run with a Bonferroni adjustment for multiple comparisons[2] unless otherwise noted.

Training Performance

The first comparison was on overall RT differences between the array types to test if learning of the repeated arrays occurred. A repeated-measures MANOVA was run on the RT with the factors of array type (random, NC, C, switch-NC, switch-C; within) and training amount (short, medium, long; between). As illustrated in Figure 4.2, there was a significant difference in RT between array types, $F(4,84) = 19.85$, $p < .05$, $\eta_p^2 = .49$. Planned comparisons showed this difference was driven by the NC arrays having significantly faster RTs than the random, switch-NC, and switch-C array types (these pairwise comparisons against the NC arrays, $p < .05$). No other paired differences were significantly different. That the NC arrays had significantly faster RTs than all other array

[2]The Bonferroni adjustment for multiple comparisons allows for comparison of the adjusted LSD probability against a set Type I error level ($\alpha = 05$). The Bonferroni adjusted probability is found by multiplying the LSD probability by the number of post hoc comparisons.

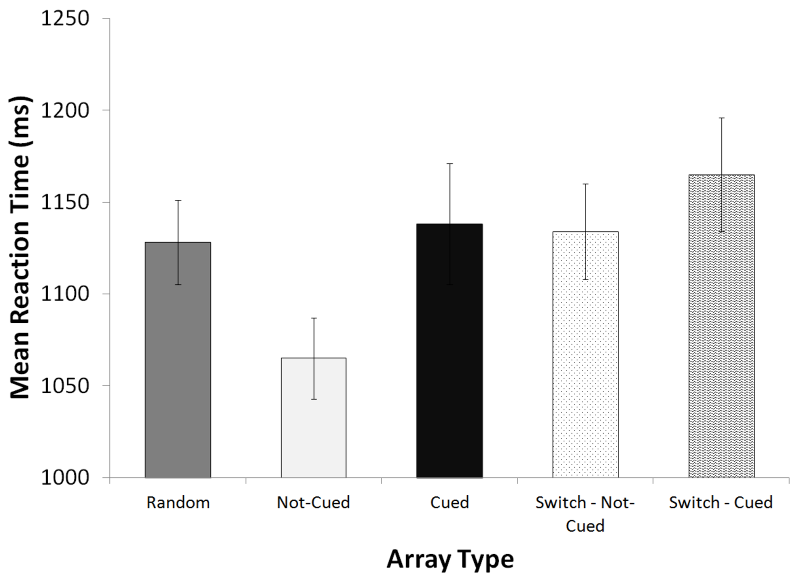

Figure 4.2. Mean RT during training for each array type. Only the not-cued arrays had significantly faster RTs than any of the other array conditions. Error bars represent one standard error.

types suggests that the fastest performance was for the arrays that were never cued, hinting that explicit knowledge of the repetition could harm reaction speed [6].

There was also an RT difference for the different training lengths, F(2,87) = 4.36, $p < .05$, $\eta_p^2 = .09$, as shown in Figure 4.3. The short training group (M = 1224 ms) had significantly longer RTs than the medium (M = 1081 ms) and long (M = 1073 ms) training groups. The interaction between the type of array and amount of training was not significant, F(8,170) = .69, $p > .05$, $\eta_p^2 = .03$, indicating no differential learning effect between the different array types with greater amounts of training.

To directly test the claim that the cued arrays would benefit from greater exposure [26], two additional analyses were performed. The first examined differences in performance within the long training group using a repeated-measures MANOVA with array type (random, NC, C, switch-NC, and switch-C; within) as the only factor. There was a significant difference between array types (mean RT by array type in ms: random = 1227, NC = 1156, C = 1245, switch-NC = 1216, switch-C = 1252),

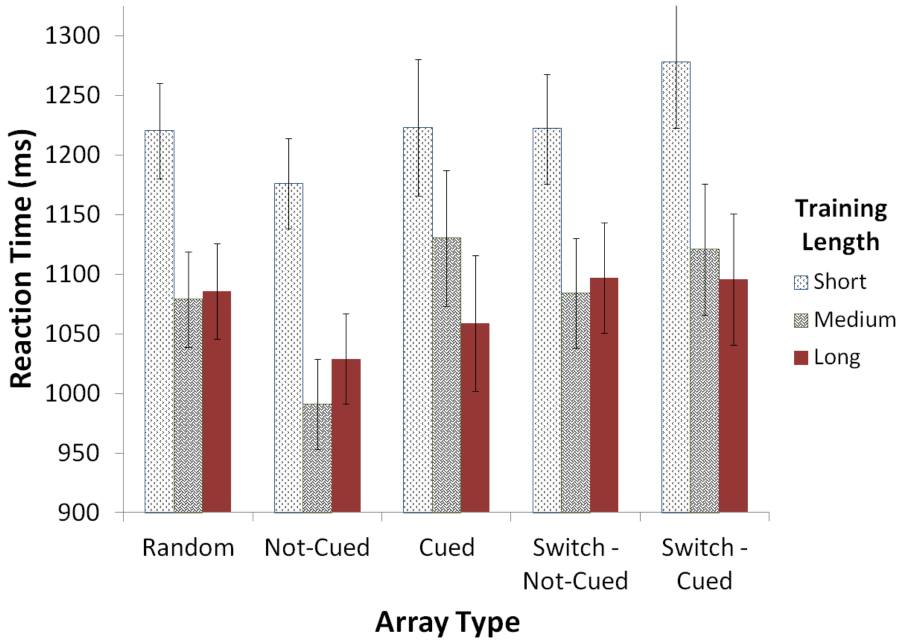

Figure 4.3. Mean RT during training for each array type crossed by length of training. The short training group responded significantly slower than the medium and long training group. There was not an interaction between array type and training group. Error bars represent one standard error.

F(4,26) = 6.20, $p < .05$, $\eta_p^2 = .49$. Pairwise comparisons showed that this difference was driven by the NC arrays being responded to significantly faster than the random and switch-C arrays ($p < .05$). All other comparisons were non-significant ($p > .05$).

In case the advantage for cued arrays only emerged later in training, a new repeated-measures MANOVA was run with the RTs only from the last 3 blocks of training from the long training group, again with array type (random, NC, C, switch-NC, and switch-C; within) as the only factor. There was a significant effect of array type (mean RT by array type in ms: random = 1036, NC = 991, C = 968, switch-NC = 1046, switch-C = 1051), F(4,26) = 2.56, $p < .05$, $\eta_p^2 = .31$. However, pairwise comparisons did not show any significant differences (all $p > .05$), possibly indicating a lack of comparative power.

The contextual cuing effect is usually described at different points within the learning curve [e.g., 19, 20, 36]. However, comparisons between differing amounts of training has not yet been done. Given the complexity of the current experiment, the changes over time were examined in several steps. The RTs across the different array types and training lengths by epoch are shown in Figure 4.4. In order to compare the different training lengths, the analyses were conducted in stages to include the available training lengths. The first analysis compared all three training lengths, but only for the first two epochs. The second analysis compared the medium and long training groups from epochs three through six. The final analysis only contained the long training group for epochs seven through ten. Thus, at each step all available training data were included for the comparison of interest. To further simplify the comparisons, transfer RTs were used rather than raw RT. This allows for more direct examination of how each learnable array type was being searched compared to random visual search.

The first set of analyses focused on the arrays that were not part of the switch condition (i.e., C and NC). To better get a sense of the effect of training, the transfer RTs were compared in three repeated-measures MANOVAs. As previously described, the first analysis only included the first two epochs. Specifically, the first repeated-measures MANOVA was run on the first two epochs with epoch (1-2; within), cue condition (NC or C; within), and training group (short, medium, long; between) as factors. As shown in Figure 4.5 for epochs 1 and 2, the NC arrays had greater transfer RTs (M = 61 ms) than the C arrays (M = -42 ms), $F(1,87) = 4.26$, $p < .05$, $\eta_p^2 = .05$. This suggests that the repetition cuing is hurting the contextual cuing effect, at least very early in training.

There was also a main effect of epoch, $F(1,87) = 69.40$, $p < .05$, $\eta_p^2 = .44$, with greater transfer RTs with more training (mean transfer RT by epoch in ms: 1 = -49, 2 = 68). The interaction between cue type and epoch was not significant, $F(1,87) = .44$, $p > .05$, $\eta_p^2 = .01$, failing to support the idea that the different cue types transfer RTs differentially changed with increasing amounts of training. The different training groups did not have different transfer RT scores, $F(2,87) = .09$, $p > .05$, $\eta_p^2 = .002$, and training group did not interact with any other factor (all $F < 1$).

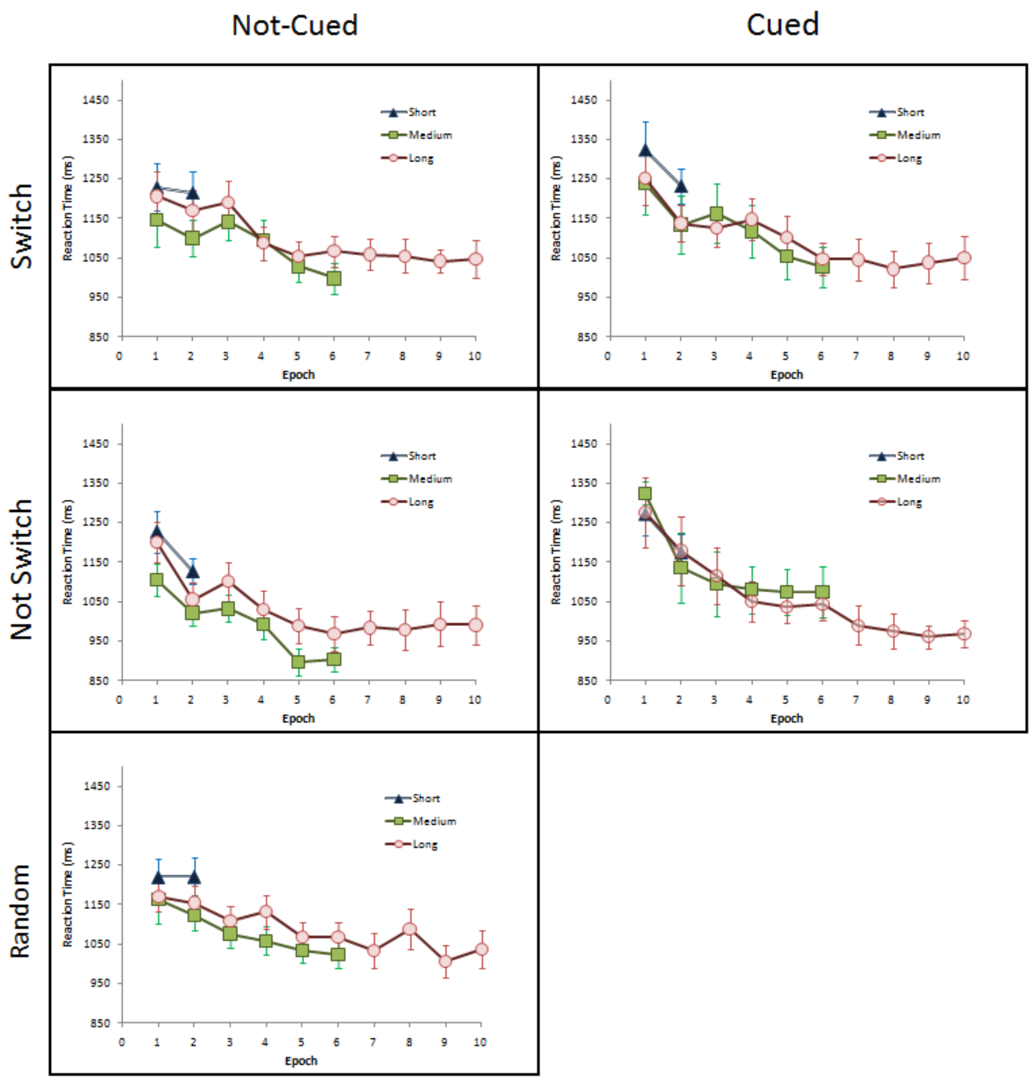

Figure 4.4. The mean RT for each array type, epoch, and training length. One epoch contains the means of three training blocks. The left column has the means for not-cued arrays, and the right column for the cued arrays. The top row contains the arrays that switch cue-type halfway through, the middle row has the arrays that are only shown in one experimental half in one cue-type, and the bottom has the random arrays. Error bars represent one standard error.

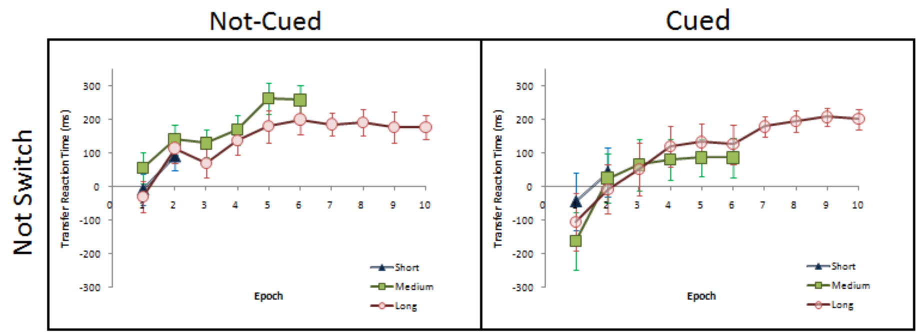

Figure 4.5. Mean transfer RT for the cued and not-cued arrays by epoch and training group. A positive transfer RT indicates that the trained array was responded to faster than the random array. Error bars represent one standard error.

The second repeated-measures MANOVA only included the medium and long training groups for epochs three through six. This repeated-measures MANOVA was run with epoch (3-6; within), cue type (NC or C; within), and training group (medium or long; between) as factors. There was again a difference between array types, $F(1,58) = 5.51$, $p < .05$, $\eta_p^2 = .09$, with greater transfer RTs for the NC arrays (M = 177 ms) than the C arrays (M = 95 ms). This suggests that overt repetition knowledge reduces the contextual cuing effect at moderate amounts of training.

Increasing exposure to the arrays improves RT for the repeating arrays overall, given the main effect of epoch, $F(3,56) = 10.41$, $p < .05$, $\eta_p^2 = .36$. The difference between epochs seems to be between the epochs 3/4 and 5/6 (mean transfer RT by epoch in ms: 3 = 80, 4 = 128, 5 = 167, 6 = 168). The cuing of the array interacted with these epochs, $F(3,56) = 4.43$, $p < .05$, $\eta_p^2 = .19$, with a greater increase in transfer RT for the NC arrays (mean transfer RT by epoch in ms: 3 = 100, 4 = 155, 5 = 223, 6 = 230) than the C arrays (mean transfer RT by epoch in ms: 3 = 80, 4 = 101, 5 = 110, 6 = 107). This also fits with the contextual cuing effect being dampened by repetition knowledge. Training length, as in the first epoch set, did not have an effect on transfer RT, $F(1,58) = .05$, $p > .05$, $\eta_p^2 = .001$, and did not react with the other factors (all $p > .05$).

The third and final analysis for the non-switched arrays was run on only the long training groups data for epochs seven through ten. This repeated-measures MANOVA included epoch (6-10; within) and cue type (NC or C; within) as factors. There were no differences between array type (mean transfer RT by array type in ms: NC = 184, C = 197), $F(1,29) = .26$, $p > .05$, $\eta_p^2 = .01$, which does not support contextual learning occurring at this point in training. There was also no difference between epochs (mean transfer RT by epoch in ms: 7 = 184, 8 = 194, 9 = 194, 10 = 191), $F(3,27) = .07$, $p > .05$, $\eta_p^2 = .008$, which also does not support configuration-specific learning occurring at this training amount. The interaction between array type and epoch was also not significant, $F(3,27) = .13$, $p > .05$, $\eta_p^2 = .02$.

Combined, the results from these analyses suggest that cuing the repeating arrays reduces the contextual cuing visual search speed benefit, at least up through moderate amounts of training. However, beyond the first two epochs, the cued arrays are responded to faster than the random arrays; thus there is a contextual cuing benefit from repeated exposures, just not as quickly as when the arrays are not cued.

Effect of Switching Cue Types

The next series of repeated-measures MANOVAs only include data from the arrays that were repeated during the full training period and switched cue status halfway through. If having explicit repetition knowledge is beneficial for contextual cuing [26], response times should be faster overall when the arrays are cued. If an interaction is found between switch condition and cue type, it would suggest that having the repetition knowledge is more beneficial if it occurs at a particular time. The repeated-measures MANOVA was run on the mean transfer RT with the factors of cue type (C or NC; within), order in which the switch arrays were encountered (C-NC or NC-C; between), and training group (short, medium, or long; between). There were no significant differences for cue type (mean transfer RT by cue type in ms: not-cued = -3.1; cued = -22.8), $F(1,84) = .51$, $p > .05$, $\eta_p^2 = .006$; amount of training (mean transfer RT by training length in ms: short = -2.9;

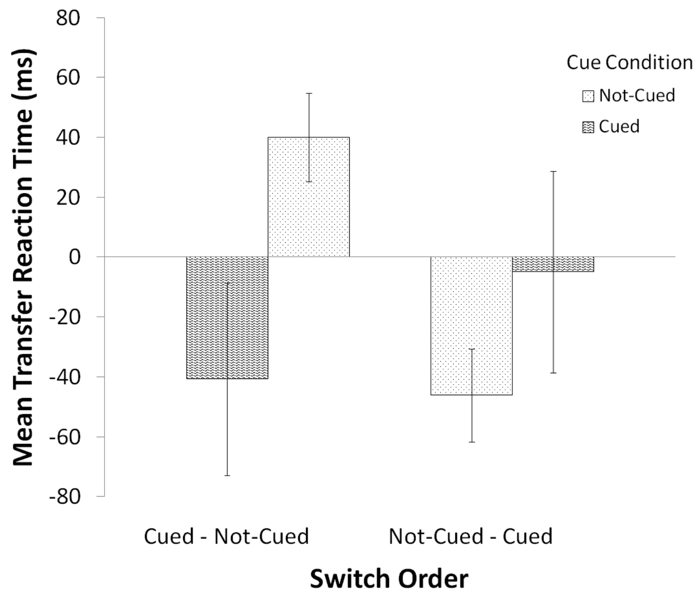

Figure 4.6. Overall mean transfer RT for the arrays that switched cue status midway through the experiment by order cue type and order the cues were presented. Error bars represent one standard error.

medium = -29.0; long = -7.0), F(2,84) = .48, $p >$ .05, $\eta_p^2 =$ .01; or order in which the cuing for the switch arrays were encountered (mean transfer RT by switch order in ms: C-NC = -.4; NC-C = -25.5), F(1,84) = 1.19, $p >$ .05, $\eta_p^2 =$ .01.

There was an interaction between the type of cue and switch condition order, F(1,84) = 4.84, $p <$ .05, $\eta_p^2 =$ .05. As shown in Figure 4.6, transfer times were negative for the first cue type shown regardless of whether it was C or NC. Both were tested to see if they were significantly less than zero: C-NC - cued was not, t(46) = 2.29, $p >$.0125[3], Cohen's d = .48; while NC-C - not-cued was, t(42) = 2.75, $p <$.0125[3], Cohen's d = .61. In the second half of training, only the C-NC - not-cued repeated arrays showed a positive transfer RT, t(46) = 3.0, $p <$.0125[3], Cohen's d = 63. The switch from not-cued to cued did reduce the negative transfer RT when compared with the first half, however these cued arrays were not responded to significantly faster than random arrays, t(42) = .09, $p >$.0125[3], Cohen's d = .02. All other interactions were non-significant ($p >$ .05).

[3]Bonferroni adjustment for multiple comparisons

Table 4.2. Mean probability of responding 'old' to an array on the recognition test by cue type (red-tinted arrays, i.e. cued, or gray scale arrays, i.e., not-cued), array type (switch, cued, not-cued, or random), and length of training (short, medium, or long).

		Inclusion			Exclusion		
Test Type	Array Type	Short	Medium	Long	Short	Medium	Long
Cued	Switch	.48	.47	.49	.37	.39	.44
	Cued	.42	.46	.46	.39	.34	.42
	Not-Cued	.41	.43	.44	.42	.44	.40
	Random	.41	.37	.31	.35	.30	.33
Not-Cued	Switch	.45	.45	.42	.37	.33	.40
	Cued	.38	.43	.35	.38	.35	.34
	Not-Cued	.43	.40	.36	.44	.43	.39
	Random	.41	.44	.39	.39	.34	.35

Process-Dissociation Recognition Test

For the PD recognition tests in the current experiment, participants were shown visual search arrays and instructed to indicate if they had seen the configuration during training or not under specific instructions (Inclusion - anything encountered under the current cue condition 'old'; Exclusion - exclude the switch sequence).

The mean probabilities of each array type being identified as 'old' by cue type, test type, and training length are shown in Table 4.2. To test if the process estimates were artifacts of a strategy difference [4], the random 'old' identification rates were compared in a repeated-measures ANOVA with cue type (cued or not-cued; within), test type (Inclusion or Exclusion; within), and training length (short, medium, or long; between) as factors. All comparisons were not significantly different ($p > .05$).

The split-half reliability of the recognition tests was also checked to make sure participants were answering consistently [188]. Each part of the test (i.e., cued or not-cued, Inclusion or Exclusion) was divided into two halves, which were then correlated with each other. There were strong correlations for the cued - Exclusion, $r(88) = .95$, $p < .05$, Cohen's $d = 4.3$, cued - Inclusion, $r(88) = .94$, $p < .05$, Cohen's $d = 4.0$, not-cued -

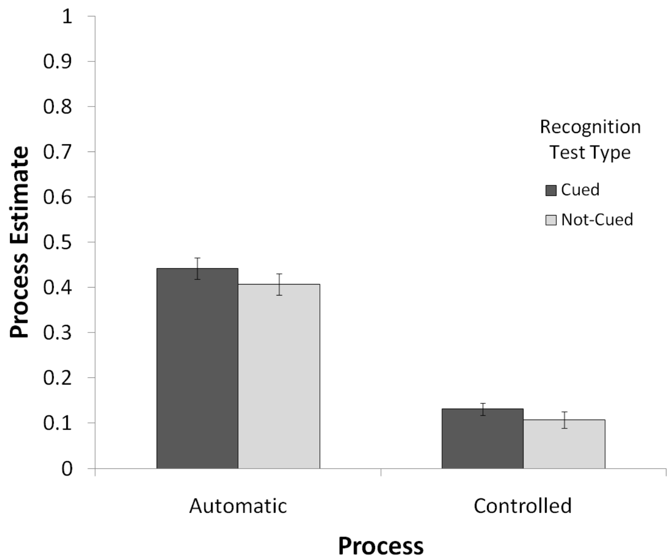

Figure 4.7. Mean process estimates for cued and not-cued recognition tests for the switch arrays. All estimates were significantly above zero ($p < .05$), but there were no differences between test types. Error bars represent one standard error.

Exclusion, r(88) = .93, $p <$.05, Cohen's d = 3.6, and not-cued - Inclusion tests, r(88) = .93, $p <$.05, Cohen's d = 3.6. Therefore, it is likely participants were responding reliably.

The process estimates were calculated from the PD formulas given in the Introduction (see page 16). A repeated-measures MANOVA was run on each type of process estimate with cue type of the recognition test (cued or not-cued; within), length of training (short, medium, or long; between), and switch order as factors (C-NC or NC-C; between).

Based on Logan's [102] instance theory of automatization, greater exposure to the repeating information should lead to an increase in the automatic process estimate. This should be reflected in a difference between training duration groups, specifically greater automatic estimates with greater training lengths. For the automatic process estimates, there was not an effect of recognition test cue type, F(1,84) = 2.66, $p >$ .05, $\eta_p^2 = .03$; length of training (mean automatic process estimate by training length: short = .42; medium = .40; long = .46), F(2,84) = .73, $p >$ .05, $\eta_p^2 = .02$; order of the switch arrays (mean automatic process estimate by switch array order: C-NC = .40; NC-C = .45), F(1,84) = 1.53, $p >$ .05, $\eta_p^2 =$ .02; or a significant interaction between factors (all $F < 1$). However, the automatic process estimates were significantly above zero for both C, t(89) = 18.29, $p <$.025[4], Cohen's d = 2.74, and NC recognition tests, t(89) = 17.16, $p <$.025[4], Cohen's d = 2.57, see Figure 4.7. Automatic processes were almost certainly being used at test; however, these do not seem affected by the length of training or nature of the repetition cue. The lack of a training length interaction could either suggest that Logan's [102] instance account of automaticity does not apply for contextual cuing, or only a very small number of instances are required in this task so that even the short training group has enough instances stored to boost automatic performance.

If explicit knowledge is supporting performance on contextual cuing [26], greater training lengths should have greater controlled process estimates independent of repetition cue. A repeated-measures MANOVA was run on the controlled process estimates with recognition test cue type (cued or not-cued; within), training length (short, medium, or long; between), and order the switch arrays were encountered (C-NC or NC-C; between) as factors. There were no effects of recognition test cue type, F(1,84) = 1.64, $p >$ .05, $\eta_p^2 =$ .02; length of training (mean controlled process estimate by training duration: short = .12; medium = .15; long = .09), F(2,84) = 1.70, $p >$ .05, $\eta_p^2 =$ .04; or order the switch arrays were encountered (mean controlled process estimate by switch array order: C-NC = .13; NC-C = .11); nor any interaction between factors (cue type by switch order, F(1,84) = 1.15, $p >$ .05, $\eta_p^2 =$ .01; all other $F < 1$). The controlled process estimates were significantly above zero for C, t(89) = 7.52, $p <$.025[5], Cohen's d = 1.13, and NC recognition tests, t(89) = 8.28, $p <$.025[5], Cohen's d = 1.24. This suggests that controlled processes can be used for contextual cuing, but that they are not a necessary outcome of learning that increases with greater exposure.

[4]Bonferonni adjustment for multiple comparisons
[5]Bonferonni adjustment for multiple comparisons

Table 4.3. Correlations of the controlled process estimates with transfer scores from training. A positive correlation between process estimate and transfer RT indicates that with greater controlled process estimates a stronger contextual cuing RT benefit was found (comparing the array type against random arrays). A negative correlation indicates that greater controlled process estimates were associated with lower or reversed contextual cuing RT differences. The starred correlations were significant at the $p = .05$ level.

Short Training

Controlled Process Estimate by Recognition Test	Training Array Type			
	Not-Cued	Cued	Switch - Not-Cued	Switch - Cued
Cued	-.05	-.13	-.28	-.02
Not-Cued	-.14	.24	.12	-.01

Medium Training

Controlled Process Estimate by Recognition Test	Training Array Type			
	Not-Cued	Cued	Switch - Not-Cued	Switch - Cued
Cued	-.05	*-.67**	-.18	*-.61**
Not-Cued	*-.37**	-.30	.22	*-.48**

Long Training

Controlled Process Estimate by Recognition Test	Training Array Type			
	Not-Cued	Cued	Switch - Not-Cued	Switch - Cued
Cued	.15	-.17	-.09	.04
Not-Cued	.16	.12	.02	.18

Controlled Processes Helping Contextual Cuing?

The contribution of controlled processes to contextual cuing task performance was tested by correlating the controlled process estimates with transfer score (the mean RT difference between random arrays and trained arrays) for the different array types. A significant correlation between controlled process estimates and size of the contextual cuing benefit would indicate the controlled processes are serving a useful function in the task. Furthermore, differences between the correlations for the different training lengths would provide evidence for changes in the use of controlled processes across the course of learning.

The correlations are shown in Table 4.3. The only significant correlations between controlled process estimates and training transfer RTs were in the medium training group. There was a significant negative correlation between controlled process estimate from the cued PD recognition test and C training arrays, $r(29) = -.67$, $p < .05$, Cohen's $d = 1.2$. There was also a negative correlation between the cued PD recognition test's controlled process estimate and switch-C training arrays, $r(29) = -.61$, $p < .05$, Cohen's $d = 1.08$. The negative correlations for both types of cued training arrays with the cued array recognition test suggests that with higher controlled process estimates there was less of a benefit from the explicitly cued repeating arrays, possibly even slower RTs for the cued compared to random arrays.

There were significant negative correlations between the not-cued PD recognition test controlled process estimates and NC training arrays transfer RT, $r(29) = -.37$, $p < .05$, Cohen's $d = .60$, as well as the switch-C training arrays transfer RT, $r(29) = -.46$, $p < .05$, Cohen's $d = .73$. These negative correlations suggest that there is a RT cost associated with overtly learning the cued repeating arrays. While the correlations cannot speak to the direction of the relationship, it is possible that the participants with greater use of controlled processes for switch-C arrays are relying on a slower, more controlled search through memory for the target's location rather than using the automatic processes associated with contextual cuing [19, 38, 196] or are simply performing the visual search task without using previously learned information [197–200] for the switch-C trials.

Contextual Cuing Effect in the Absence of Controlled Processes?

To determine if controlled processes are required for contextual cuing, the overall training data were separately analyzed with repeated-measures MANOVAs for participants who did not show use of controlled processing at test for the cued recognition test (N by training length: short = 8; medium = 12; long = 13), and not-cued recognition test (N by training length: short = 13; medium = 9; long = 11) with array type (random, NC, C, switch-NC, and switch-C; within) and training length (short, medium, or long;

Table 4.4. Number of participants for each amount of training under the different possibilities from the two PD recognition tests.

Number of Participants with Controlled Process Estimates by PD Recognition Test				
	Both Cued and Not-Cued	Neither Cued or Not-Cued	Only Cued	Only Not-Cued
Short	15	6	7	2
Medium	12	3	6	9
Long	12	6	5	7
Total	39	15	18	18

between) as factors. The full breakdown for the number of participants who showed use of controlled processes for the two PD recognition tests is included in Table 4.4.

Cued PD Recognition Test

Participants with zero controlled process estimates on the recognition test for cued arrays still showed evidence of having learned some of the repeating configurations, F(4,27) = 9.04, $p <$ .05, $\eta_p^2 =$ .57, as shown in Figure 4.8. The difference between array types was driven by the NC arrays being responded to faster (M = 1058 ms) than random (M = 1131 ms) arrays, as determined through planned pairwise comparisons (all other $p >$ .05). There was not a difference between training groups, F(2,30) = .145, $p >$ .05, $\eta_p^2 =$ .01, nor an interaction between amount of training and array type, F(8,56) = 1.14, $p >$ .05, $\eta_p^2 =$ .14.

Not-Cued PD Recognition Test

Participants with zero controlled process estimates from the not-cued array recognition test also showed evidence of having learned some of the repeating spatial configurations with a main effect of array type, F(4,27) = 7.83, $p <$ .05, $\eta_p^2 =$ .54. As shown in Figure 4.9 and verified with planned pairwise comparisons, NC arrays were responded to faster (M = 1059 ms) than random (M = 1131 ms) and switch-C (M = 1128 ms) array types. As with the cued array recognition test's zero controlled process estimate comparison, there was not a main effect of training length, F(2,30) = .99,

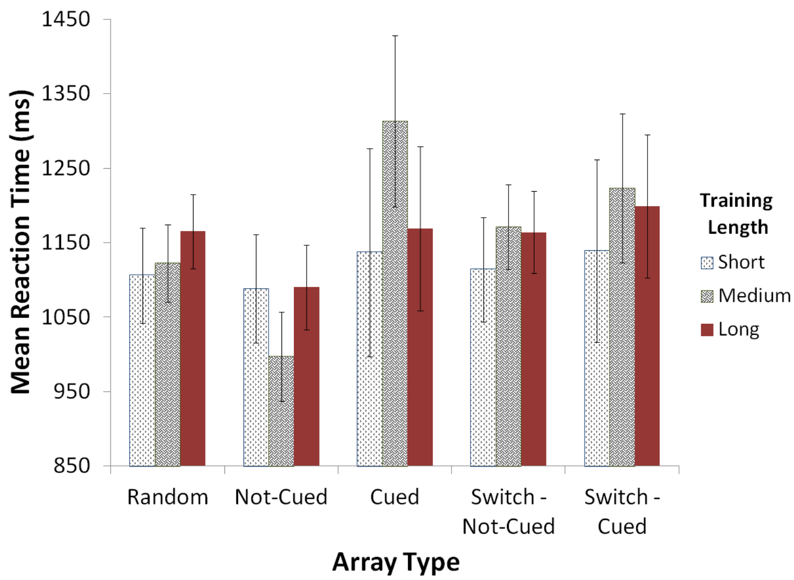

Figure 4.8. Mean training RT differences for participants with zero controlled process estimates from the recognition test for cued arrays. Error bars represent one standard error.

$p > .05$, $\eta_p^2 = .06$, nor an interaction between array type and training length, $F(8,56) = 1.73$, $p > .05$, $\eta_p^2 = .19$.

That learning, indexed by faster RTs for the NC arrays than the random arrays, is found for the participants who failed to demonstrate significant controlled processing on the recognition tests suggests that controlled processes are not required to benefit from the repeating configurations in contextual cuing. This also argues against the claim that controlled processes are mandatory for the contextual cuing RT benefit [26], and instead supports the theory that this performance difference can be supported by automatic processes. However, these participants did not have significantly faster RTs for the cued or switch arrays compared with random arrays which could indicate that they were unable to learn the arrays when they were cued as repeating.

Discussion

Participants were able to benefit from the repeating configurations in visual search time on the not-cued arrays [6]. The search time benefit was reduced and delayed for cued

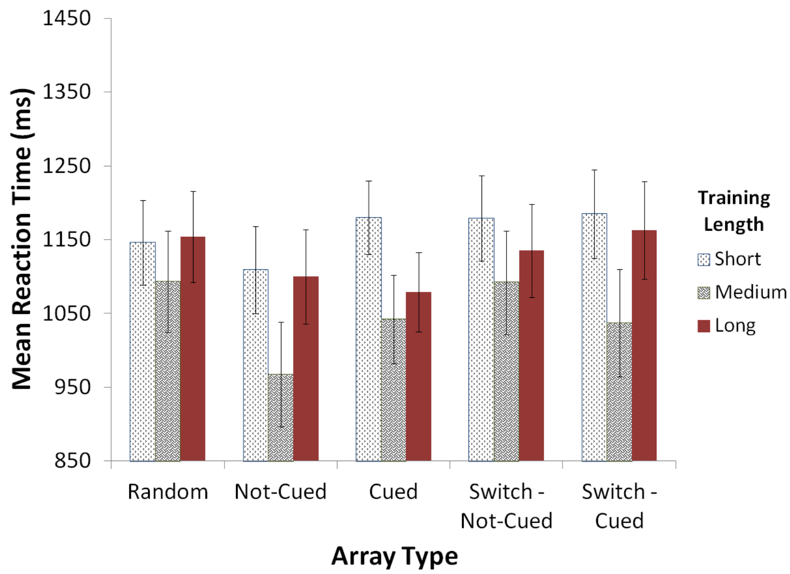

Figure 4.9. Mean training RT differences for participants with zero controlled process estimates from the recognition test for not-cued arrays. Error bars represent one standard error.

arrays up through moderate amounts of exposure (i.e., 18th block of training) [26]. The amount of training did not impact visual search times when amount of exposure was equated. These results suggest that the contextual cuing benefit is most quickly acquired without the learner's intent. The cued arrays were learned more slowly, either through the small but significant controlled process contribution, or through slowed automatic processes due to interference from the cue. Furthermore, the participants who failed to show evidence of controlled processes at test were still able to learn the not-cued spatial repetitions [6, 19, 36], suggesting that controlled processes are not required for the traditional (i.e., only not-cued repetitions) contextual cuing benefit [cf. 26].

The current experiment cannot speak to the participants' actual intent to learn the cued arrays during the task, and it is possible they disregarded the cue; however, the cue did slow performance, so participants were affected by it in some way. One possible way to address this is to build in an incentive, such as points or physical reward, for learning the cued arrays.

The lack of a cued-repeated configuration reaction time advantage partially replicates Chun and Jiang's [6] findings. The current experiment as well as Chun and Jiang used explicit learning directions, and in the case of the current experiment a repetition cue, to provide participants with knowledge of the repeating arrays. Smyth and Shanks [26] did find an advantage to awareness of the repetition, but they relied on the participants to develop awareness of the repetition spontaneously. It is possible that having knowledge of the repeating arrays is not beneficial unless it is internally generated by the participant.

Since all process estimates, both controlled and automatic under cued and not-cued PD recognition test conditions, were significantly above zero, it appears that both automatic and controlled processes were used by many participants[6]. This argues against the idea that contextual cuing results from purely implicit [6, 19, 20, 36] or explicit [14, 26] learning, but rather reflects a mixture of the two [3]. However, this is not the case for participants with controlled process estimates of zero: without sufficient evidence of using controlled processes, these participants were almost certainly learning implicitly [but see 14, 15, 26].

The lack of interaction between process estimates and amount of training suggests several possibilities. First, since contextual cuing has been shown to emerge quickly [6], it is possible that the amount of training in the short training groups still took participants beyond the point at which process estimates were changing. Future experiments that end training before the sixth repetition may find differences. Second, participants may have never formed a complete memory for many of the arrays, but rather only partial knowledge of a subset of the full collection of arrays [26]. Reducing the number of arrays to be learned, both cued and not-cued, may help produce differences in controlled process estimates. Finally, it is possible that the contextual cuing task is sensitive to deliberate,

[6]It is inappropriate to make comparisons between the automatic and controlled process estimates as they are mathematically dependent. This is part of why the repetition-knowledge technique was incorporated, as it allows for comparisons within each process type.

intentional processes beyond a certain point [6, 19], and that manipulations focused on altering levels of attention or intent will not have an effect.

Consistent with Chun and Jiang [6], knowledge of the repetition did not help performance early in training; rather, there seemed to be a performance decrement associated with the cued arrays up through mid-levels of training. This would suggest that explicit repetition knowledge is not required for the contextual cuing effect to emerge [cf. 26]. However, there was no difference between the cued and not-cued arrays late in training, suggesting that these arrays were eventually learned. It would be interesting to test the effects of the different cue types on the transferability of what was learned, as automatic processes tend to be rigid and controlled processes more flexible. If after learning the repeating spatial configurations with cues, it was found that participants could transfer the configurations to novel contexts, this would be highly suggestive that the configurations were also being acquired explicitly, and that the repeating configurations are only acquired the fastest in an implicit manner, and that the configurations can be learned explicitly but that requires more time. Alternatively, it is possible that the long training groups stopped trying to learn the cued arrays and shifted their strategy to only trying to find the target without memorizing the arrays. The previously mentioned implementation of a reward for learning the cued arrays might help reduce the likelihood of this happening.

The order the switch arrays were encountered affected the visual search performance. There were savings in learning between the first and second halves of training, in that the mean transfer RT increased for both C-NC and NC-C groups. However, the savings were greater for the C-NC group, with the not-cued arrays having the targets found on average 40 ms faster than random visual search trials. The ’improvement’ for the NC-C group resulted in the cued array targets being found as quickly as random visual search trials. This could suggest that in the NC-C group participants were less able to take the information learned from the first half into the second half than the C-NC group. Since both order groups had similar process estimates, this could further indicate that the controlled processes used by both groups did not help performance beyond simply searching for the target, and possibly even overrode the automatic processes for the NC-C group in the second half. In contrast, automatic processes may have formed in parallel with the controlled processes in the first half of training for both groups [27], and these were allowed to proceed unrestricted in the second half for the C-NC group.

The current experiment demonstrates that having knowledge of the underlying environmental regularities does not always result in beneficial changes in performance or cognitive processes. If anything, there seems to be an early cost associated with having knowledge of the underlying repetition. It is possible that forcing the knowledge on participants is harmful, whereas letting participants develop awareness of the repetition on their own provides the previously reported RT benefit [26]. Given the correlations between controlled process estimates and RT at medium amounts of training, it is also possible that repetition knowledge is pushing participants towards using an inefficient controlled strategy based on retrieved memories rather than relying on the faster automatic processes. The presence of this correlation indicates that some participants are successfully recognizing the repeated arrays during the PD recognition test. It is possible that this is indicative of a trade-off in contextual cuing between visual search speed during training and memory of the arrays at test.

This experiment also suggests that the contextual cuing effect is not simply based on implicit [e.g., 19, 36] or explicit knowledge [14, 26]. There do not seem to be systematic differences in automatic or controlled process estimates due to the amount of training when external repetition cues are used. However, there does seem to be an early reaction time cost associated with the external repetition cue. It is possible that the cued arrays would eventually overtake the not-cued arrays in reaction time speed with larger amounts of training, so pushing training past normal amounts of training (i.e., 30 blocks) may reveal differences in both visual search performance as well as process estimates.

Chapter 5

General Discussion

This dissertation examined the feasibility and utility of using the process-dissociation (PD) procedure [3] to measure the automatic and controlled cognitive processes [1, 2] supporting performance differences after training on implicit learning tasks. This was proposed as an alternative to attempting to measure the awareness of what was learned [11–15].

All three experiments found use of both automatic and controlled processes by participants on the recognition tests that followed training. The first experiment tested the feasibility of using PD in the serial reaction time task (SRTT) including computing automatic and controlled process estimates. In addition to finding evidence of both processes being used by participants, those participants who did not show use of controlled processes still had a significant transfer cost from the trained sequence suggesting automatic processes are enough to support performance differences in this implicit learning task.

The second experiment added a manipulation in which participants were informed that some sequences were repeating, and that repeating sequences would be cued. This allowed for a comparison between items that were overtly cued as repeating and the more traditional covertly repeating sequences. Participants learned all repeating sequences, cued and not-cued. There was evidence of both controlled and automatic processes, with significantly greater use of controlled processes for the not-cued than the cued recognition test.

The third experiment used the contextual cuing task, an implicit learning task that is based on training visual spatial attention rather than motor learning. As in Experiment 2, some arrays were repeated covertly as in most contextual cuing experiments [19, 36], and others were overtly cued as repeating [6]. This experiment also manipulated the amount of training given to participants to see if the process estimates would change over time. Participants were able to learn the not-cued arrays quickly, as a difference emerged in the first six blocks of training. The contextual cuing visual search time benefit was also found for the cued arrays; however, the effect did not appear until mid-levels of training. It appears that both automatic and controlled processes were used by many participants[1], but there were not significant differences in either controlled or automatic process estimates based on whether the recognition test was for the cued or not-cued arrays, and neither process estimate varied by amount of training.

Overall, it seems that examining the extent to which participants can control their acquired knowledge is a viable way to avoid the issues associated with measuring and comparing knowledge or awareness of what was learned. Furthermore, Experiments 2 and 3 illustrated that manipulating the knowledge participants have at the beginning of the study about repeated information can lead to different performance and processing outcomes for different implicit learning tasks. SRTT performance in Experiment 2 benefited from explicit knowledge of the repeating sequences; whereas in Experiment 3 participants did not benefit from cuing of the repetition in contextual cuing. Process estimates for both tasks had non-significant differences between cued and not-cued in the automatic component. There was a difference in controlled process estimates for the SRTT such that there was a greater estimate for the not-cued sequence than the cued. This could reflect a shift away from controlled processing for the cued sequences. No

[1]As mentioned on page 93, it is inappropriate to directly compare the automatic and controlled process estimates as they are mathematically linked.

differences between controlled process estimates were found for contextual cuing, suggesting that cuing when a stimulus was repeated did not significantly affect underling processing in a useful way.

Neural Mechanisms

There has been recent interest in comparing sequence learning and contextual cuing performance, both in healthy adults [169], as well as special populations [54, 201]. For example, college-aged dyslexics are impaired on sequence learning but not contextual cuing implicit learning tasks [201]. Part of the interest is that the two tasks are impaired in different disorders, yet both meet the definition of implicit learning. Functional neuroimaging studies find the two tasks use different brain areas. Sequence learning tends to recruit the supplemental motor area [202, 203], sensorimotor areas [202–204], premotor cortex [205, 206], and caudate [207]. Contextual cuing relies on the hippocampus [208–210] and surrounding medial temporal lobe [211–213], as well as the anterior prefrontal cortex [214].

More complex forms of sequence learning (e.g., alternating responses between a repeating sequence and random items; [215]) are not as resistant to the effects of normal aging as contextual cuing is [54]. It is proposed that the hippocampus and medial temporal lobe, which support contextual cuing performance, do not degrade as fast as the fronto-striatal-cerebellar network supporting sequence learning.

Relation to Cognitive Models

Willingham's control-based learning theory (COBALT; [216]) posits that there are two mechanisms supporting motor learning. The first mechanism involves an unconscious tuning of the processes that are independent of the frontal cortex. These processes select objects or targets for movement, plan sequences of movement, and learn new patterns of muscle activation. Each time an action is carried out with appropriate feedback, this mechanism tunes the response to be more efficient. Consequently, non-conscious knowledge exists in the form of the process tunings, and is specific to the training conditions. The other mechanism involves learning through conscious strategic processes, and relies on the frontal lobe mechanisms. These conscious processes can be used to select better movement goals or can use conscious knowledge to better accomplish the task in other ways.

Willingham drew comparisons with information processing by explaining how the process use likely changes over time (p. 577). He proposed that early in learning, the unconscious mode is inefficient as the tuning of processes has yet to occur, and so the conscious mode is used. Over time, the tuning of processes improves, leading to a gradual shift away from the conscious mode. This shift mirrors the transition towards automaticity with increasing practice. This also agrees with Logan's [102] view on automaticity as greater tuning is accomplished through more encoded experiences with the sequence.

The cognitive process measures from this dissertation have a clear relationship with the COBALT model; Willingham's strategic processes are equivalent to controlled processes and the non-strategic processes are effectively automatic processes. At the point training with the sequences ended in Experiment 2, higher controlled process estimates were measured for the not-cued than cued version of the switch sequence. Future experiments could reduce the amount of training (as was done in Experiment 3 with contextual cuing) to test if Willingham's shift from conscious to unconscious mode (i.e., controlled to automatic) is observed using the process estimates.

Keele and colleagues neurocognitive model of sequence learning systems ([147]; also see [217]) adds to Willingham's [216] COBALT model by emphasizing a multidimensional component and further specifying attention's role in learning. In Keele's model, there is the unidimensional learning system as well as a multidimensional one. For clarification, within sequence learning research, a dimension can be thought of as a response modality or mechanism (e.g,. responding with the hands verses the feet), or as a type of perceptual feature (e.g., color of items). The model specifies the unidimensional system is restricted to implicit associations within one dimension, and relies on the dorsal ('where/how') stream. This unidimensional system is capable of abstracting regularities, with or without attention. The multidimensional system can learn implicitly or explicitly across dimensions, and relies on the ventral ('what') stream. This system can acquire knowledge that relies on explicit representations accessible to conscious awareness, and is controlled by attention. Keele argued that contextual cuing requires the multidimensional system due to the necessity of forming relationships across feature dimensions.

Both the unidimensional and multidimensional learning systems automatically extract information; however, the multidimensional system requires the to-be learned information be attended in order to be processed. This suggests that both learning systems are using automatic processes, but only the multidimensional system would make use of controlled processes. The results from this dissertation imply both sequence learning and contextual cuing make use of the multidimensional system as controlled processes were found in all three experiments. However, it is possible that some participants do not employ the multidimensional system as evidenced by their lack of a significant controlled process estimate.

Implications

One recent experiment [169] pit sequence learning against contextual cuing to determine if the two tasks would interfere with each other if trained concurrently. It was found that as long as both tasks remained implicit, there was no interference. However, when sequence learning was explicit, the contextual cuing benefit was reduced. They argue that the finding that the two tasks do not interfere with each other indicates that different resources are used to learn the repeating information within the two tasks. The results from this dissertation support this idea in that the cuing of repeating information (i.e., sequences or arrays) is more beneficial for sequence learning than contextual cuing, indicating they may rely on different resources. Jimenez and Vazquez further argue that this means that the two implicit learning tasks do not require the same automatic processes. This dissertation further implies that the two tasks involve different controlled processes as well. This view is consistent with what is known about executive attention in multi-task performance (borrowing from Wickens' multiple resource theory; [218]). The different effects of overt cuing of repetition versus covert repetition without cuing in the two tasks suggest that even though both tasks are considered to be implicit learning tasks, they may differ in many ways (i.e., processes supporting learning, outcomes of learning, brain areas subserving the tasks).

A possible extension of this dissertation would be to adapt other measures of recollection and familiarity to determine if PD is the 'best' method to use. Another measure used in examining dual-process models of recognition memory is the receiver operating characteristic (ROC) procedure [174, 219, 220], which is rooted in signal detection theory. This procedure examines the hit and false alarm rate on a recognition test relative to confidence estimates. A major advantage of this technique is it requires only one recognition test, rather than the two sets of test directions used in PD. This reduces the chance that participants change strategy during testing. However, ROC does require additional assumptions,including: (1) the automatic process is assumed to follow signal detection theory characteristics, such that it has an equally distributed Gaussian function; and (2) controlled processes are only associated with confident responses, while automatic processes will be represented by a wider range of confidences.

Experiments 2 and 3 also manipulated the overt knowledge of repetition during training with the task to determine the outcome on underlying cognitive processes. The controlled process estimates for sequence learning, which benefits from overt repetition knowledge [e.g., 5], shifted towards what appears as less controlled when cued, similar to expert motor performance [e.g., 192]. The automatic process estimates were not affected by repetition knowledge, supporting the theory that these are separate and independent learning processes [27]. On the other hand, the controlled process estimates for contextual cuing, which does not reliably benefit from repetition knowledge [6], were not affected by the repetition cuing. Together, these experiments show that there are meaningful differences between the implicit learning tasks which, when investigated in concert with each other, could help identify what precisely changes with learning. Furthermore, it was possible to examine the differences in controlled and automatic processing with explicit and implicit learning conditions because of the process-dissociation procedure. As applied in these experiments, the PD procedure can be a useful tool for investigating the changes associated with implicit and explicit learning.

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Appendix A

Experiment 2: Overlap Between Sequences

The following analyses were run to address the concern about the differing amounts of overlap between the sequences used in the counterbalance conditions and possible effects on training and PD recognition test performance. These analyses mirror those presented in the results section for Experiment 2 (page 52), but either with the added factor of counterbalance sequence identity group for the first set, or limited to analyzing the first sequence identity combination. The first sequence identity combination had the unique sequence as the switch sequence and the two overlapping sequences as the C and NC sequences (i.e., 'ideal', since this combination of the three is the one that yields a unique switch sequence). The second sequence identity combination included the unique sequence as C and the overlapping sequences as switch and NC (i.e., 'hard NC', since discriminating between switch and NC sequences on the PD recognition test will be more difficult given the overlap). The final sequence identity combination had NC sequence as the unique, non-overlapping sequence, and the overlapping sequences as C and switch ('hard C', since discriminating between the switch and C sequences will be more difficult given the overlap).

As in the results section of Experiment 2, all pairwise comparisons use a Bonferroni adjustment for multiple comparisons unless otherwise noted.

Analyses with the counterbalance sequence identity group as an additional factor

The first set of analyses included the full data set, but included the counterbalance sequence identity group as an extra factor in all analyses. This was done to examine the observable effect of sequence overlap on training and test performance.

Training Performance

Overall Performance

To determine if learning of the trained sequences occurred, a repeated-measures MANOVA was run on the mean of median RTs with the factors of sequence type (random, NC, C, switch-NC, switch-C; within), block (1-6; within), and sequence identity combination (ideal, hard NC, hard C; between). The sequence identity combination did not interact with sequence type, F(8,98) = 1.19, $p > .05$, $\eta_p^2 = .04$; or block, F(10,96) = .83, $p > .05$, $\eta_p^2 = .03$; or interact with sequence type and block, F(40,66) = .91, $p > .05$, $\eta_p^2 = .04$. There was a main effect of sequence identity combination (mean of median RT by sequence identity combination in ms: ideal = 434.62, hard NC = 402.14, hard C = 372.42), F(2,51) = 4.95, $p < .05$, $\eta_p^2 = .16$. Pairwise comparisons showed that the hard C participants overall responded faster than the ideal participants ($p < .05$, all other $p > .05$).

Is Explicit Knowledge of the Sequence Beneficial Early in Training?

There should be an early RT advantage for the C sequence compared against the NC sequence in the first half of training if having knowledge of the sequence repetition is beneficial. As on page 53, the transfer costs will be compared. A repeated-measures MANOVA was run on the transfer costs with the factors of cue type (NC or C; within), block (1-6; within), and sequence identity combination (ideal, hard NC, or hard C; between). The sequence identity combination did not interact with cue type, F(2,51) = 1.91, $p > .05$, $\eta_p^2 = .07$; block, F(10,96) = .72, $p > .05$, $\eta_p^2 = .03$; nor sequence type and block, F(10,96) = 1.67, $p >$ .05, $\eta_p^2 =$ .06. There was also not a main effect of sequence identity combination, F(2,51) = 1.84, $p >$ .05, $\eta_p^2 =$ .07.

Effect of switching cue types

If repetition knowledge of the sequence is beneficial, the switch sequence should have faster RTs when cued regardless of which half it is cued. A new repeated-measures MANOVA was run on the transfer costs with the factors of cue type (C or NC; within), order the switch sequence was encountered (C-NC or NC-C; between), and sequence identity group (ideal, hard NC, hard C; between). The sequence identity group did not interact with the cue type, F(2,48) = 2.17, $p >$ .05, $\eta_p^2 =$ .08; order, F(2,48) = 2.40, $p >$ .05, $\eta_p^2 =$ .09; or cue type and order, F(2,48) = 2.75, $p >$ .05, $\eta_p^2 =$ .10. There was a main effect of sequence identity group (mean transfer cost by sequence identity group in ms: ideal = 28.55, hard NC = 24.98, hard C = 40.28), F(2,48) = 3.22, $p <$ .05, $\eta_p^2 =$ .12.

Process-Dissociation Recognition Test Performance

Proportion "Old" Responses

The first set of repeated-measures MANOVAs were run on the proportion of "old" ratings from the recognition test with the factors of cue-test type (cued or not-cued recognition test), test directions (Inclusion or Exclusion), and sequence type (random, switch, NC, C). The first repeated-measures MANOVA separated participants' data by sequence identity (i.e., which sequence was used in which counterbalance condition).There was no overall difference between the training groups in proportion of "old" ratings, F(2,51) = .22, $p >$ .05, $\eta_p^2 =$ .01. The training group factor did not interact with: the sequence type, F(6,100) = 1.44, $p >$ .05, $\eta_p^2 =$ .08; the type of recognition test (cued or not-cued), F(2,51) = 1.65, $p >$ .05, $\eta_p^2 =$ .06; the form of test directions given (Inclusion or Exclusion), F(2,51) = 1.74, $p >$ .05, $\eta_p^2 =$ .06. There were also not three-way interactions between: the training group, sequence type, and recognition test cue type, F(6,100) = 1.19, $p >$ .05, $\eta_p^2 =$ .07; training group, sequence type, and test directions, F(6,100) = .85, $p >$ .05, $\eta_p^2 \ = $ .05; the recognition test cue type, test directions, and training group, F(2,51) = .34, $p >$ .05, $\eta_p^2 \ = $ .02. Finally, there was no four-way interaction between sequence type, recognition test cue type, test directions, and sequence identity group, F(6,100) = 1.37, $p >$ .05, $\eta_p^2 \ = $ .08.

It is possible that there would be differences in recognition ratings between participants who had an 'easy' comparison (i.e., unique sequence different from recognition test's comparison sequence) and those who had a 'hard' comparison (i.e., switch sequence overlap with recognition test's comparison sequence). The first repeated-measures MANOVA compared proportion "old" ratings between those who had a hard comparison (switch sequence overlapped with the C sequence; $N \ = $ 15) and easy comparison (switch sequence did not overlap with the C sequence; $N \ - $ 39) on the cued recognition test. There was no overall difference between the participants' proportion "old" ratings by the easy and hard comparison, F(1,52) = .35, $p >$ .05, $\eta_p^2 \ = $ .01. The difficulty of the comparison did not interact with: the sequence type, F(3,50) = 2.94, $p >$ .05, $\eta_p^2 \ = $ .12; the recognition test cue type, F(1,52) = 2.29, $p >$ .05, $\eta_p^2 \ = $ .04; or the type of test directions, F(1,52) = 3.53, $p >$ .05, $\eta_p^2 \ = $ .06. There were also no three-way interactions between: the difficulty of comparison, sequence type, and recognition test cue type, F(3,50) = 1.18, $p >$ .05, $\eta_p^2 \ = $ .07; the difficulty of comparison, sequence type, and test directions, F(3,50) = .57, $p >$ .05, $\eta_p^2 \ = $ .03; or the difficulty of comparison, recognition test cue type, and test directions, F(1,52) = .04, $p >$ .05, $\eta_p^2 \ = $ .001. There was also no four-way interaction between all factors, F(3,50) = 2.6, $p >$ .05, $\eta_p^2 \ = $ .14.

The same analysis was run for the 'easy' (i.e., switch sequence did not overlap with the NC sequence; $N \ = $ 35) and 'hard' (i.e., switch sequence overlapped with the NC sequence; $N \ = $ 19) sequence comparisons for the not-cued recognition test. There was not a difference in proportion "old" responses between the hard and easy comparison groups, F(1,52) = .001, $p >$ .05, $\eta_p^2 \ = $ .001. The comparison difficulty did not interact with: sequence type, F(3,50) = 1.43, $p >$ .05, $\eta_p^2 =$ .08; recognition test cue type, F(1,52) = 2.53, $p >$ .05, $\eta_p^2 =$ .05; or test directions F(1,52) = .53, $p >$ .05, $\eta_p^2 =$ .01. There were no three-way interactions between: comparison difficulty, sequence type, and recognition test cue type, F(3,50) = 1.85, $p >$ .05, $\eta_p^2 =$ .10; comparison difficulty, sequence type, and test directions, F(3,50) = 1.14, $p >$ .05, $\eta_p^2 =$ .06; or comparison difficulty, recognition test cue type, and test directions, F(1,52) = .40, $p >$ .05, $\eta_p^2 =$ .01. There was also no four-way interaction between all factors, F(3,50) = .95, $p >$ .05, $\eta_p^2 =$ .05.

Process Estimates

The next set of analyses tested for differences between process estimates between the different counterbalance groups. The first repeated-measures MANOVAs were run between the different sequence-condition identities, as was done for the proportion "old" responses. There was no difference between sequence-condition identities for overall controlled process estimates, F(2,51) = .65, $p >$ .05, $\eta_p^2 =$ .03, nor an interaction with the recognition test cue type, F(2,51) = .09, $p >$ .05, $\eta_p^2 =$ .004. The same held true for the automatic process estimates, with no overall difference between sequence-condition identify groups, F(2,51) = 1.34, $p >$ .05, $\eta_p^2 =$ .05, nor an interaction with recognition test cue type, F(2,51) = 1.21, $p >$ .05, $\eta_p^2 =$ .05.

To test for process estimate differences between 'easy' and 'hard' comparisons, the controlled and automatic process estimates were separated into the 'easy' and 'hard' comparisons for each recognition test cue type. For the cued recognition test, there was no overall difference in controlled process estimate by comparison difficulty, F(1,52) = .77, $p >$ .05, $\eta_p^2 =$ .02, nor an interaction with recognition test cue type, F(1,52) = .002, $p >$ .05, $\eta_p^2 =$ .001. There was also no overall difference by comparison difficulty for the automatic process estimate, F(1,52) = 1.73, $p >$ .05, $\eta_p^2 =$ .03, or an interaction with recognition test cue type, F(1,52) = 2.06, $p >$ .05, $\eta_p^2 =$ .04.

The next analyses were for the ‘easy’ and ‘hard’ comparisons on the not-cued recognition test process estimates. There was no overall difference for controlled process estimates by comparison difficulty, F(1,52) = .06, $p > .05$, $\eta_p^2 = .001$, nor an interaction with recognition test cue type, F(1,52) = .14, $p > .05$, $\eta_p^2 = .003$. There were also no overall differences for automatic process estimates by comparison difficulty, F(1,52) = .06, $p > .05$, $\eta_p^2 = .001$, or an interaction with recognition test cue type, F(1,52) = .01, $p > .05$, $\eta_p^2 = .001$.

Summary

The sequence identity group did not interact with any of the other factors. This suggests that the different roles the overlapping and non-overlapping sequences took did not differentially impact performance. There were instances of a main effect by sequence identity, specifically a difference in overall performance and the effect of switching cue types.

Analyses only with the ‘ideal’ counterbalance sequence identity group

Of the sequence identity groups, the ‘ideal’ group represents the arrangement of overlapping and non-overlapping sequences that would come the closest to entirely non-overlapping sequences. There were 20 participants in this counterbalance group. This group’s data were subjected to analyses mirroring Experiment 2 (page 52).

Training Performance

Overall Performance

Learning of the sequences has probably occurred if the trained sequences have faster RTs than the novel, random sequences. The RT mean of median RTs were compared in a repeated-measures MANOVA with the factors of sequence type (random, NC, C, switch-NC, switch-C; within) and block (1-6; within). There was a main effect of sequence type (mean of median RT by sequence type in ms: random = 452.38, NC = 436.85, C = 432.52, switch-NC = 434.77, switch-C = 416.58), F(4,16) = 17.58, $p < .05$, $\eta_p^2 = .82$. Pairwise comparisons showed that the random sequence had slower responses than switch-C ($p < .05$). All other paired differences were non-significant ($p > .05$). There was not a main effect of block, F(5,15) = 2.10, $p > .05$, $\eta_p^2 = .41$; nor an interaction between sequence type and block, F(20,380) = 1.33, $p > .05$, $\eta_p^2 = .07$.

Is Explicit Knowledge of the Sequence Beneficial Early in Training?

There should be an early C advantage over NC if having repetition knowledge of the sequence is beneficial. The mean transfer costs were compared in a new repeated-measures MANOVA with the factors of cue type (NC or C; within) and block (1-6; within). There was no main effect of cue type (mean transfer cost by cue type in ms: NC = -18.86, C = -13.74), F(1,19) = 1.16, $p > .05$, $\eta_p^2 = .06$. There was a main effect of block (mean transfer cost by block in ms: 1 = -36.02, 2 = -20.02, 3 = -34.79, 4 = -3.23, 5 = -16.55, 6 = 12.83), F(5,15) = 7.29, $p < .05$, $\eta_p^2 = .71$. Planned comparisons showed that block 3 was significantly different from block 6 ($p < .05$, all other $p >$ ..05). There was also an interaction between sequence type and block, F(5,15) = 3.25, $p < .05$, $\eta_p^2 = .52$. Post-hoc t-tests (with Bonferroni adjustment of α to .008) did not reveal any significant differences when comparing C and NC in individual blocks.

Effect of switching cue types

If knowledge of the sequence repetition is beneficial to performance on SRTT, RTs for the switch sequence should be faster, regardless of whether it was presented in the first or second half. Mean transfer costs were compared in a repeated-measures MANOVA with the factors of cue condition (NC or C; within) and exposure order (C-NC or NC-C; between). There were marginal main effects of cue type (mean transfer RT by cue type in ms: C = , NC =), F(1,18) = 3.59, $p > .05$, $\eta_p^2 = .17$, and exposure order (mean transfer RT by exposure order in ms: C-NC = 21.40, NC-C = 35.70), F(1,18) = 3.88, $p > .05$, $\eta_p^2 = .18$. There was an interaction between cue condition and exposure order, F(1,18) = 23.29, $p < .05$, $\eta_p^2 = .56$. The interaction was such that there was no significant difference in transfer cost in the first half of training between C-NC - cued, (M = 2.52 ms) and NC-C - not-cued, (M = -7.59 ms), $t(18) = .68$, $p > .025$[1], Cohen's d = .32; but there was a significant difference in the second half between C-NC - not-cued, (M = 40.28 ms), and NC-C - cued, (M = 79.0 ms), $t(18) = 2.63$, $p < .025$[1], Cohen's d = 1.25. This suggests that shifting to the cued sequence is more beneficial after exposure to it than switching to the sequence not-cued.

Test Performance

Process Estimates

The process estimates for the two cue types were calculated from the formulas included on page 16. These were entered into t-tests by process estimate. There were no detectable differences between automatic, (mean automatic process estimate by recognition test cue type: cued = .51, not-cued = .39), $t(19) = 1.52$, $p > .05$, Cohen's d = .49, or controlled process estimates, (mean controlled process estimate by recognition test cue type: cued = .18, not-cued = .28), $t(19) = 1.55$, $p > .05$, Cohen's d = .50.

Summary

Testing the 'ideal' sequence identity group revealed some of the same patterns from the full analyses in Experiment 2. Many of the effects probably did not occur with this subset of the data as the power has been cut by approximately one-third of the full set. It is likely that future experiments that eliminate sequence overlap would find similar differences to those reported in Experiment 2.

[1]Bonferroni correction for two comparisons

Appendix B

Contextual Cuing Array Generation Code

The following code was written in Matlab and was used to generate the visual search arrays used by the contextual cuing experiments. Brian Mong contributed extensive help in writing this program.

```matlab
% Contextual Cuing Array Generation
% Usage:
%   function ccgen(num_T,context,batch_num,num_gens)
% num_t = number of target runs; should be equal to or smaller than num_gens
% context = [0,1]; generating repeated (1) or random (0) configurations?
% batch_num = number to identify the run number, or when this was generated
% num_gens = number of pictures to generate total
function ccgen(num_T,context,batch_num,num_gens)
debug = 0;

% Characteristics of the display
Msize = [768,768]; % [y,x]
obj_size = 31; % how long the side of the 'square' is for each object
fullness = 0.30; % how thick the T and Ls should be

% How many objects per quadrant?
num_obj_pq = 3;

% How many possible locations per quadrant, by x and y?
quad_div_x = 4;
quad_div_y = 4;

% Color array
colors(1,:) = [211,211,211]./255; % Background color
colors(2,:) = [255,0,0]./255; % Red
colors(3,:) = [0,255,0]./255; % Green
colors(4,:) = [0,0,255]./255; % Blue
colors(5,:) = [255,255,0]./255; % Yellow
num_colors = 4;
```

```
% GENERATED NUMBERS FROM INITIAL VAULES
% Centers for the locations for the objects
for i = 1:quad_div_x*2
    x_centers(i) = (Msize(1,2)/(quad_div_x*2))*(i-1) + (Msize(1,2)/(
        quad_div_x*2))/2;
end
for i = 1:quad_div_y*2
    y_centers(i) = (Msize(1,1)/(quad_div_y*2))*(i-1) + (Msize(1,1)/(
        quad_div_y*2))/2;
end

% The sub-meowtrix definitions of the T and L
O_M(:,:,1) = zeros(obj_size); % L, distracters
for i = 1:obj_size
    for j = 1:obj_size
        if j <= obj_size*fullness | i <= obj_size*fullness
            O_M(i,j,1) = 1;
        end
    end
end
O_M(:,:,2) = zeros(obj_size); % T, target
for i = 1:obj_size
    for j = 1:obj_size
        if (j > round((1-fullness)*(obj_size/2)) && j <= round((1+
            fullness)*(obj_size/2))) | i > obj_size*(1-fullness)
            O_M(i,j,2) = 1;
        end
    end
end
% Everything above this line is based on initial conditions and should
    not need to change

%
% This is the batch code where many pictures will be generated
context_gen = 0; % the context has not been generated yet
for pic_num = 1:num_gens
    if context_gen == 0;
        % BEGIN: These will run once then change only if this is a
            random run
        %
        %% Generating randomness in locations for all 4 quadrants
        for k = 1:2
            for l = 1:2
                for i = 1:num_obj_pq
                    pos_obj(1,i,k,l) = ceil(rand*quad_div_x) + (k-1)*
                        quad_div_x;
                    pos_obj(2,i,k,l) = ceil(rand*quad_div_y) + (l-1)*
                        quad_div_y;
                    if i > 1
                        for j = 1:i-1
                            while pos_obj(:,i,k,l) == pos_obj(:,j,k,l)
                                pos_obj(1,i,k,l) = ceil(rand*quad_div_x)
                                    + (k-1)*quad_div_x;
```

```
                                pos_obj(2,i,k,l) = ceil(rand*quad_div_y) + (l-1)*quad_div_y;
                                if debug==1; disp('dupe-regenning locatios'); end;
                            end
                        end
                    end
                end
            end
        end
        if debug==1
            pos_obj
        end
        %
        % END: These will change only if this is a random run
        %
        T_list = randperm(4*num_obj_pq);
        for i=1:4*num_obj_pq
            if T_list(i) == 4*num_obj_pq; T_list(i) =  1;
            else T_list(i) = 0;
            end
        end
        if context == 1
            context_gen = 1;
        end % do not run the generation of the context again for context case
    end % if context_gen == 0

    % Generating the background image
    M = ones(Msize); % make the whole image grey

    % Permuting the colors/orientations meow
    % color gen
    if mod(4*num_obj_pq,num_colors) ~= 0; disp('colors and number of objects do not play nice'); end
        color_list = ceil(randperm(4*num_obj_pq)*num_colors/(4*num_obj_pq));
        % orientation gen
        orent_list = ceil(rand(1,4*num_obj_pq)*4);
        if pic_num <= num_T
            M_list = T_list;
        else
            M_list = zeros(1,4*num_obj_pq);
        end
        for k = 1:2
            for l = 1:2
                for i = 1:num_obj_pq
                    % This is the sub-meowtrix image of the object being placed
                    A = rot90( O_M( :,:,1+M_list( (((k-1)*2 + (l-1))*num_obj_pq + i ) ) ) , orent_list( ((k-1)*2 + (l-1))*num_obj_pq + i) ).*(color_list(((k-1)*2 + (l-1))*num_obj_pq + i));
                    % places the object in the meowtrix
```

```
                    M(x_centers( pos_obj(1,i,k,l))-(obj_size-1)/2:x_centers(pos_obj(1,i,k,l))+(obj_size-1)/2,y_centers(pos_obj(2,i,k,l))-(obj_size-1)/2:y_centers(pos_obj(2,i,k,l))+(obj_size-1)/2 ) = M(x_centers( pos_obj(1,i,k,l))-(obj_size-1)/2:x_centers(pos_obj(1,i,k,l))+(obj_size-1)/2,y_centers(pos_obj(2,i,k,l))-(obj_size-1)/2:y_centers(pos_obj(2,i,k,l))+(obj_size-1)/2 ) + A;
                end
            end
        end
        % Writing the image
        if context == 0
            bmpwrite(M,colors,['random_R' num2str(batch_num) '_' num2str(pic_num) '.bmp'])
        elseif context == 1
            bmpwrite(M,colors,['context_C' num2str(batch_num) '_' num2str(pic_num) '.bmp'])
        end
    end
end
% And now, I am free
```