STATISTICALLY LEARNED VISUAL REPRESENTATIONS SUPPORT VISUAL WORKING MEMORY

by

Gregory L. Wade

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ABSTRACT

Visual statistical learning (VSL) refers to the human ability to unintentionally extract statistical information from our environment. VSL has been proposed to have wide-reaching influence on a number of aspects of cognition. However, direct evidence that statistically learned information is used by other cognitive processes is lacking. While most prior VSL research has focused on factors that influence the learning itself, less is known about how statistically learned information transfers across task contexts, despite claims that depend on VSL generalizing widely. In this dissertation, motivated by commonalities of "chunking" concepts used by the VSL and visual working memory (VWM) literatures, I seek evidence that memory representations formed by VSL could support subsequent VWM performance, by employing the same regularities between tasks. In a series of experiments, I examined the extent to which representations formed during a VSL training task can generalize to a VWM test context. I established that such transfer is possible, but that its likelihood seems to be highly dependent on the similarity between training and test contexts. Limitations of this transfer suggest that previous measures may be overstating the generalizability of VSL. Nevertheless, the ability for VSL to support VWM demonstrates one way in which incidental learning could support cognition.

Chapter 1

GENERAL INTRODUCTION

1.1 Introduction

Sensitivity to perceptual regularities allows us to inadvertently extract stimulus information from our environment. The propensity of perceptual systems to pick up on said regularities or patterns of stimuli is referred to as statistical learning, (Aslin & Newport, 2012; Fiser & Aslin, 2002a, 2001, 2002b, 2005; Park, Rogers, & Vickery, 2018; Saffran, Aslin, & Newport, 1996; Turk-Browne, Isola, Scholl, & Treat, 2008; Turk-Browne, Jungé, & Scholl, 2005; Zhao, Al-Aidroos, & Turk-Browne, 2013). Statistical learning is thought to be incidental and unintentional, as it allows for associations to be formed without the need for explicit feedback, and in the absence of instructions specifying to learn such information (Fiser & Aslin, 2001). The core finding of statistical learning is that repeated exposure of stereotyped sequences of phonemes, shapes, or other stimuli, leads to better recognition of those sequences compared with novel combinations of the same stimuli. Surprisingly, this learning occurs rapidly – learning can be evidenced after only minutes of training.

The rapid and apparently effortless acquisition of knowledge via statistical learning marks its potential to be one of the fundamental ways in which we learn about our complex perceptual environment. This allows us to passively gain information about our environment even while we are engaging in a separate activity. Further, we possess this ability to statistically learn at an early age (Bulf, Johnson, & Valenza, 2011; Fiser & Aslin, 2002a; Kirkham, Slemmer, & Johnson, 2002; Saffran et al., 1996); it has even been demonstrated that infants can statistically learn sequences of shapes, as early as 2 months of age (Kirkham et al., 2002). We retain this ability well into adulthood, as statistical learning is most commonly studied in adults. Statistical learning has been observed within multiple sensory modalities including vision, auditory, and tactile sensory systems (Conway & Christiansen, 2005). While it is proposed that the mechanisms that are responsible for statistical learning are domain general (Kirkham et al., 2002), statistical learning mechanisms vary across different learning modalities due to stimulus specificity, (Frost, Armstrong, Siegelman, & Christiansen, 2015; Shafto, Conway, Field, & Houston, 2012). However, the overall propensity for learning still manifests across multiple modalities. Statistical learning appears to be an innate ability that we can to effortlessly and unintentionally absorb complex information from our perceptual environment, across multiple sensory systems.

While statistical learning is observed with many different types of stimuli and contexts, the broader utility of this information is still poorly defined. Studies have provided evidence that statistical learning information can aid performance in a plethora of tasks, including speeding of reaction time, recognition of learned information, as well as perceptual prediction of statistical stimulus sequences. However, most studies use a basic familiarization/recognition judgment to show preference towards the statistically paired items. This method offers a convenient means to investigate the characteristics of the learned memory representations responsible for the common recognition effects but provides little insight into what the information is later used for. The main takeaway from these recognition studies is that statistical learning aids in the formation of chunked representations of the learned information. Chunked representations are characterized as higher order representations which contain multiple pieces of lower order stimulus information. Beyond recognition, other tasks used to investigate transfer have been limited and highly similar to (or even integrated with) the familiarization task. Thus, little research has been conducted looking at how these chunked representations are utilized after their initial learning in different contexts. In my view, an implicit argument in the VSL literature (and statistical learning, more broadly) is that this form of learning is always-on and contributes to a wide range of cognitive abilities. However, because the tasks used at test are so limited, little progress has been made in constructing a powerful argument that VSL is capable of supporting broad functions.

In this dissertation, I investigated whether VSL produces representations that can be utilized by another cognitive system, visual working memory (VWM). I make the argument that VWM is a good candidate for this kind of transfer, as there is a straightforward potential benefit to being able to utilize chunked representations in VWM. Further, evidence suggests that VSL produces and high-performance VWM relies upon on similar, chunked representations. Finally, there are potentially broad consequences for the transfer of representations produced by VSL to a VWM context, since VWM arguably plays a ubiquitous role in everyday cognition.

In a series of experiments, I attempted to pre-train VSL representations prior to a VWM task that is known to be sensitive to perceptual regularity. If VWM has access to the pre-trained VSL memory representations, then an initial increase in VWM capacity for the paired associates should be expected. Previewing my results, I did find that, under some circumstances, pre-training chunks in a VSL task does benefit subsequent VWM. However, I also demonstrate some important preconditions and boundary conditions of this transfer, which raises questions about the general usefulness of VSL for VWM. Overall, I find evidence in support of VSL supporting VWM performance. VWM memory capacity for statistically paired items is greater than that of previously unpaired stimuli. I reason that these effects are likely caused by the formation of chunked representations of statistically paired stimuli prior to the beginning of the VWM task.

1.2 Types of statistically learned information

Our perceptual worlds are replete with statistical contingencies, and the power of statistical information to influence performance is well-established. During scene perception we know that the predictability of an object can influence an individual's ability to recognize and identify said object (Biederman, 1981) (See Figure 1.1). For example, you would likely be much faster to identify a toaster when it is placed in a kitchen scene rather than a bathroom scene. Another example that demonstrates proficiency in employing statistics is that subjects are also more capable of quickly identifying scenes where foreground and background information is congruent, e.g. a football player in front of a field is better identified than if they are presented in a church (Davenport & Potter, 2004). Broadly speaking, this work implies that perception is powerfully impacted by statistical relationships. In classic examples, however, the stimuli are filled with semantic relationships – to what extent do such capabilities depend on our explicit, semantic knowledge? Do we need to understand the basic function of a toaster or its semantic links with other objects before we can determine where it is "supposed" to be located? Can statistical relationships be learned without a prior link to semantic knowledge?

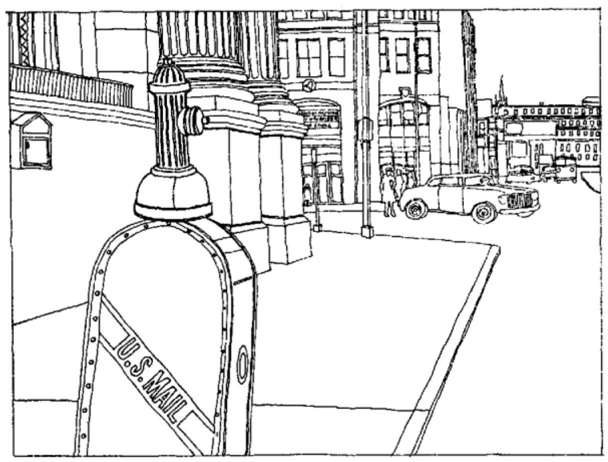

Figure 1.1: An example from Biederman (1981) where the fire hydrant is located in a statistically unlikely place, making it harder to identify within the scene.

Statistical learning studies suggest that part of such learning might occur through sheer exposure to statistical relationships, since most naturalistic examples also co-occur statistically frequently with related objects within our perceptual environment. Back to the example with the toaster, it is much more likely that you would see a toaster in the kitchen rather than in the bathroom. Through repeated exposure of the more frequent kitchen-toaster relationship, we can begin forming predictions of where we believe the toaster will appear. The ability to obtain statistical information about our surroundings allows us to begin forming the basic building blocks of structure within our perceptual environment, without the need for explicit rules or knowledge about semantic relationships amongst items. Thus, statistical learning research introduces the possibility that statistical knowledge alone may be incredibly powerful in everyday cognition, even in the absence of semantic knowledge.

In this section, I provide a brief history of statistical learning that is divorced from semantics. I will first review statistical learning effects where learning and test are performed simultaneously in an “online” fashion – that is, statistical learning effects are observed within the familiarization context. I then examine compelling evidence that people learn auditory statistical information even when it cannot aid the task at hand, as evidenced by transfer of that learning to a novel test context. I then describe how these effects have been shown in the visual domain, as well, using novel visual objects to remove any possibility of semantic information influencing learning. In the next section, I will critique the reviewed effects, examining how current experimental evidence leaves a gap between proof-of-concept statistical learning and how statistical learning can affect cognition in a manner that could impact everyday thinking and behavior.

For the purposes of this dissertation, I will first be focusing on scenarios where subjects are unintentionally learning contingencies as well as lacking semantic knowledge about the inherent structure of statistical relationships. Such evidence suggests that people can learn statistics in an on-line fashion, while performing the task that includes statistical information, and applying it to the task at hand without the need for instruction, and frequently without awareness of said statistics being present. This on-line learning of statistical information was critical for establishing statistical learning as a skill that can potentially support ecological behavior.

A number of studies have shown that statistics embedded within a task improve behavior in that task. A classic example of this is shown through studies of serial reaction time (SRT). In their seminal experiment, Nissen and Bullemer (1987) gave participants a reaction time task where they had to press buttons located underneath a set of four different lights. As the lights lit up participants were instructed to hit the corresponding button as quickly as they could. One group experienced the lights appearing in a repetitive sequence of ten locations, while the other group was exposed to a random sequence of lights. Reaction time results showed a consistent decrease in response latency in the repeated sequence group, compared to the random sequence group. Participants in the repetitive group were apparently able to learn the order in which the lights would light up without being informed of any explicit structure from the task instructions. Using this structure, participants were able to infer which light would appear next, allowing for decreased response latency (Figure 1.2). Even though participants were not informed of this structure, they still learned it and expressed it, suggesting that the learning of statistical regularities takes place without explicit instructions to do so, with no direct feedback or reinforcement, and in the absence of semantic knowledge related to the underlying structure. This result shows that we can use statistical information in order to speed motor decision making. Previewing statistical learning effects that occur when training and test are different tasks, other SRT studies have suggested that sequence learning can occur even if participants merely observe visual stimulus patterns without making a motor response to each stimulus (Howard, Mutter, & Howard, 1992). During a motor response test, participants who simply viewed a sequence of asterisks presented in four locations on a screen for the first three blocks exhibited equivocal response times in a fourth block as individuals that were making motor responses in response to the asterisks from the beginning of the experiment. This was taken as evidence that motor responses were not necessary to learn the sequence; although, others have suggested that this learning was explicit and not similar to traditional SRT effects, (Willingham, 1999; Willingham, Wells, Farrell, & Stemwedel, Maurine, 2000). In both cases, participants were still uninformed about any statistical regularity but can learn it on-the-fly and apply it to the task at hand.

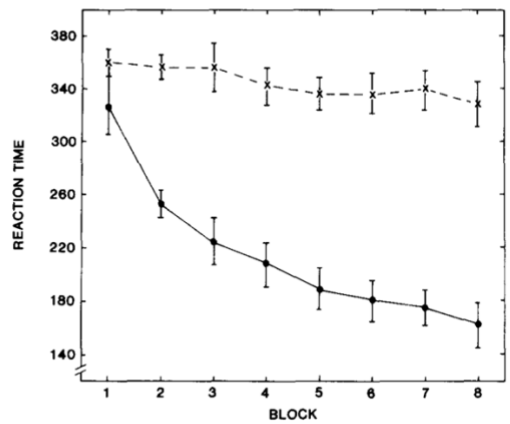

Figure 1.2: Reaction time results from Nissen & Bullemer (1987) where participants viewing the patterned sequence (dark circles) have reduced reaction time over block, while the participants viewing the random sequences response times (Xs) remain consistent.

Another example of statistical learning enhancing performance, and in this case not directly linked to motor control and learning, is the contextual cueing phenomenon. Growing evidence suggests that history is a powerful determinant of attentional selection performance (Awh, Belopolsky, & Theeuwes, 2012). The nature of the selection history that impacts performance can be very complex and statistical in nature, as demonstrated by classic studies by Chun and Jiang. Chun and Jiang (1998) showed that participants respond faster towards target locations in repeated scene contexts during a visual search task. In their experiment, participants were tasked with identifying the direction of a “T” target stimulus, tilted to the right or left, within an array of distractor stimuli (Figure 1.3). Some of distractor stimulus arrays were repeated through the experiment, with distractors and targets presented in the same spatial configuration from block to block. Though subjects were uninformed that some configurations would repeat, participants were faster at identifying the targets that were presented in the repeated arrays, compared to novel configurations of distractors. This pattern of data suggested that participants used statistically learned spatial information to guide attention within the learned contexts, which resulted in the decreased response latency. In a post-test recognition block, subjects' ability to identify repeated contexts compared to random configurations was at chance. This suggests that statistical learning occurred without explicit knowledge of statistically learned contexts.

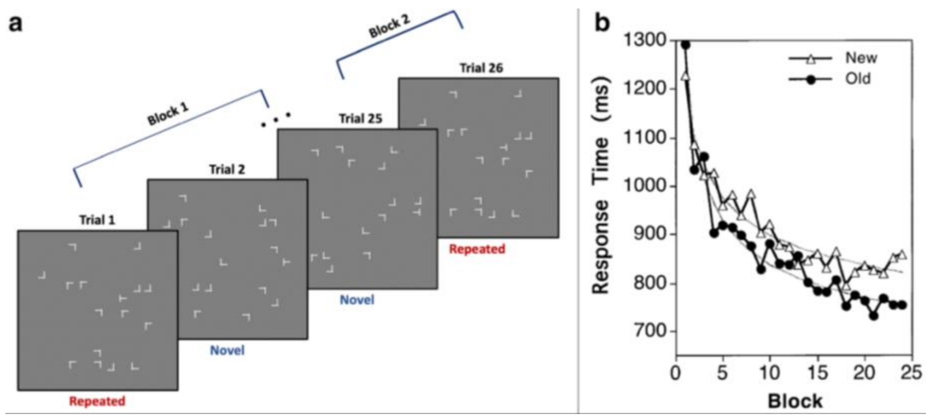

Figure 1.3: An example of a contextual cueing display from Sisk, Remington, and Jiang (2019). When search displays are repeated across blocks, participants became faster at identifying the targets within the repeated/old contexts compared to the novel/new contexts.

Contextual cueing and SRT provide strong evidence that statistical relationships can be learned if they immediately benefit on-line performance, as these forms of learning manifest during and are indexed by the training task itself. They serve as powerful demonstrations that statistics can be absorbed unintentionally and provide advantages to behavior expeditiously. These experiments still do not offer clear evidence that statistics retained from one task context can play a role in cognition outside of the learning task context. However, there are many domains in which learning statistics of the environment would be very advantageous, even though it is not possible or likely that the "task" to which such learning would transfer to can be employed. A classic example of this is language learning during development.

Language is something we begin learning before we can produce it, and therefore are unable to learn language production in an on-line fashion. One way that is theorized that infants begin to understand semantic rules of language is through auditory statistical learning (ASL). Picking up on semantic relationships between spoken language provides a critical basis of semantic knowledge required for language production and comprehension to begin. ASL is thought to be critical for language acquisition (Romberg & Saffran, 2010), as we learn language in a perceptual environment that does not always offer comprehensible feedback. In the experiments conducted by Saffran et al., (1996), 8-month old infants were presented with streams of auditory stimuli consisting of four, three syllable words that were always presented together, but without any feature that clearly distinguished between-word from within-word transitions. After training, the infants were presented with individual "words" which appeared in the familiarization phase, or "non-words" which consisted of the same syllabic sounds, but in a randomized order that was not presented during training. The overall finding was that infants paid less attention, measured by listening duration, to the statistically learned "words", compared to the novel "non-words". The decreased listening time of the "words" suggests that infants had already learned the inherent structure of the statistically paired triplets, as infants attention is drawn more to novel objects (Hunter, Ames, & Koopman, 1983; Rose, Gottfried, Melloy-Carminar, & Bridger, 1982). The novel non-word sequences were less familiar, therefore they were focused on longer compared to the previously familiarized "words". This type of learning is another way we can measure statistical learning after the initial learning has taken place.

The now-classic Saffran et al. (1996) study described triggered an explosion of studies that examined statistical learning in various domains and age groups. It has been found that statistical learning occurs in multiple sensory domains (Conway & Christiansen, 2005; Frost et al., 2015) and across the lifespan (Campbell, Healey, Lee, Zimerman, & Hasher, 2012). The critical feature of these studies was that statistical relationships were not cued during training, and often exposed with light (one-back task) or minimal task demands (passive exposure) during training, and then followed by a test task to probe learning and memory in a completely distinct task context.

For the bulk of this dissertation I will be focusing primarily on visual statistical learning (VSL), specifically, the learning of spatial and temporal contingencies between different visual stimuli (Aslin & Newport, 2012; Fiser & Aslin, 2001, 2002b; Park et al., 2018; Turk-Browne et al., 2008; Turk-Browne & Scholl, 2009; Vickery, Park, Gupta, & Berryhill, 2018). Most of this research follows suit with the training/test paradigm described above – light demands during training, and a recognition task at test. In order to control for semantic knowledge about the stimuli, novel shapes are often used as the stimuli in hopes that participants are exposed to these stimuli for the very first time during the experiment. These experiments aim to understand how begin to form an understanding of visual environmental structure in the face of unfamiliarity. Typically, presentation streams of stimuli consist of presenting stimuli one or two at a time on the screen, depending on whether the participant is learning spatial or temporal contingencies. Many VSL training tasks involve some sort of minimal memory task, such as N-back detection, for the cover task during training. While the participants are performing the cover task, unbeknownst to them, the stream of stimuli that are being presented contains statistical regularities between the stimuli. To test sensitivity to these regularities, participants are given a recognition or familiarization task (depending on task instructions), in which they are shown two sets of stimuli, one of which appeared in the exposure stream, and a foil set which is composed of the same stimuli but in an ordering that wasn't present within the stream. Participants make a two-alternative forced choice (2AFC) response to the two presented pairs on each recognition judgment. The general finding is that the statistically paired stimulus sets are recognized at above chance levels compared to the foils. Across a number of different presentation styles, participants reliably show an above chance recognition of statistically learned visual stimuli, (Fiser & Aslin, 2001, 2002b; Park et al., 2018; Turk-Browne et al., 2008, 2005; Turk-Browne & Scholl, 2009; Vickery et al., 2018). These effects of VSL are quite reliable, easily induced, and flexible to variation in stimulation.

The first demonstration of VSL was by Fiser and Aslin (2001). To examine spatial statistical learning with limited semantic information, the authors exposed participants to a series of 3 x 3 grid arrays containing pairs of novel shapes (Figure 1.4). These pairs of shapes were considered base pairs, where the stimuli were presented consistently together through training, and in the same spatial configuration. Multiple base pairs appeared within each presentation array, with varied relative locations within the grid, making the base pairs less evident during presentation. During test, participants made a 2AFC response between a base pair and a “foil” non-base pair (a novel pairing of the same object stimuli used during training), as to which pair of stimuli was more familiar to them. Results showed that participants chose the base pair over the foil pair significantly above chance. This was taken as evidence that even when participants are not informed or aware of regularity within their environment, they will still unintentionally learn statistically spatial relationships between visual stimuli.

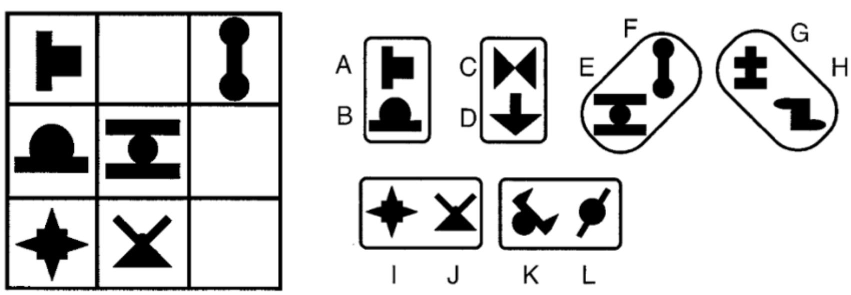

Figure 1.4: Right: An example of one of the displays presented in Fiser and Aslin (2001). Left: The single display contains 3 base pairs [A,B], [F,E], [I,J].

This study paved the way for many more studies like it looking at different aspects of information that we are able learn through VSL, and constraints on the capacity. Fiser and Aslin (2002b) replicated VSL, but with a temporal training paradigm to test if VSL could occur across multiple stimulus presentations. In their temporal training paradigm individual stimuli appeared from behind an occluding rectangle in the center of the screen. Unknown to the participants, stimuli appeared in consistent triplet sets throughout training. Participants were then tasked with making familiarity judgments, where target and foil stimuli appeared in a temporal fashion one at a time. Participants chose the more familiar triplet. Results showed that participants were successful in identifying the triplets at above chance in the temporal familiarization task. These results showed that VSL can occur across temporal relationships between stimuli as well as spatial relationships.

Subsequent evidence suggested that the representations formed by VSL can be somewhat flexible to manner of presentation. For example, Turk-Browne and Scholl (2009) trained participants in a spatial VSL task, and tested using a temporal task, and vice versa. In the first version of the experiment, the temporal training was similar to that of Fiser and Aslin (2002b). After completing the temporal training, participants were tasked with either a temporal or spatial recognition judgment task. Participants were able to recognize base pairs at above chance levels with both the spatial and temporal presentations of the triplets during the recognition task following the temporal training. In a subsequent experiment, participants completed a spatial VSL training. Participants were then tasked with identifying repeated items in a single stream of stimuli presented in the center of the screen, with a speeded reaction time response. Two singleton stimuli were included in the response stream to prevent reinforcement or weakening of statistical relationships between stimuli during test. Target stimuli appeared in a “critical pair” with the first item of a pair preceding the target item of the pair, with the target appearing in and serial position between three and thirteen. Results suggested that when the target items were preceded by their paired constituents, reaction times were faster compared to when the target was preceded by non-base pair stimuli. These experiments provided evidence that representations formed during VSL training are flexible and can potentially generalize across different contexts, at least from temporal to spatial and vice-versa.

While evoking VSL is fairly simple, we still do not know why we retain this information. It has been shown that VSL effects can remain consistent over long periods of time, (Arciuli & Simpson, 2012). In their experiment Arciuli & Simpson, (2012) measured VSL recognition twenty-four hours after initial learning and participants still recognized the triplets at above chance levels, as well as consistent recognition at the other four intermediate timepoints of measurement. So not only is this information learned, but it is retained in memory long after training. If VSL information is being retained after initial learning, then I would expect that we utilize this information to support some other cognitive system, as the memory resources maintaining these representations could be allocated elsewhere. This shows evidence that we will retain information that is learned through VSL, but for what end?

Statistical learning of this nature (unintentional and not directly relevant to the cover task) has various effects on behavior that seem to favor learned structure. The propensity of our perceptual systems to pick up on this statistical information seems to be present in many different contexts and lead to some flexibility in expression. VSL occurs very quickly after mere minutes of exposure, and unintentionally, without explicitly tasking the participants to learn the structure of stimuli. Statistical learning has been proposed as a tool that we can use to attempt to understand our environment or improve interactions with it when feedback or semantic knowledge are not present. In the next section, I consider the extent to which statistical learning has really been demonstrated to have such utility.

1.3 Utilization of statistically learned information

While statistical learning effects are somewhat easy to establish in lab environments, little evidence has been given to elucidate what the real-world purpose of acquiring this information is. What use do we have for such information reflected by increased recognition of learned sequences? While recognition effects are well studied, they offer minimal evidence that statistical learning supports cognition overall. With the usage of recognition judgments, we are only offered a vague idea of how this information could potentially be used. Recognition could be caused by a number of different factors that might not extend to their employment in language, visual scene segmentation, and so on. Many studies claim that statistical learning has a wide reach across cognition in general, but what is the evidence of such a vast impact?

It is widely argued that auditory statistical learning supports language ability, (Aslin, Saffran, & Newport, 1998; Daltrozzo et al., 2017a; Romberg & Saffran, 2010; Saffran, 2003; Saffran et al., 1996; Saffran, Newport, Aslin, Tunick, & Barrueco, 1997). Many studies have shown correlations between statistical learning ability and various language learning abilities (Christiansen, Conway, & Onnis, 2012; Conway & Pisoni, 2008; Daltrozzo et al., 2017; Shafto, Conway, Field, & Houston, 2012). For example, Daltrozzo et al. (2017), demonstrate that statistical learning ability in a visual non-linguistic task is correlated with language abilities derived from grammaticality judgment scores. While these correlations offer evidence that statistical learning and language ability are related, it is not known if language acquisition is partially dependent on statistical learning, or if language and statistical learning simply share some underlying cognitive mechanisms or dependencies. For instance, working memory is also associated with language (Adams & Gathercole, 2000; Goff, Pratt, & Ong, 2005), and if VSL depends on working memory as well, a correlation between statistical learning and language abilities might be expected without implying dependence.

There are a large number of VSL studies that show that participants are able to extract information from either spatial or temporal training paradigms (Aslin et al., 1998; Daltrozzo et al., 2017b; Fiser & Aslin, 2001; Otsuka & Saiki, 2016; Slone & Johnson, 2015; Turk-Browne et al., 2008, 2005; Turk-Browne & Scholl, 2009). However, most of these studies rely on simple familiarity judgments of a paired set of stimuli compared to unpaired combinations of stimuli. While these effects remain consistent across many different paradigms, they offer little information as to how statistical learning information might actually be employed. Instructions for making familiarity judgments tend to be underspecified, so it is hard to tell what criteria participants are using to determine which stimulus they choose to select over the other.

Some evidence suggests that learning of statistical regularities enables the perceptual anticipation of stimuli. Turk-Browne, Scholl, Johnson, and Chun (2010) provided evidence that predictive stimuli enhance categorization for second items in pairings, and activate perceptual anticipation mechanisms within the hippocampus. They trained participants on face/scene pairs during a face/scene categorization response task. Within the training stream they also included singleton stimuli, stimuli that appear without a statistical associate. Results from the behavioral categorization task showed that participants were faster at categorizing the second item of a pair compared to the singletons and first items of the pairs, and were marginally more accurate in responding to the second items in the pair as well. Participants also underwent an fMRI scan while performing the task. BOLD contrasts showed increased right anterior hippocampal activity related to the first item of a pair compared to a singleton. This effect of the hippocampus also correlated with increased activity in early visual cortex, thought to be representative of anticipatory visual processing of the upcoming, predicted stimulus. Greater activation of the hippocampus and surrounding areas is believed to be broadly related to associative memory systems (Cohen & Eichenbaum, 1993), suggesting that the first stimulus engaged associative memory to a greater extent than a singleton. This was taken as evidence that VSL information allows for us to make future directed predictions about our perceptual environment. While the data are suggestive of predictive mechanisms, the test task was not separable from the training itself, as in this paradigm training and test occurred simultaneously. Thus, this paradigm resembles paradigms like contextual cueing, rather than the original ASL/VSL paradigms with clearly distinct training and test phases. The observed activity may only reflect ongoing predictive mechanisms that do not generalize to other contexts outside of training. So, while we are able to predict upcoming stimuli, would such prediction be applied to the same stimuli in a novel context? This study offers hints at a neural basis for VSL, which were surprising in the sense that VSL is thought by many to be implicit, while many have argued that the hippocampus represents declarative knowledge (Eichenbaum, 1999; Tulving & Markowitsch, 1998). However, the study offers little information on what we do with VSL information after learning. Would the same stimuli activate the hippocampus outside of the categorization context? Would behavioral facilitation persist across a change in task?

Visual statistical regularities have also been shown to engage attention in a similar manner as objects. Lengyel et al. (2021) trained participants to learn spatial regularities between stimuli. After VSL, participants performed a target detection task where they had to determine if two targets were in a vertical or horizontal configuration, or if there was only one target. The results from this study reflected those of similar target detection studied using objects, in which invalidly cued targets are responded to faster when they are within the same object boundaries than targets appearing across object boundaries, (Egly, Driver, & Rafal, 1994). In Lengyel et al., (2021) participants responded faster when the two targets appeared within a chunk (presented horizontally or vertically), compared to responses on trials where the targets appeared across chunks. The authors also correlated their target detection task performance to familiarity judgments and found a statistically significant correlation between first block performance and recognition. This evidence suggests that the representations formed by VSL may influence attention in a similar manner as to object-based representations. The effects found by Lengyel et al., (2021), while intriguing, are also suspect as their main effect of object attention are only present in their first block. Their correlation between the observed attentional effects and VSL was significant, but their measure of VSL was still based off of recognition judgments.

Even though the VSL memory representations that are formed are robust when it comes to recognition, there is limited evidence from other paradigms that VSL supports cognition. The only other demonstrations of VSL are claims that VSL supports predictive responding; for example, after learning statistical regularities in the visual spatial domain, target detection in a speeded serial response task is speeded for more statistically predictive targets (2nd or 3rd stimulus in a triplet) than those earlier in position of the learned sequence (Turk-Browne et al., 2005, 2010). However, one large critique of these experiments suggests that the speeded reaction time towards statistically predictable targets is often confounded with serial position in the recognition stream (Rawal & Tseng, 2021). In many experiments where the triplet sequences are only pseudo-randomized (Fiser & Aslin, 2001, 2002b; Turk-Browne et al., 2005), the consistency between target positions allows for participants to anticipate the target based on its position in the stream rather than the stimuli the precede it. Rawal and Tseng (2021) addressed this issue by shifting the location of the targets by including partial triplets at the beginning and end of the stream. When the location of the targets was counterbalanced, reaction time effects based on the predictability of the stimuli were eliminated. These results show that many studies that only use this type of pseudo-randomization could be inflating effects of VSL due to confounding variables that are present in the training stream.

The current methods that are used in the testing of VSL only provide limited evidence as to how the memory representations that are formed are utilized by other cognitive systems. The nature of memory representations formed during statistical learning are still ill-defined, as well as their broader utility in cognition (i.e.: whether VSL occurring during passive viewing of image sequences can aid working memory). What kinds of cognitive operations could be supported by learning of such visual regularities, if any? Much of the current literature claims that VSL has broad influence on cognition in general (Arciuli & Simpson, 2012; Otsuka & Saiki, 2016; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009). However, few studies have explored the utility and generalizability of VSL representations to new testing contexts, past measuring said learning through recognition judgments. If these learned contingencies support cognition, their effects should be observable on performance in a multiple task contexts. Observations of such alternative measurement could motivate

VSL as a useful learning method, that could benefit task performance in environments lacking explicit feedback, or implicitly form chunked representations. Still, many studies pose VSL as having a very broad impact on our cognition, yet offer no clear, empirically-backed evidence that it has such impact.

The goal of my dissertation research is to take a step in this direction, by exploring whether VSL representations learned in one context (a relatively passive one-back task) can transfer to and benefit performance in a different, more demanding context -- a visual working memory (VWM) task with several remembered stimuli on every trial. The motivation for this is (a) the plausibility that VSL and VWM are reliant on similarly "chunked" representations, (b) the demonstration that VWM can benefit from statistical learning during demanding VWM tasks, and (c) the well-recognized importance of VWM in general cognition. I argue that if such a link can be established, this will strongly suggest a plausible route for VSL to enhance cognition outside of training tasks. The following sections build supporting arguments for such a connection and the potential broad import of such a link.

1.4 Visual working memory and compression

Visual working memory is a thoroughly studied system within cognitive psychology field. VWM is able to sustain or maintain visual information via rehearsal for a short period of time, (Atkinson & Shiffrin, 1968; Baddeley, 2010), as compared to the rapid decay of iconic memory. VWM maintenance is required for the consolidation of information into long term memory (Vogel, Woodman, & Luck, 2006; Woodman & Vogel, 2005). We can hold information in VWM while completing various tasks, such as remembering where you parked your car while you are shopping in a store. While we can sustain information in VWM, there are strict limits on our ability to store information (Baddeley, 1983, 2010; Brady, Konkle, & Alvarez, 2011a; Burtis, 1982; Fougnie & Marois, 2006; Light & Anderson, 1985; Luck & Vogel, 1997; Turner & Engle, 1989). It is debated whether memory storage should be conceptualized as individual item slots (Adam, Vogel, & Awh, 2017; Luck & Vogel, 1997; Zhang & Luck, 2008), or if VWM resources are more fluid in nature, taking into consideration the complexity of stimuli as a factor in resource allocation (Alvarez & Cavanagh, 2004; Bays, Catalao, & Husain, 2009; Eng, Chen, & Jiang, 2005). Regardless of the characterization of VWM, the problem remains that both the slots, and shared resources models, impose a fixed limit on the amount of information that can be retained.

One way in which capacity limitations can be overcome to some degree is by relying on chunking mechanisms (Bellezza & Young, 1989; Brady, Konkle, & Alvarez, 2009; Burtis, 1982; Egan & Schwartz, 1979; Fountain & Doyle, 2012; Gilchrist & Cowan, 2012; Miller, 1956; Simon, 1974). Originally coined by Miller (1956), a “chunk” refers to information within the cognitive system that is recoded and organized in a way such that it becomes more effective than storing individual characteristics about complex stimuli. For example, when tasked to remember individual units of information such as letters, there is a limited number of items that can be stored in memory (~7 +/- 2). If this letter information is chunked into words, than we typically can remember many more letters than just seven. Miller believed that the limit to storage capacity of working memory was tied to the number of chunks, rather than the number of individual characteristics of stimuli. Simon (1974) sought to discover how much information could be stored in these chunks. One limit he discovered was that once chunks were formed, the organization of information was not always optimal upon the addition of new information needing to be retained in memory. In this sense chunks are limited to the level of cognitive organization that can be applied to a set of stimuli. This recoding of information is thought to reduce the overall VWM resources used to recall two chunked stimuli compared to two associated stimuli where the information is not recoded, but an established link is created between two stimuli (Figure 1.5).

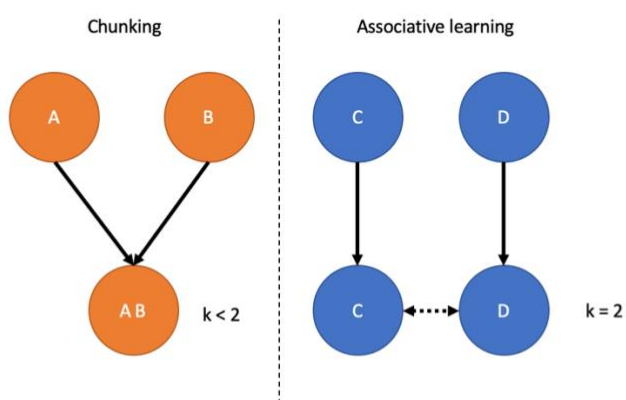

Figure 1.5: Left: Depiction of the combination of information into a higher-order chunked memory representation being compressed into a single representation. Right: Depiction of associative memory, resulting in an associative link between both of the input stimuli.

Visual working memory exploits chunked representations in order to reduce overall memory load, increasing available resources to retain information, thus allowing for improved measures of VWM capacity (Brady et al., 2009, 2011a; Chekaf, Cowan, & Mathy, 2016; Nassar, Helmers, & Frank, 2018; Riaz, Wolden, Gelblum, & Eric, 2016). Particularly relevant to the current dissertation, people can learn to form chunks when statistical regularities are introduced in VWM stimuli (Brady et al., 2009). Brady et al. (2009) showed two groups of participants displays containing four sets of concentric circles, each containing two colors. Participants were presented with the colored displays, waited for a retention period, and were subsequently tasked to recall the color at a cued location (Figure 1.6). One group of participants were exposed to a randomized set of colors on each trial, while the other group of participants were exposed to specific color pairs on about 80% of the displays. Participants in the paired condition showed an increase in working memory capacity measures (k) compared to those who were shown randomized color displays. In a final block, the participants in the paired display condition were presented with a block containing randomized displays. All benefit from the learned pairs was eliminated in this condition. Brady et al. (2009) were also able to replicate their findings using a second display where colors appeared in four sets of two separate circles side by side. The data from these experiments show that chunking of the statistically likely pairs of colors subsequently allowed for increased storage of information in visual working memory compared to the same features containing no associative information.

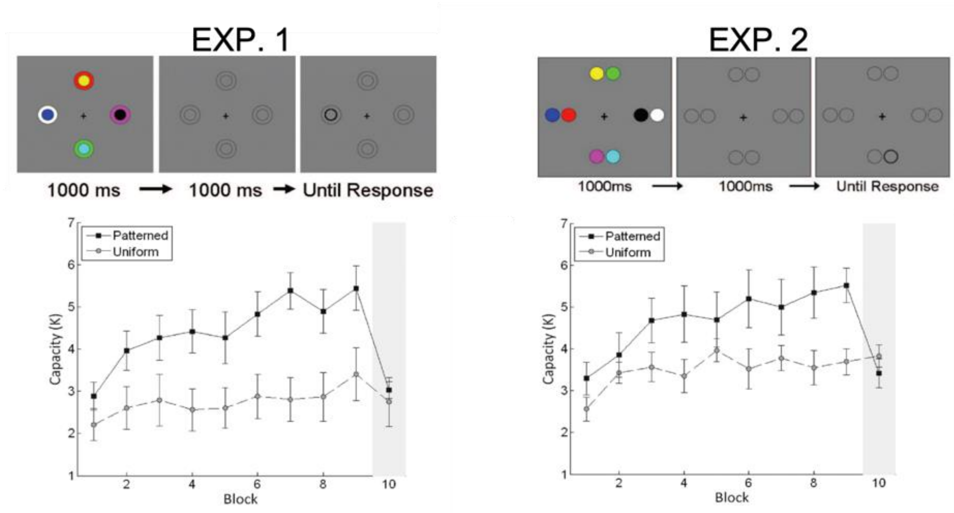

Figure 1.6: Procedure and results from Brady et al. (2009) Experiments 1 and 2. Procedure shows color presentation differences between Experiment 1 and 2. Results shown are those of the paired group exposed to regularities compared to the group shown randomized displays.

It is notable that the procedure used by Brady and colleagues strongly resembles visual statistical learning paradigms. An exception, however, is that the training and test are integrated instead of separate phases as in the typical VSL study. Critically, to this proposal, the statistical associations among colors were learned in the context of the VWM task that also served as the test task. If VSL due to relatively passive processing, produces similar chunked representations to those derived from VWM-based training, can VWM tasks exploit such previous learning to its advantage? This domain is a prime target to test for transfer effects of VSL and to broaden the potential utility of VSL-derived representations in cognition.

Both VSL (Fiser & Aslin, 2005; Jost, Conway, Purdy, Walk, & Hendricks, 2015; Lengyel et al., 2021; Slone & Johnson, 2015, 2018) and VWM (Bellezza &

Young, 1989; Brady & Alvarez, 2011; Brady et al., 2009; Burtis, 1982; Nassar et al., 2018; Olson, Jiang, & Moore, 2005; Riaz et al., 2016) are proposed to utilize chunked representations of statistically co-occurring stimuli. The sensitivity of VWM towards statistical regularity in Brady et al. (2009) makes this type of task an ideal candidate for potentially measuring VSL effects without relying on familiarity judgments, but rather performance on a cued recall task. The concept of chunking predates VSL, and one critical difference between most previous uses of chunking as a concept to explain information compression and chunking in the context of VSL is that putative chunking in VSL results from unintentional, incidental learning processes. However, I believe that by utilizing a training and test task that are reliant on the same type of memory representations, we can observe an initial increase in VWM capacity based upon the learning of VSL representations prior.

1.5 VSL forms chunked representations

What is the nature of representations formed from VSL? For the purposes of this dissertation, I will focus on representations that are created during serial presentation VSL training tasks, because the representations that are the outcome of such exposures have been the most well-studied. In serial presentation streams of stimulus presentations appear one at a time on the screen. When a participant is performing a VSL cover task, a number of stimuli are entering their working memory, as tasks such as N-back are also typically used in the study of VWM (Jaeggi, Buschkuehl, Perrig, & Meier, 2010; Owen, McMillan, Laird, & Bullmore, 2005).

During serial presentation, multiple object representations can be co-stored together at the same time inside working memory, and have the opportunity to become "chunked" together. Items presented in stereotypical pairs are able to be co-stored throughout the experiment, allowing for the opportunity for these regularities to become chunked or compressed together. Sequentially presented stimuli are thought to be co-stored when the stimulus first appears, and while the memory trace of the N-1 stimulus is still active in VWM (Schapiro, Turk-Browne, Botvinick, & Norman, 2017). This evidence suggests that VSL is one way in which we create "chunked" representations, by analogy or completely consistent with the sense of "chunking" that has long been employed throughout the literature on learning and, most relevantly, learning and/or strategies that enhance VWM (Lengyel et al., 2021; Otsuka, Nishiyama, Nakahara, & Kawaguchi, 2013; Slone & Johnson, 2015, 2018). This chunking of stimuli together would also account for the increased familiarity effects, as the learned pairs have been recoded into chunks, while foil pairs have not.

Several empirical papers have reported evidence that chunking is taking place during VSL (Fiser & Aslin, 2005; Lengyel et al., 2021; Slone & Johnson, 2015, 2018). Slone and Johnson (2015) examined how chunking results from VSL in a series of experiments that tested recognition accuracy of various shape/color triplets. In their critical experiment, they presented triplets of shapes such that the statistical contingencies of one item following another was always 50%. In order to do this, one stimulus may appear in multiple triplets. As shown in Figure 1.7, the tan hourglass has a 50% chance of following the red circle and the black heart has a 50% chance of following the tan hourglass. This particular method of forming the triplets allows the creation of “illusory triplets”, where each stimulus in the “illusory triplet” sequentially follows the 50% contingencies of the learned triplets, but these exact combinations never actually appeared in that order during training (Figure 1.7). Slone and Johnson (2015) hypothesized that if participants were representing the statistical likelihoods of one shape following another, then they should “recognize” the illusory triplet at an equal level as a triplet that was actually presented during training. However, if chunking were the outcome of learning, real triplets should be preferred over illusory triplets.

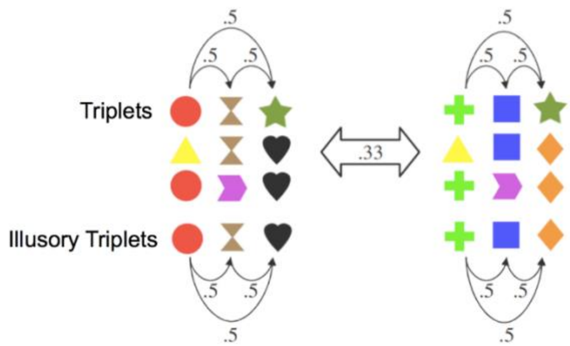

Figure 1.7: Stimulus contingencies in Slone & Johnson, (2015). The top three rows show the triplets shown at testing. The bottom line is the illusory triplet which has the same statistical frequency between its items as the learned triplets.

Overall, what they found was a significant preference for the learned triplets, compared to the illusory triplets. These results argue against a purely statistical model in which the memory representations formed during VSL would be based solely on the statistical probability of one stimulus following another (right side of Figure 1.7).

Rather the data suggest recognition was based on the information being organized into "chunks" of information containing representations of all three items within the triplet. Since the illusory triplet was never actually presented in the training, that specific order of stimuli were never able to be chunked together. This evidence strongly suggests that VSL relies on the formation of chunked memory representations.

Further supporting the existence of chunking, Park, Rogers and Vickery (2018) demonstrated that participants responded at above chance recognition levels during for not only for the learned sequences, but also to scrambled triplet sequences, compared to foil triplets. While other VSL studies (Otsuka et al., 2013), have shown recognition test performance suffers when presented in non-stereotypical order, regardless of this dent in performance, when triplets (a group of 3 statistically paired stimuli) are presented in reverse order at test, these backwards presentations are still recognized at above chance levels. This evidence supports the idea that the representations formed during VSL consist of the three stimuli chunked together, as participants are still aware that the group of stimuli go together regardless of the order they are presented in. For example, the first item of the triplet was never followed by the third item, however during test the triplet was still identified when presented in this scrambled order. VSL representations are highly flexible, suggesting that the learned representation is invariant to some degree to timing/ordering and thus more "chunk-like" than a set of simple, directed associative links.

While VSL representations' flexibility allows for deeper learning of regularity than mere reproduction, the data provided in these experiments still does not offer much information about how these chunked representations later are utilized by cognition. The literature on VSL effects is full of these types of recognition/familiarization effects that measure how “well” information is learned. I wish to take this question a step further and ask: What do we do with this information after it is learned? Based on the literature surrounding VWM, I believe that if participants are able to form chunked representations during VSL, these representations may be available to support VWM performance. If we can pre-train these chunks prior to the VWM task, I expect to be able to observe a difference in working memory capacity for the pre-chunked pairs compared to novel pairs not learned during VSL training.

1.6 Task transfer

When deciding the new testing task, we need to take into account the distance of task transfer. Task transfer is simply the idea that performing one task will improve your ability on a different, subsequent task (Barlow, 1937; Grossberg, 1971; Marini, Iani, Nicoletti, & Rubichi, 2011; Proctor, Yamaguchi, & Vu, 2007; Proctor, Yamaguchi, Zhang, & Vu, 2009; Singley & Anderson, 1989; Vu, Proctor, & Urcuioli, 2003). It has also been shown that task transfer is influenced by the number of contextual differences between training and test, the number of contextual differences is referred to as transfer distance (Barlow, 1937; Healy, Wohldmann, Sutton, & Bourne, 2006; Linares, Borella, Teresa Lechuga, Carretti, & Pelegrina, 2019; Richmond, Morrison, Chein, & Olson, 2011). While training of a task usually increases performance on the task itself (Bors & Vigneau, 2003; Conde et al., 2015), transfer of one skill across cognitive domains is not commonly observed (tasks having a far transfer distance) (Chase & Ericsson, 1981; S. M. Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Singley & Anderson, 1989). Task transfer difficulties pose another possible issue for the generalization of VSL representations to VWM contexts, as task transfer often shows that learning is frequently context-specific (Healy et al., 2006; Kole, Healy, Fierman, & Bourne, 2010; Melby-Lervåg, Redick, & Hulme, 2016). However, if VSL representations are not transferable, we would argue that their overall usefulness to cognition may be overestimated. By limiting the distance between our training and test, we can improve our chances at measuring VSL using VWM capacity.

1.7 Summary

This proposal seeks to explore effects of visual statistically learned information beyond the basic recognition of learned pairs and examine if the learned representations can be utilized by another cognitive system that is also thought to be reliant on similar types of representations – namely, VWM. If VSL and VWM are operating using similarly chunked representations, then I would predict that we will see an initial boost in VWM performance for the trained stimulus pairs learned/chunked during the training task, compared to stimuli that were not presented in a statistically consistent manner. This prediction is based on the commonality of the formation of chunked representations during VSL training and VWM tasks.

This dissertation begins with a replication of the basic effect of Brady et al., (2009), using the object stimuli typically used in VSL studies. This serves as a check to make sure we obverse the same chunking effects as shown by Brady et al., (2009) in our version of the VWM task. With this replication in hand, in a series of subsequent experiments I will attempt to preemptively train the VWM chunked repetitions needed to increase VWM capacity, with VSL training. If we see an initial difference in VWM performance based on learning in the VSL training, it would suggest potentially broad usefulness of VSL representations to any cognitive process that depends on VWM.

Chapter 2

EXPERIMENT 1

2.1 Introduction

Most VSL employ unfamiliar shapes, but the extant work showing strong SL effects during VWM employed color stimuli (Brady et al., 2009) and employed between-group designs. Thus, my first aim was to replicate those findings with shape stimuli that will be used in the remainder of the dissertation, enabling more diverse but still heterogenous stimulus sets. In Experiment 1, I adapted the paradigm used by Brady et al. 2009 where subjects were tasked to remember a color of a cued region from one of eight locations. The main finding from their experiment was that when two colors were statistically likely to co-occur in spatial configuration (concentric circles or side-by-side) ~80% of the time, participant's working memory capacity (indexed using the k-value) was significantly higher than participants who were not exposed to statistical regularities within the display.

I used a within-subjects design where each subject was shown configurations of one of two sets of eight stimuli in separate VWM trials. One set of eight shapes appeared in statistical pairs (side-by-side) 100% of the time, while the other set of eight stimuli appeared in random pairs (25% probability of appearing next to any other random-pair item). I chose to present the paired images paired 100% of the time in order to strengthen the chances for VSL to occur. Participants were then asked to recall one of the shapes at a cued location using a keypress response. I expected that participants would exhibit larger working memory capacity (k) for the statistically paired stimulus set compared to the randomized set, based on the previous findings of Brady and colleagues (2009). This experiment serves as the basis for a series of experiments that introduce shape contingencies in a separate training task taking place before this VWM task.

2.2 Methods

All experimental procedures were reviewed and approved by the University of Delaware's Institutional Review Board, and informed consent was obtained prior to participation.

2.2.1 Participants

All subjects were drawn from the University of Delaware community, and were compensated with either course credit or pay. I planned to collect 20 subjects in experiment, replicating the sample size used by Brady et al., (2009) (Figure 1.6). Due to variable scheduling, twenty-four subjects completed the experiment.

2.2.2 Apparatus

The task was implemented using MATLAB (2017b, The Mathworks; Natick, MA) using Psychtoolbox-3 (Brainard, 1997; Kleiner, Brainard, & Pelli, 2007; Pelli, 1997), and the Stream toolkit (Wade & Wyble, 2016). Participants were seated approximately 52 cm (unrestricted) from a 22-in LED computer monitor, and made responses using a keyboard.

2.2.3 Stimuli

Stimuli in the experiment consisted of sixteen Ndjuka characters. The sixteen stimuli were randomly divided into two unique groups for every participant. In the VWM task stimuli were presented in side-by side boxes that are 2.90 degrees of visual angle (dva) by 2.90 dva each. The stimuli themselves were approximately 1.65 dva by 1.65 dva. In the first set of stimuli, referred to as the paired group, the stimuli were assigned to pairs. These stimuli appeared in their respective pairs side by side in the memory array 100% of the time. The other set of eight stimuli, referred to as the unpaired group, appeared in randomized pairs on every trial throughout the experiment (appearing in each possible pairing only 25% of the time). On each trial, four sets of two reference boxes were displayed as the memory array (above, below, right, and left of fixation) (Figure 2.1). Stimuli appeared side by side inside the reference boxes, with eight stimuli in total presented on each trial. Paired trials consisted of the presentation of the paired stimuli randomly presented at the possible reference locations. Unpaired trials consisted of the randomized stimulus combinations presented at the reference locations. In the paired condition each pair was spatially consistent, (e.g. item A always appears in the right box while item B appears in the left). I controlled for this in the unpaired condition by having four items consistently presented on the right-hand side and the other four on the left, however the pairing of these stimuli was randomized.

2.2.4 Procedure

At the beginning of the trial participants were shown a display with a fixation cross in the center of the screen, and four reference locations on the top, bottom, left, and right consisting of two black outlined boxes side-by-side. This screen was presented for 1000 msec. The memory items then appeared on the screen for 3000 msec. The stimuli then disappeared, while the boxes remained on the screen, and 1000 msec later one of the reference boxes was highlighted in green, prompting the participant to recall the shape at the cued location. Participants made a keyboard response using the 1-8 keys at the top of the keyboard to indicate their response based on a randomized response map displayed at the bottom of the screen. On half of the trials the paired set was displayed with the four pairs being shuffled around the different locations. On the other half of trials, the randomized stimulus set was presented in random pairs at the four reference locations. Participants completed 4 blocks consisting of 64 trials each. Accuracy scores were calculated into k-values which are representative of how many stimuli are needed to be stored in working memory in order to achieve the measured percent correct. I did this using the same formula as Brady et al. (2009):

$$K = [(PC * 8 * 8) - 8]/7$$

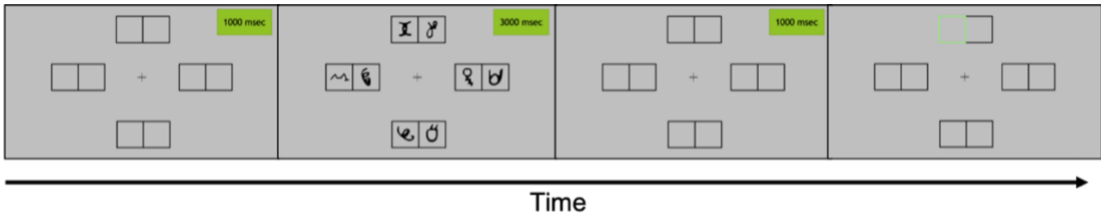

Figure 2.1: Depiction of the VWM task procedure. Eight stimuli appear in reference locations for 1000 msecs, with a 3000 msec interval before one of the reference locations is highlighted in green indicating the target item for recall.

2.3 Results

2.3.1 VWM task

A 2x4 RM-ANOVA was applied to the participant's k-values of the VWM task (Figure 2.2). Factors were pairing type (paired and random) and block (4 blocks of 64 trials each). The main effect of stimulus set was significant, $F(1,23) = 20.07$, $p < .001$, $\eta_p^2 = .466$, reflecting better performance in paired vs. random. The main effect of block was also significant, $F(3,69) = 10.15$, $p < .001$, $\eta_p^2 = .306$. The interaction between stimulus set and block was also significant, $F(3,69) = 9.33$, $p < .001$, $\eta_p^2 = .289$. Post hoc tests showed that k-values increased for the paired condition across block compared to the randomized stimulus set. No significant difference was observed between the paired and the random stimulus sets during the first block, $t(23) = 0.887$, $p = .384$, $d = 0.101$. Significantly higher performance in the paired condition compared to the randomized condition was observed for blocks two, $t(23) = 3.301$, p

= .003, d = 0.674, block three, t(23) = 4.597, p < .001, d = 0.938. , and block four, t(23) = 4.602, p < .001, d = 0.939.

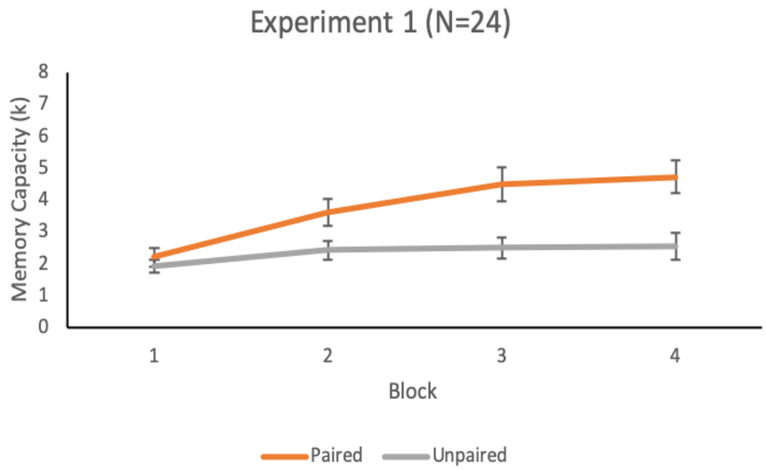

Figure 2.2: VWM results from Experiment 1. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

2.4 Discussion

My results effectively replicate the basic findings of Brady et al. (2009), but with 100% instead of 80% pairing contingency, and shape stimuli instead of colors. I observed a significant increase in working memory capacity for the paired stimulus condition compared to the randomized stimulus condition. This suggests that when the statistically paired shapes are co-stored in memory, they are chunked together in order to free up available working memory resources in order to encode more items, compared to when working memory is tasked with storing the same number of unpaired stimuli. These are important precursor results to establish the viability of subsequent experiments in this proposal, which employ variations of this paradigm to measure transfer of learning effects from VSL to VWM.

Chapter 3

EXPERIMENT 2

3.1 Introduction

The next experiment examines whether the representations that participants acquire during VSL can aid them in the VWM task performed in Experiment 1. Whereas Experiment 1 and the experiments of Brady and colleagues demonstrate that statistical associations can be learned during a high-load VWM task, they leave open the question of whether such statistical associations learned in a different context can extend across tasks to a high-load VWM context. Much prior evidence suggests that far less intensive training (including passive viewing) can lead to memory for associations. Are such associations capable of supporting performance in a VWM task?

To begin to answer this, in Experiment 2 participants were trained on two sets of stimuli in a 1-back VSL training task (the *VSL Training Task*), then tested with high-load VWM tasks (the *VWM Test Task*). During training, stimuli appeared in a stream and participants were tasked to press the spacebar when they detected a 1-back repetition (same stimulus back-to-back). One of the sets of stimuli was paired consistently throughout the VSL training (100%) while the other set will be presented in random pairs (25%). Thus, both paired and random stimuli appeared an equal number of times during training. After the VSL training, participants performed the

VWM test task. The group of stimuli that were paired during VSL continued to appear in their respective pairs during the VWM task. The set of stimuli that were randomly presented during VSL were assigned into novel pairs for the first time at the beginning of training. The stimuli in the random condition appeared in their novel pairs for the duration of the VWM task. Since both paired and random stimuli were always grouped into consistent pairs during the VWM task, contrasting performance between paired and random (especially early during test) would reveal the potential contribution of VSL occurring prior to the VWM task on VWM task performance, equalizing learning that could occur do to the VWM test task, alone. I conducted three variations of this experiment, wherein each variation employed a different VSL training presentation. With each iteration of the VSL learning task we made the training more contextually similar to the VWM task in order to test for larger transfer effects when the training/test context was the most similar. Considering transfer distance, I predicted that Experiment 2A with the most contextual differences would show the least amount of transfer, while 2C would have the most transfer as it is the closest contextually to the VWM test task.

3.2 Methods

All experimental procedures were reviewed and approved by the University of Delaware's Institutional Review Board, and informed consent was obtained prior to participation.

3.2.1 Participants

All subjects were drawn from the University of Delaware community, and were compensated with either course credit or pay. I planned to collect 20 subjects in each variation, consistent with Experiment 1. Experiment 2A and 2B were terminated after collection of 16 and 19 subjects, respectively, when analysis revealed no hint of a training effect specific to VSL-paired stimuli. 21 subjects were collected for Experiment 2C.

3.2.2 Stimuli

The three experiments differed only in terms of the presentation of stimuli and the precise task during the training procedure (see Figure 3.1). In Experiment 2A stimuli appeared one at a time in the center of the screen with the dimensions of 3.30 dva by 3.30 dva. In Experiment 2B the training stimuli were the same size as Experiment 2A, but two stimuli appeared simultaneously, centered 6.09 dva apart. In Experiment 2C, two stimuli appeared simultaneously inside the pairs of reference boxes that are 2.90 dva by 2.90 dva. The stimuli themselves are approximately 1.65 dva by 1.65 dva within the reference boxes.

3.2.3 Training Procedure

For each training procedure participants were tasked with a 1-back cover task, in which participants indicated with a spacebar keypress whenever the current item on the screen matched the last item that had appeared. All training three methods are illustrated in Figure 3.1. In terms of similarity between training and test (VWM task), these progress from least to most similar.

3.2.3.1 Experiment 2A

In this VSL training participants were displayed with a single item RSVP stream of the object stimuli (Figure 3.1). Each object appeared one-by-one in the center of the screen. The statistical associations in this stream were temporal in nature, as the first item of the pair was always presented prior to the subsequent item. Participants made a response whenever the single item repeated within the display (1-back response). The VSL stimuli always appeared one after another in their assigned pairs, making a total of 4 pairs of stimuli. The unpaired stimuli appeared in shuffled pairs, totaling 16 different possible pairings. Each of the 4 paired stimuli were exposed to participants 20 times during the VSL training, while each of the unpaired stimuli (16 pairs) only appeared 5 times in the entire sequence. Thus, each individual shape stimulus appeared an equal number of times. Along with the sequentially presented pairs, 32 stimuli were inserted into the stream to be used as the 1-back repetition trials split evenly amongst paired and unpaired items. The total training procedure consisted of 352 presentations in total. Items were presented for 500 msec with a 500 msec inter-stimulus interval.

3.2.3.2 Experiment 2B

In the second variation of the training task, participants were exposed to a dual RSVP stream consisting of 2 stimuli presented simultaneously (Figure 3.1). The statistical pairings in this stream co-occurred, meaning that two items appeared on the screen at the same time. Participants were prompted to only respond whenever both of the stimuli repeated within the display. VSL pairs (4) were simultaneously exposed 24 times while each of the unpaired stimulus combinations (16) only appeared 6 times in the entire sequence, with 32 1-back presentations split evenly amongst paired and unpaired items. The stream was 224 presentations in total, with each presentation consisting of two simultaneously presented stimuli. Pairs of stimuli were presented for 500 msec with a 500 msec inter-stimulus interval.

3.2.3.3 Experiment 2C

During this training phase, the RSVP of stimulus pairs, similar to 2B, were presented randomly in one of the four reference locations used in the VWM task (Figure 3.1). The statistical pairings in this training also co-occurred, with the critical difference being that the stimuli appeared within the VWM display configuration, in the same locations used in the VWM task. The training stream consisted of VSL pairs (4) that were simultaneously exposed 24 times each, unpaired stimulus combinations (16) only appeared 6 times each, as well as 32 one back presentations distributed such that they were split evenly amongst paired and unpaired items. The training stream was 224 presentations in total. Each pair was presented for 500 msec with a 500 msec inter-stimulus interval.

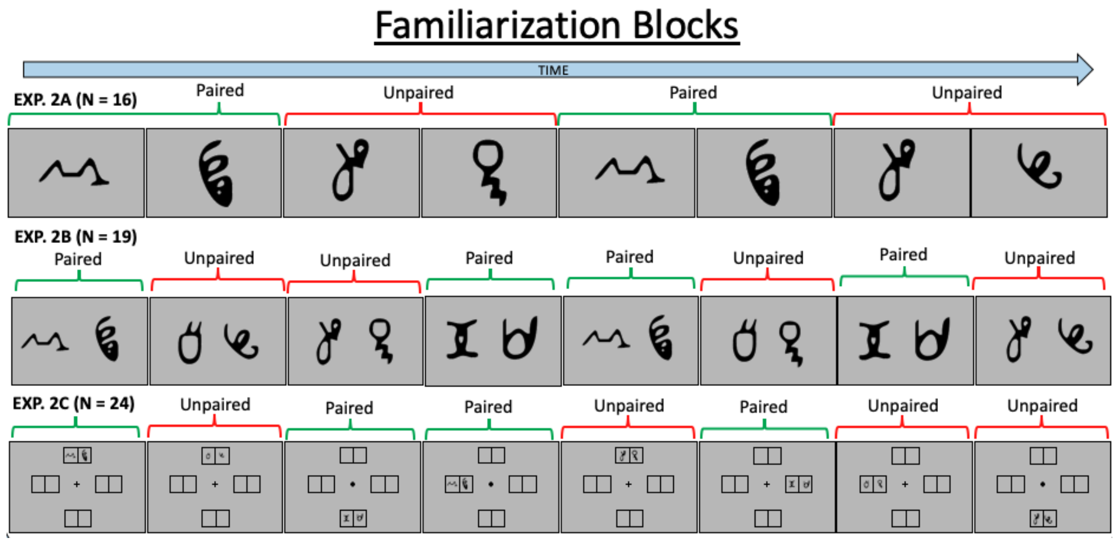

Figure 3.1: Examples of the VSL sequences used in all three versions of Experiment 2. In Experiment 2A statistical pairs occurred across displays, while in 2B and 2C pairs appeared simultaneously.

3.2.4 Experimental Procedure

The experimental procedure was identical to Experiment 1 with the following differences. In the cued memory recall task, instead of one set of stimuli being presented in randomized pairs, the VSL pairings remained consistent from the VSL training task to the cued memory task, while unpaired stimuli, that were shuffled during training, were assigned to appear in consistent pairs at the beginning of the cued memory task. In the cued memory recall task, displays consisted entirely of paired or unpaired stimuli, to form a clear contrast based on the VSL training. Experiment 2A was 4 blocks (64 trials each), while 2B and 2C were only 3 blocks in length.

3.3 Results

3.3.1 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit rate for Experiment 2A was 94.14% with 1.36% standard error. Mean false alarm rate for Experiment 2A was 0.63% with 0.17% standard error. Mean hit accuracy for Experiment 2B was 84.38% with 2.26% standard error. Mean false alarm rate for Experiment 2B was 2.15% with 0.24% standard error. Mean hit accuracy for Experiment 2C was 71.88% with 3.05% standard error. Mean false alarm rate for Experiment 2C was 7.39% with 1.41% standard error.

3.3.2 VWM Test Task

In each of the experiments I analyzed k-values which are reflective of working memory capacity. Analyses were conducted on the VWM task k-value data for Experiments 2A, B, & C, with stimulus set (paired during VSL training vs. unpaired during VSL) and block (4) as main factors. We also conducted planned-comparisons tests on the first block of the data of each experiment (paired vs. unpaired during VSL training) to see if there was an initial difference that might not be apparent from the full ANOVA results.

3.3.2.1 Experiment 2A

I applied a 2x4 RM-ANOVA to the k-value data collected from the VWM task (Figure 3.2). The analysis was run between the paired and unpaired stimulus sets that were shown during the VWM task (paired during VSL and unpaired during VSL) and block (4 blocks of 64 trials each). The main effect of stimulus set was not significant, $F(1,15) = 0.091$, $p = .768$, $\eta_p^2 = .006$. The main effect of block was significant, $F(3,45) = 8.71$, $p < .001$, $\eta_p^2 = .367$. First block performance was significantly lower than last block performance for both the paired, $t(15) = -3.538$, $p = .003$, $d = -0.885$, and unpaired conditions, $t(15) = -3.370$, $p = .004$, $d = -0.843$. The interaction between the two factors was not significant, $F(3,45) = 0.250$, $p = .861$, $\eta_p^2 = .016$. The pair-wise t-test between the first block of the paired set and unpaired stimulus set was also insignificant $t(15) = 0.750$, $p = .465$, $d = 0.188$.

3.3.2.2 Experiment 2B

I applied a 2x3 ANOVA on the k-value data collected from the VWM task (Figure 3.2). The analysis was run between the factor of stimulus sets that were shown during the VWM task (paired during VSL and Unpaired during VSL) and block (3 blocks of 64 trials each). The main effect of stimulus set was not significant, $F(1,18) = 0.580$, $p = .456$, $\eta_p^2 = .031$. The main effect of block was significant, $F(2,36) = 7.98$, $p < .001$, $\eta_p^2 = .307$. First block performance was significantly lower than last block performance for both the paired, $t(18) = -2.275$, $p = .035$, $d = -0.522$, and unpaired conditions, $t(18) = -3.130$, $p = .006$, $d = -0.718$. The interaction between the two factors was not significant, $F(2,36) = 0.444$, $p = .645$, $\eta_p^2 = .024$. The pair-wise t-test between the first block of the paired set and unpaired stimulus set was insignificant $t(18) = -0.037$, $p = .971$, $d = -0.008$.

3.3.2.3 Experiment 2C

I applied a 2x3 ANOVA on the k-value data collected from the VWM task (Figure 3.2). The analysis was run between the factor of stimulus sets that were shown during the VWM task (paired during VSL and Unpaired during VSL) and block (3 blocks of 64 trials each). The main effect of stimulus set was not significant, F(1,20) = 0.046, p = .832, $\eta_p^2 = .002$. The main effect of block was significant, F(2,40) = 70.79, p < .001, $\eta_p^2 = .780$. First block performance was significantly lower than last block performance for both the paired, t(20) = -9.941, p < .001, d = -2.169, and unpaired conditions, t(20) = -8.027, p < .001, d = -1.752. The interaction between the two factors was not significant, F(2,40) = 1.453, p = .246, $\eta_p^2 = .068$. The pairwise t-test between the first block of the paired set and unpaired stimulus set was insignificant t(15) = 0.750, p = .465, d = 0.188.

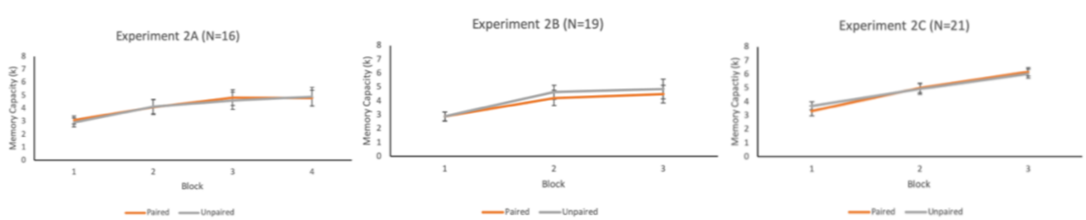

Figure 3.2: VWM results from Experiment 2A, 2B, and 2C. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

In the current experiments (Figure 3.2), I observed no significant differences between VWM performance of the VSL paired stimulus set and the VSL randomized stimulus set. I applied Bayesian ANOVA to the data in order to determine evidence for the null hypothesis (BF01), using the default settings in JASP (0.8). BF01 is representative of evidence in favor of the null hypothesis, where values greater than 1 are taken as evidence for the null, and values less than one are taken as evidence for the alternative hypothesis. A BF01 between 1 and 3 is taken as anecdotal evidence in support of the null, between 3 and 10 is taken as moderate evidence, and greater than 10 is interpreted as strong evidence. BF01 values less than 1 are interpreted as anecdotal evidence in support of the alternate hypothesis, less than .33 as moderate evidence, and less than .10 as strong evidence (Kass & Raftery, 1995). In Experiment 2A the main effect of pairing showed moderate evidence in support of the null with a BF01 value of 5.241 with 1.189% error. BF01 values for the main effect of block and the interaction were $< .01$ providing strong evidence for the alternate. In Experiment 2A the main effect of pairing had a BF01 value of 3.871 with 3.293% error providing moderate evidence in favor of the null. BF01 values for the main effect of block and the interaction were $< .01$ providing strong evidence in favor of the alternate. In Experiment 2C the main effect of pairing had a BF01 value of 5.230 with 1.805% error, again showing strong evidence in favor of the null. BF01 values for the main effect of block and the interaction were $< .01$ showing strong evidence for the alternate hypotheses. In this case in all three experiments there seems to be no effect of VSL pairing on VWM performance.

3.4 Discussion

Results of Experiment 2 did not provide evidence of any type of transfer effect of the VSL associations to the VWM task, across multiple variations of training sequences. It seems that the VSL pairings prior to the VWM task have little effect on the performance of the VWM task. Learning was still observed, overall, within the VWM task for both sets of stimuli, with better performance in later blocks. This may have been a general practice effect with the VWM task, which implies that the participants utilized the statistical regularities within the VWM task to increase their recall performance over time. It could also be due to general improvement in the VWM task with practice.

What reasons might underlie the lack of a transfer effect in this experiment? First, the obvious possibility is that VSL-style training might not lead to representations that can be employed by VWM. However, there are several other possibilities that I sought to eliminate with subsequent experiments. First, the VSL training streams I used in Experiment 2 only contain 50% structured stimuli, compared with a typical VSL stream that is often 100% structured (Slone & Johnson, 2015; Turk-Browne et al., 2008, 2005; Vickery et al., 2018). It may be possible that participants did not effectively learn the structure of the stream in the presence of the "noise" of the unstructured items. Since I did not test for recognition of pairs in Experiment 2, we cannot know for sure if the VSL training was enough to initiate VSL. In Experiment 3, I sought to confirm that the VSL training employed here could lead to evidence of pair memory.

Chapter 4

EXPERIMENT 3

4.1 Introduction

In Experiments 2A-2C, I had participants perform a VSL training task, but did not include an index of the learning that I presumed was occurring during the VSL training. The reason for this decision was that introducing the recognition task could cue subjects into the structure prior to the VWM task and might induce new opportunities for explicit learning that could impact the VWM task. However, it is possible that VSL did not occur in our training task, or at weak levels, due to the degree of regularity within the streams I used. In contextual cueing, a form of spatial statistical learning, the initial presence/absence of regularities in the stream can reportedly influence participants' ability to update representations, (Jungé, Scholl, & Chun, 2007). In their task, participants who were initially exposed to displays containing regularities were able to show a significant learning effect, while participants initially exposed to no-signal displays failed to learn the regularities presented later in the experiment. In the Experiment 2 training task, only 50% of the stimuli have structure, so it could be possible that the intrusion of "noise" blocked learning of the structured pairs. The VSL stream instead could be equally training perceptual fluency of the stimuli, which is why I did not see a difference between the stimulus sets during the VWM task. In Experiment 3, participants completed a replication of Experiment 2C, with the addition of an intermediate recognition test, wherein they were asked to judge which of two pairs of stimuli was more familiar than another. This test allows us to ask if the VSL sequence is effectively training the participants to learn the statistical contingencies that I predicted they would use in the VWM task. I also increased the length of the training task, to boost potential VSL for both the recognition task and the VWM test task.

4.2 Methods

Experiment 3 is identical to Experiment 2C with the following changes.

4.2.1 Participants

Nineteen students from the University of Delaware subject pool were recruited to participate in the study for course credit or pay.

4.2.2 Stimuli

Stimuli in the recognition task were presented in two sets of side-by-side boxes that were 2.90 dva by 2.90 dva, with the stimuli inside measuring 1.65 dva by 1.65 dva.

4.2.3 Training Procedure

VSL training duration was increased compared to Experiment 2C. Each of the VSL pairs were exposed 40 times in the training sequence. I increased the training from Experiment 2 to ensure and enhance VSL from the training sequence. The unpaired stimuli appeared in shuffled pairs, and each of the pair configurations only appeared 10 times in the entire sequence. There were also 32 one back presentation trials split evenly amongst paired and unpaired items. The total training stream was 352 presentations in total. Each pair of stimuli were presented for 500 msec with a 500 msec inter-stimulus interval.

4.2.4 Recognition Procedure

After completing the VSL training, I then asked participants to perform a recognition judgment. Two pairs of stimuli appeared on the screen simultaneously on the left and the right side (Figure 4.1). Participants were prompted to select the stimulus pair that is more familiar to them. On each trial, both pairs of stimuli were from the same stimulus set (VSL paired, or VSL unpaired). In the paired condition, one of these shape pairs was the statistical pair present in the stream, while the other stimulus was a foil composed of characters from the paired stimulus set. Participants completed 64 trials, and reported which of two pairs of stimuli were more familiar using a left or right arrow keypress in an untimed keyboard response. On trials presenting the VSL unpaired stimuli, 2 foil sets (2 sets of 4 pairs each) were created to contrast from one another, one pair from each foil set was present on each trial in the VSL unpaired condition. Participants responded to which one was more familiar, even though both pairs were equally presented in the training. One of these foil sets was preserved to be used in the subsequent VWM task as the unpaired stimulus set, in order to keep exposure of the statistical regularities between paired and unpaired stimuli equal during recognition and the VWM task. No additional learning could take place in the recognition stage, due to these controls.

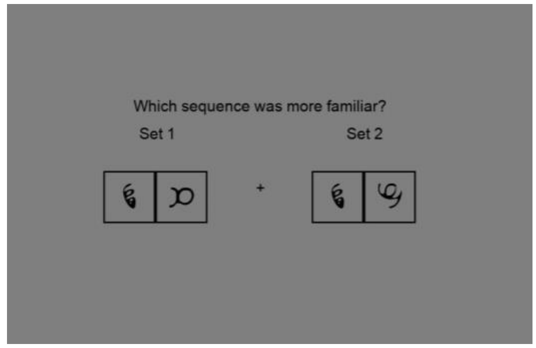

Figure 4.1: One of the trial presentations for the recognition block of the task. Participants responded which pairing was more familiar to them using an arrow button press.

4.2.5 Experimental Procedure

The VWM procedure used was identical to that of Experiment 2C.

4.3 Results

4.3.1 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit accuracy was 73.19% with 3.23% standard error. Mean false alarm rate was 3.75% with 0.58% standard error.

4.3.2 VSL Recognition

To determine if there was an effect of VSL I conducted one-sample t-tests comparing rates of target-pair selection vs chance (50%). Mean recognition accuracy for the paired stimuli was 77.12% with a standard deviation of 17.08%. Mean accuracy for the unpaired stimuli was 51.96% with a standard deviation of 14.99%. Recognition of the paired stimuli was significantly higher than chance, $t(18) = 6.923$, $p < .001$, $d = 1.588$. Paired recognition accuracy was also significantly higher compared to unpaired recognition accuracy, $t(18) = 5.171$, $p < .001$, $d = 1.186$. While the VSL randomized stimuli were not presented in a stereotypical order during VSL, two sets of foil pairs were used as a judgement basis in the recognition task. Between the foil sets there was not a significant difference from chance, $t(18) = +/-0.584$, $p = .573$, $d = +/-0.132$.

4.3.3 VWM Test Task

I applied a 2x3 RM-ANOVA on the k-values collected from the VWM task (Figure 4.2). The analysis was run between the two stimulus sets used in the memory display (paired in VSL/unpaired in VSL) and block (3 blocks of 64 trials each). The main effect of stimulus set was not significant, $F(1,18) = 0.167$, $p = .688$, $\eta_p^2 = .009$. The main effect of block was significant, $F(2,36) = 32.34$, $p < .001$, $\eta_p^2 = .590$. First block performance was significantly lower than last block performance for both the paired, $t(20) = -9.941$, $p < .001$, $d = -2.169$, and unpaired conditions, $t(20) = -8.027$, $p < .001$, $d = -1.752$. The interaction between the two factors was not significant, F(2,36) = 1.161, p = .325, η_p^2= .061. The pair-wise t-test between the first block of the paired set and unpaired set was not significant t(18) = 1.037, p = .313, d = 0.238.

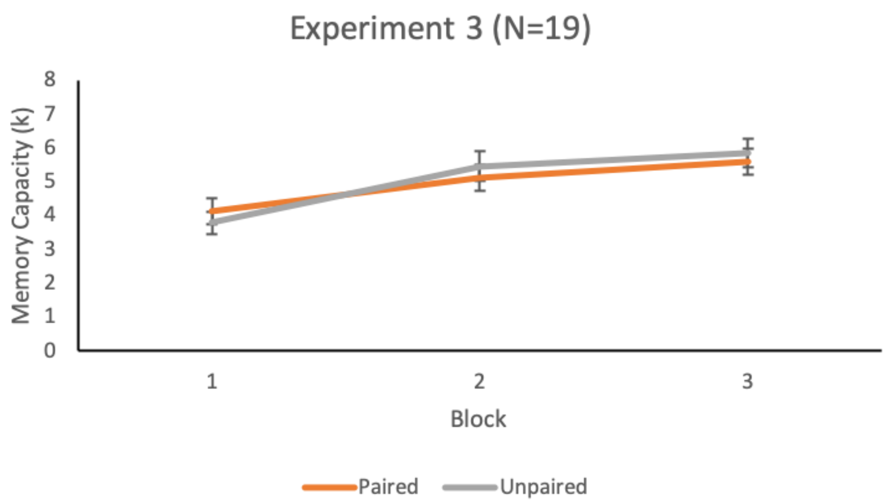

Figure 4.2: VWM results from Experiment 3. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

In summary, I observed a significant effect of learning during the recognition phase. However, once again I observed no significant difference in VWM performance across the stimulus sets. I applied Bayesian ANOVA to the data in order to determine evidence for the null hypothesis (BF01). In Experiment 3 the main effect of pairing had a BF01 value of 4.946 with 1.055% error, showing strong evidence in support of the null. BF01 values for the main effect of block and the interaction were < .01, showing strong support for the alternate hypothesis. This again provides evidence that there was support for the null hypothesis in the case of VSL pairing affecting VWM performance.

4.4 Discussion

Evidence from this experiment suggests that participants are in fact capable of learning statistical regularities in the VSL training task I employed, reflected by above chance recognition of the paired stimuli. Regardless of VSL occurring, there was no evidence that the contingencies learned in the VSL task benefited performance in the VWM task. There may be other factors influencing the performance in the VWM task that might have obscured any effects of the VSL-based representations. For example, explicit associative knowledge of the stimulus pairs (both paired and unpaired) could be learned within the VWM test display. This seems to be potentially due to the 100% contingency of the pairs of stimuli appearing consistently together throughout the test task. If participants have learned the associations between stimuli, participants can recreate the entire display of the cued memory task while only explicitly remembering 3/8 of the stimuli and their locations. The rest of the display can be recalled using the associative information of only three stimuli from separate pairs and process of elimination. It could be the case that participants are not relying on the VSL chunked representations that they have formed, rather they are implementing a strategy for performing the VWM task that is based on the explicit associations between the stimulus pairs. If this is the case, then perhaps the VSL representations effects on VWM are muted when explicit information is available.

In the VWM task used in Experiments 1-3, both sets of stimuli appeared in pairs 100% of the time. It is possible that participants rapidly recognized the explicit associative information, possibly enhanced by over familiarization with the stimuli during the training and recognition stages. Notably, the 100% contingency was a departure from the method of Brady et al. (2009). Those authors employed 80% contingency, and yet still observed a benefit of the statistical associations. In order to reduce explicit awareness of the pairs during VWM, in the next version of the experiment we made the VWM task more difficult by reducing items' appearances in paired configurations to 80%.

Chapter 5

EXPERIMENT 4

5.1 Introduction

The results of Experiment 3, in particular, raise concerns about the potential transfer of learning from VSL tasks to VWM tasks, as we see clear evidence that the VSL training task does in fact encourage participants to form representations of the paired stimuli. A potential issue is that the associations exposed during the VWM task may be too evident and easily learned by subjects early-on during the VWM test phase. In our previous versions of the VWM task, the stimuli appeared in pairs 100% of the time. The formation of explicit representations of the pairs may cause participants to abandon the more implicit representations formed in the VSL task. In Brady et al., (2009), seven out of the ten participants in the paired condition reported that they were aware of the statistically paired colors by the end of the task (600 trials), when the statistical pairs were only present on ~80% of trials. Participants may rapidly form explicit associations of the paired stimuli, eliminating the need to utilize the statistically learned representations. It may be the case that the more implicit representations formed during VSL could have reduced effects during the VWM task, because participants are aware that all shapes now appear with an associate and immediately, effortfully, and consciously begin to exploit this circumstance. In other words, we may have observed a ceiling effect, whereby the additional knowledge of pairings gained from VSL could no longer aid performance in the presence of strategic use of explicit pair knowledge. In Experiment 4 I made the VWM task harder to reduce the chances of overlearning the explicit associative information, allowing for a chance for the VSL representations to be utilized. In order to do this I added a condition to the VWM experiment. Now instead of appearing in pairs 100% of the time, the stimulus sets will only appear paired 80% of the time, and for the other 20% of the time the stimuli will be showed in scrambled pairs. These randomized trials are not included in the analysis, but act as a buffer to prevent or delay explicit recognition from forming. Finally, I also sought a large sample (exceeding 100 subjects) to account for the possibility that transfer effects might be small and previous designs underpowered to detect true effects.

5.2 Methods

Experiment 4 is identical to Experiment 3. except for changes noted below.

5.2.1 Participants

Participants were recruited from the University of Delaware subject pool to participate in the study online for course credit or pay. Initially I aimed to collect 100 subjects, but I also had a target of opportunity, due to the availability of excess credits at the end of the semester, to sample an even larger group of subjects. In addition to aiding power through larger sample, this provided the opportunity to account for potentially degraded performance in an online sample. In total, 154 subjects completed the study.

5.2.2 Apparatus

Participants completed the task on their own laptop or desktop computer, as data for this experiment was collected online. Online data was hosted on Pavlovia.org and was programmed using PsychoPy-3 (Peirce et al., 2019; Peirce, 2007, 2009). Participants were not able to complete this experiment from their phone's web browser.

5.2.3 Stimuli

Stimuli were measured in pixels, as dva cannot be calculated without knowing the viewing distance. The side-by-side reference boxes were 70 by 70 pixels, and the stimuli that appeared inside them were 69 by 69 pixels. Stimuli are all the same size across training, recognition, and VWM recall tasks.

5.2.4 Training Procedure

The training procedure was similar to that of Experiment 3. Paired stimuli were exposed 40 times within the VSL test task, at the 4 different locations. Each of the unpaired stimulus configurations only appeared 10 times in the entire sequence. I also increased the number of one back responses to 60 in order to engage the participant more during training. N-back responses were split evenly amongst paired and unpaired items. The total stimulus stream was 380 presentations in total. Stimuli were presented for 500 msec with a 500 msec inter-stimulus-interval (ISI) at the center of the screen with a fixation being presented during the ISI.

5.2.5 Experimental Procedure

The experimental procedure was similar to that of experiment 3. In the VWM task both stimulus sets (VSL paired and VSL unpaired) appeared in their assigned pairs only on 80% of trials. On the other 20% of trials participants were shown scrambled pairs of either of the two stimulus sets. The shuffled trials are excluded from the analysis below.

5.3 Results

5.3.1 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit accuracy was 70.90% with 1.43% standard error. Mean false alarm rate was 6.85% with 0.48% standard error.

5.3.2 VSL Recognition

Recognition of the paired stimuli was significantly higher than chance, $t(153) = 15.81$, $p < .001$, $d = 1.275$. While the VSL randomized stimuli were not presented in a stereotypical order during VSL, two sets of foil pairs were used as a judgement basis in the recognition task. Between the foil sets there was not a significant difference in their recognition, $t(153) = +/-0.018$, $p = .986$, $d = +/-0.001$. Overall the learning effect only occurred in the VSL stream for the paired stimuli.

5.3.3 VWM Test Task

I applied a 2x4 ANOVA on the k-value data collected from the VWM task (Figure 5.1). The analysis was run between the factor of stimulus sets that were shown during the VWM task (paired during VSL and unpaired during VSL) and block (4 blocks of 32 trials each). This analysis was only run on the trials in which the stimulus sets appeared in their corresponding pairs, the randomized presentation trials were not included in the analysis. The main effect of stimulus set (previously paired vs. unpaired) was significant, $F(1,153) = 29.14$, $p < .001$, $\eta_p^2 = .160$, with higher accuracy for paired compared with unpaired. Mean k-value for the paired condition was, 2.99 with a standard deviation of 2.63. For the unpaired condition the mean k-value was, 2.39 with a standard deviation of 2.32. The main effect of block was not significant, $F(3,459) = 0.542$, $p = .654$, $\eta_p^2 = .004$. The interaction between the two factors was not significant, $F(3,459) = 1.711$, $p = .164$, $\eta_p^2 = .011$. The pair-wise t-test between the first block of the paired set and unpaired set was significant $t(153) = 4.086$, $p < .001$, $d = 0.329$. Mean k-value of the first block of paired stimuli was 3.043 with a standard deviation of 2.209. Mean k-value of the first block of the unpaired stimuli was 2.456 with a standard deviation of 1.932.

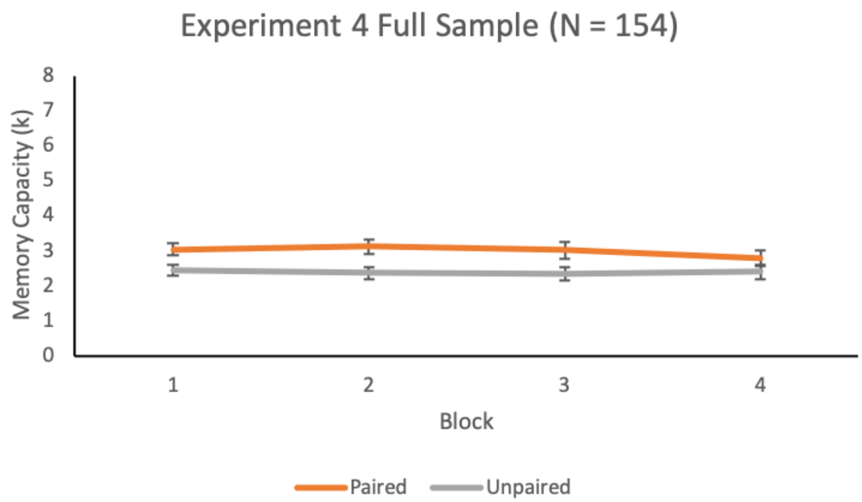

Figure 5.1: VWM results from Experiment 4. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

5.3.4 VSL/VWM Correlation

In order to see if the VSL training was related to the transfer effect we found in the VWM test, I applied a correlational analysis to the learning effect measured by the VSL recognition block (percent of responses toward paired stimuli minus 50% chance) and the VWM learning effect of the first block (paired accuracy minus unpaired accuracy). The Pearson's correlation coefficient was significantly and positively correlated with $r(152) = .328$, $p < .001$.

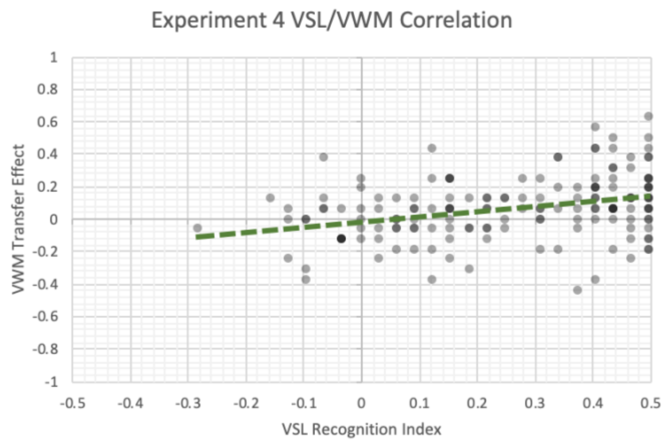

Figure 5.2: VSL and VWM effects correlation scatterplot for Experiment 4. VSL recognition index is plotted on the X axis (percent of paired responses minus chance), and VWM transfer effect on the Y axis (paired minus unpaired accuracy in block 1). Grey markers represent single data points while black parkers represent multiple data points.

5.3.5 Post-hoc analyses

Given the lack of the significant main effect of block that is representative of learning of chunks during the VWM task, we decided to conduct a post-hoc analysis using exclusion criteria. These exclusion criteria were applied only to the VWM task performance. If a participant had any cell (defined by pair type and block) that resulted in a $k < 0$, then their data were eliminated based on the fact that this would mean that participants are below chance, suggesting they are not effortfully completing the task. I proposed that the reason we do not see the main effect of block is due to participants dropping out mid experiment. Applying these exclusion criteria, I found that 84 participants were eliminated from the sample, giving us 70 viable subjects for the following analysis.

5.3.6 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit accuracy was 79.02% with 1.47% standard error. Mean false alarm rate was 4.58% with 0.41% standard error.

5.3.7 VSL Recognition

Recognition of the paired stimuli was significantly higher than chance, $t(69) = 18.87$, $p < .001$, $d = 2.256$. Mean recognition performance of the paired stimuli was 87.32% with a standard deviation of 16.54%. Mean recognition performance of the unpaired stimuli was 50.63% with a standard deviation of 16.33% While the VSL randomized stimuli were not presented in a stereotypical order during VSL, two sets of foil pairs were used as a judgement basis in the recognition task. Between the foil sets there was not a significant difference in their recognition, $t(69) = +/-0.320$ $p = .750$, $d = +/-0.038$. Overall the learning effect only occurred in the VSL stream for the paired stimuli.

5.3.8 VWM Test Task

I applied a 2x4 RM-ANOVA on the k-values collected from the VWM task. (Figure 5.2). The analysis looked at the factors of stimulus sets that were shown during the VWM task (paired during VSL and Unpaired during VSL) and block (4 blocks of 32 trials each). This analysis was only run on the trials in which the stimulus sets were appearing in their corresponding pairs, the randomized presentation trials were not included in the analysis. The main effect of stimulus set was significant, $F(1,69) = 27.92$, $p < .001$, $\eta_p^2 = .288$. Mean k-value for the paired condition was 4.96 with a standard deviation of 2.01. For the unpaired condition the mean k-value was, 3.99 with a standard deviation of 1.94. The main effect of block was significant, $F(3,207) = 15.76$, $p < .001$, $\eta_p^2 = .186$. First block performance was significantly lower than last block performance for both the paired, $t(69) = -3.765$, $p < .001$, $d = -0.450$, and unpaired conditions, $t(69) = -4.176$, $p < .001$, $d = -0.499$. The interaction between the two factors was not significant, $F(3,207) = 1.198$, $p = .312$, $\eta_p^2 = .017$. The pair-wise t-test between the first block of the paired set and unpaired set was significant $t(69) = 4.156$, $p < .001$, $d = 0.497$. Mean k-value of the first block of paired stimuli was 4.286 with a standard deviation of 1.764. Mean k-value of the first block of the unpaired stimuli was 3.363 with a standard deviation of 1.629.

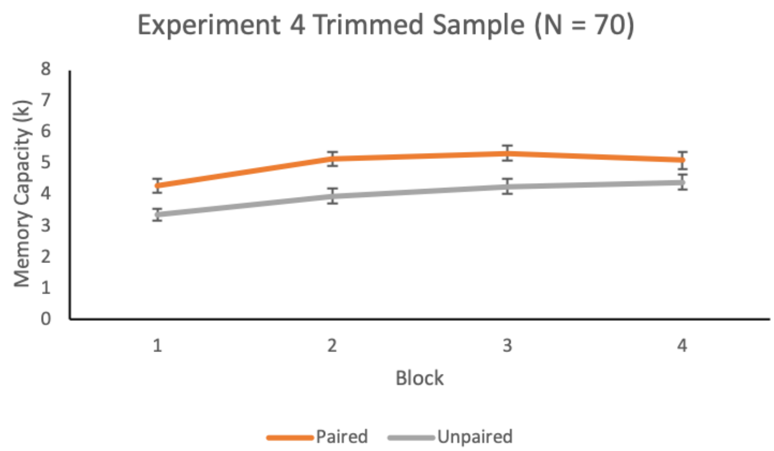

Figure 5.3: Trimmed VWM results from Experiment 4. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

5.3.9 VSL/VWM Correlation

In order to see if the VSL training was related to the transfer effect we found in the VWM test, I applied a correlational analysis to the learning effect measured by the VSL recognition block (percent of responses toward paired stimuli minus 50% chance) and the VWM learning effect of the first block (paired accuracy minus unpaired accuracy). The Pearson's correlation coefficient was significantly and positively correlated with $r(68) = .326$, $p = .006$.

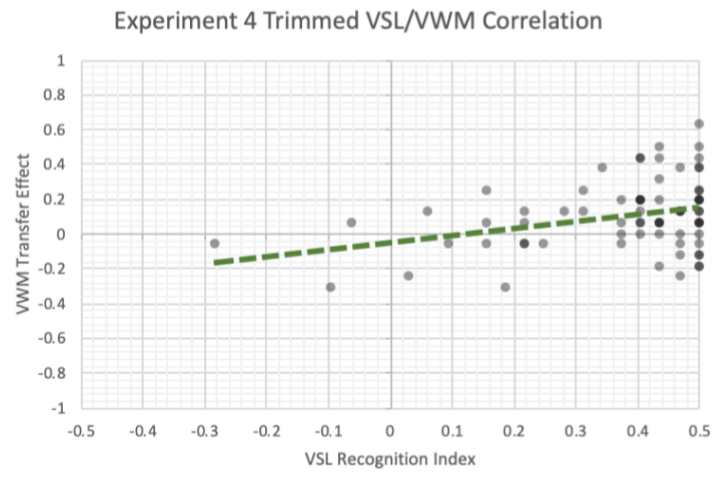

Figure 5.4: VSL and VWM effects correlation scatterplot for Experiment 4 trimmed data. VSL recognition index is plotted on the X axis (percent of paired responses minus chance), and VWM transfer effect on the Y axis (paired minus unpaired accuracy in block 1). Grey markers represent single data points while black parkers represent multiple data points.

5.4 Discussion

The results from this experiment showed that when stimuli are paired in the VSL training prior to a VWM task, that the memory representations formed during the VSL training allow for an increase of VWM memory capacity for paired items, compared to stimuli that were not initially presented in pairs. I propose that this is due to the formation of chunked memory representations during the VSL training. These chunked representations are then utilized by VWM in order to increase overall working memory capacity during our second task.

Why is this the first of the experiments to reveal this effect, so far? This effect was not present in the other experiments possibly due to participants reaching ceiling performance with the VWM displays being paired 100% of the time. While this effect was significant, we are not certain if the recognition block contributes to this effect, or aids in the formation of explicit information. It could also be the case that participants are using the familiarity task to begin determining which pairs are critical to learn. Further, despite this experiment yielding reasonably large effect sizes, the current study might be a false alarm. Given the number of failures to observe similar effects before, a replication was called for. Both the recognition block presence and replication concerns are addressed in Experiment 5.

Despite our finding of a significant main effect of VSL pairing, we did not observe a main effect of block before filtering participants, which had been previously observed in every prior experiment, representing learning of the pairs over time. When we applied exclusion criteria in a post-hoc analysis we were able to recover the main effect of block on memory capacity, but only after eliminating a very large number of subjects from our study. However, the main effect of VSL pairings, as well as the pair-wise comparison of the first block between VSL pairing conditions were both found to be significant in both analyses. With the elimination of explicit representations being formed in the previous experiments, allowing for ceiling performance, we were able to see how participants relied on their previously chunked memory representations of the paired stimuli to increase their performance in another task besides recognition or familiarization.

Chapter 6

EXPERIMENT 5

6.1 Introduction

In the previous experiment, participants showed a main effect of VSL pairings, however, participants did not show a significant effect of learning across the course of the experiment as observed in all previous versions of this task. Only after hefty subject elimination did the main effect of block resurface. Another concern is that we are uncertain if the intermediate recognition task had aided memory in some way. Finally, Experiment 4 was the first out of 5 experiments to show any such transfer effect, leading to concerns of its replicability. Experiment 5 builds off of the main findings of Experiment 4, but addresses these weaknesses. Considering the poor quality of online data collection and the need for a very high exclusion rate, I decided to preregister my methods and a priori exclusion criteria. In this version of the experiment I also eliminated the recognition task in between the VSL training and VWM cued memory recall task. This allows us to eliminate any possible benefits of the recognition task on VWM performance, as well as collect a quality data sample.

6.2 Methods

The experimental procedure is identical to that of Experiment 4 with the following changes.

Preregistration of methods for this experiment can be viewed at: https://osf.io/d7rz3/

6.2.1 Participants

Based on a power analysis of the significant pair-wise comparison in Block 1 of Experiment 4, after exclusion criteria were applied, 95% power with an alpha of .05 requires a sample of at least 55 participants calculated via G*Power (Faul, Erdfelder, Buchner, & Lang, 2009; Faul, Erdfelder, Lang, & Buchner, 2007). We set an a priori collection goal of 60 participants to slightly exceed this estimate. Data were collected in rounds – each time a round was finished, exclusions were computed, and a new sample was then drawn. This was repeated until a usable sample of 60 participants was collected. 139 students from the University of Delaware subject pool were ultimately recruited to participate in the study for course credit or pay. 79 subjects were excluded based on a priori criteria.

6.2.2 Exclusion Criteria

Subjects were eliminated from the analysis if while completing the VSL training they had a hit rate below 50% of the 1-back targets, of if their false alarm rate was over 10%. Subjects were also eliminated from the analysis if any cell of their k-value data for the VWM task was $k < 1$. The below analyses are only applied to the included participants.

6.2.3 Procedure

Procedure is identical to Experiment 4, with the removal of the intermediate recognition test.

6.3 Results

6.3.1 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit accuracy was 82.03% with 1.29% standard error. Mean false alarm rate was 3.70% with 0.34% standard error.

6.3.2 VWM test task

I applied 2x4 RM-ANOVA on the k-value data collected from the experiment (Figure 6.1). The analysis was applied to the factors of stimulus sets that were shown during the VWM task (paired during VSL and Unpaired during VSL) and block (4 blocks of 32 paired trials each, 40 total). This analysis was only run on the trials in which the stimulus sets appeared in their corresponding pairs, the randomized presentation trials were not included in the analysis. The main effect of stimulus set was significant, $F(1,59) = 17.64$, $p < .001$, $\eta_p^2 = .230$. Mean k-value for the paired condition was 5.25 with a standard deviation of 1.91. For the unpaired condition the mean k-value was 4.62 with a standard deviation of 1.86. The main effect of block was significant, $F(3,177) = 19.12$, $p < .001$, $\eta_p^2 = .245$. First block performance was significantly lower than last block performance for both the paired, $t(59) = -5.122$, $p < .001$, $d = -0.661$, and unpaired conditions, $t(59) = -5.097$, $p < .001$, $d = -0.658$. The interaction between the two factors was not significant, $F(3,177) = 1.967$, $p = .121$,

$\eta_p^2 =$ .032. The pair-wise t-test between the first block of the paired set and unpaired set was significant $t(59) = 2.749$, $p = .008$, $d = 0.355$. Mean k-value of the first block of paired stimuli was 4.467 with a standard deviation of 1.812. Mean k-value of the first block of the unpaired stimuli was 3.829 with a standard deviation of 1.529.

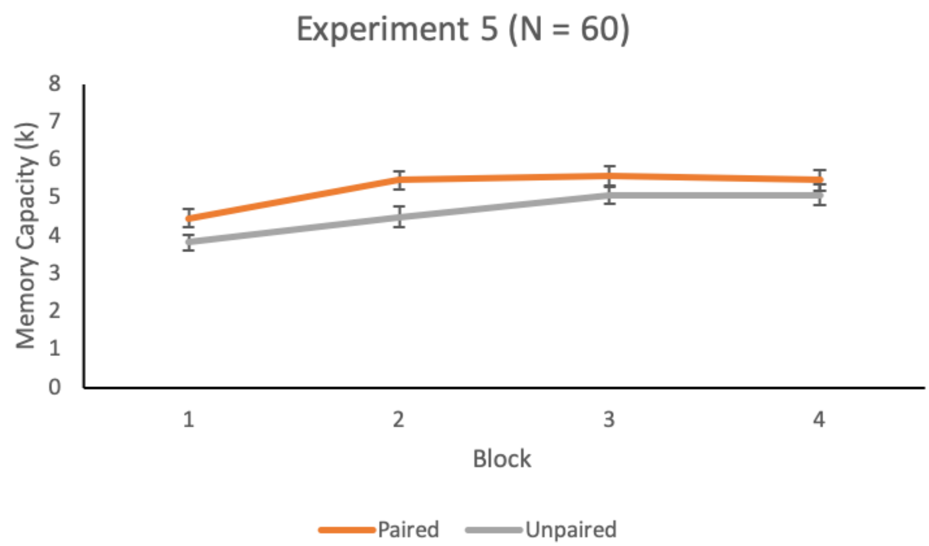

Figure 6.1: VWM results from Experiment 5. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

6.4 Discussion

The results from Experiment 5 replicated the basic findings of Experiment 4. We found that even without the intermittent recognition block, the VSL chunked representations were able to be utilized in the VWM task to aid performance by an increase to VWM capacity. These results are novel in that we were able to measure an effect of statistical learning through VWM performance rather than recognition or familiarity. These experiments show that the information learned implicitly through exposure can have an effect on working memory by reducing the cognitive resources used to maintain statistically paired stimuli compared to statistically unpaired stimuli. We believe this is due to the chunking of memory representations occurring in VSL, allowing for the immediate increase of VWM performance of paired stimuli. These chunked representations are then further compressed during the VWM task where all stimuli appear in pairs. These data allow for us to begin to explore the link between VSL and VWM.

Chapter 7

EXPERIMENT 6

7.1 Introduction

Experiment 4 and 5 revealed that VSL representations learned during serial presentation training can be employed to enhance VWM performance. However, the VSL training paradigm in Experiments 4-5 is very similar to the VWM task, as they share the same display, and stimuli appear in the same locations throughout the experiment. The concern with this is whether or not the memory representations generated during VSL can be generally applied to other VWM tasks. With Experiment 6, I sought to explore how different VSL training contexts could also transfer to the VWM test task. If the memory representations formed during VSL are generalizable to VWM, then I would expect the transfer to occur from other types of VSL training. Previous studies have shown effects of VSL that span temporal and spatial dimensions have the ability to influence one another (Turk-Browne & Scholl, 2009). I chose to use the more temporal version of the VSL training I employed in Experiment 2A. This method has been shown to produce reliable recognition effects. I hypothesized that if pairs were defined by temporal relationships during the VSL training task, they might also benefit VWM performance of spatial configurations of the same paired stimuli, using the same VWM task as in Experiments 4-5. While VSL can still form chunks during temporal training (Park et al., 2018), we do not know if the chunks will generalize to a spatial test task.

7.2 Methods

The methods of Experiment 6 are identical to Experiment 5 except for the following changes.

Preregistration of methods for this experiment can be viewed at: https://osf.io/acxez/

7.2.1 Participants

Based on a power analysis of the significant pair-wise comparison of Experiment 4 after exclusion criteria were applied, in order to get a sample with 95% power and an alpha of .05 we would need to collect a sample of at least 55 participants. We set an a priori collection goal of 60 participants post-exclusion. One-hundred and sixty students from the University of Delaware subject pool were recruited to participate in the study for course credit or pay. One-hundred subjects were excluded based on a priori criteria.

7.2.2 Stimuli

Stimuli in the VSL training task appeared one at a time in the center of the screen and were 100 by 100 pixels in size. Stimuli in the VWM appeared in boxes that measured 70 by 70 pixels. The stimuli themselves were 66 by 66 pixels in size.

7.2.3 Training Procedure

Training procedure was similar to that of Experiment 2A. Stimuli appeared alone in the center of the screen for 500 msec with a 500 msec ISI. Pairs were exposed 40 times across temporal displays while each of the randomized pairs only appeared

10 times in the entire sequence. 60 one back events were inserted into the stream split evenly amongst paired and unpaired items. The total stimulus stream was 700 presentations in total.

7.3 Results

7.3.1 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit accuracy was 84.47% with 1.26% standard error. Mean false alarm rate was 1.77% with 0.26% standard error.

7.3.2 VWM Test Task

I applied a 2x4 RM-ANOVA to the k-values collected from the VWM task (Figure 7.1). The analysis was run between the factor of stimulus sets that were shown during the VWM task (paired during VSL and unpaired during VSL) and block (4 blocks of 32 paired trials each, 40 total). This analysis was only run on the trials in which the stimulus sets were appearing in their corresponding pairs, the randomized presentation trials were not included in the analysis. The main effect of stimulus set was not significant, $F(1,59) = 2.422$, $p = .125$, $\eta_p^2 = .039$. The main effect of block was significant, $F(3,177) = 18.03$, $p < .001$, $\eta_p^2 = .234$. First block performance was significantly lower than last block performance for both the paired, $t(59) = -4.879$, $p < .001$, $d = -0.630$, and unpaired conditions, $t(59) = -3.854$, $p < .001$, $d = -0.498$. The interaction between the two factors was not significant, F(3,177) = 0.978, p = .404, $\eta_p^2 = .016$. The pair-wise t-test between the first block of the paired set and unpaired set was not significant t(59) = 1.304, p = .197, d = 0.168.

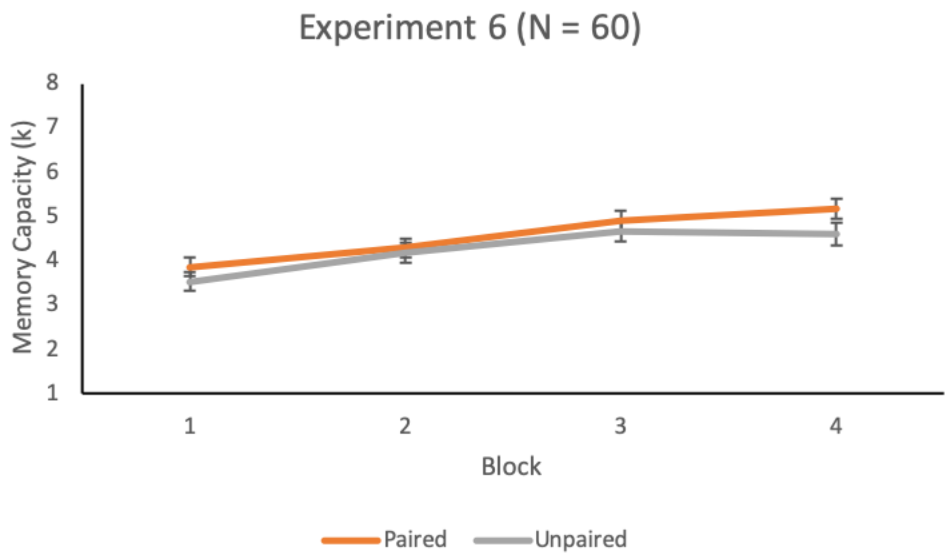

Figure 7.1: VWM results from Experiment 6. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

I observed no significant difference in VWM performance across the stimulus sets. I applied Bayesian ANOVA to the data in order to determine evidence for the null hypothesis (BF01). In Experiment 6 the main effect of pairing had a BF01 value of 0.887 with 1.521% error, showing anecdotal evidence in support of the alternate hypothesis. BF01 values for the main effect of block and the interaction were < .01, showing strong support for the alternate hypothesis. This provides evidence that there was some support for the alternate hypothesis, however evidence is not strong.

7.4 Discussion

The results from this experiment did not replicate the general finding of Experiment 4 and 5. Evidence suggests that the VSL training was not able to produce representations that were applicable to the VWM task. One issue with this type of transfer is that the ability for temporal training to effect spatial VWM could be lower due to the contextual difference. Running a power analysis on the t-test between the two pairing conditions in the first block, two-hundred and eighty subjects would be required for 80% power. The current study is severely underpowered. One way in which we could also increase the power of the effect within participants would be to increase the duration of the VSL training. There may be a difference in learning of the chunked representations based on the style of training. The simultaneous presentation of pairs in Experiments 4 and 5 may allow for more chunking to occur, versus single stimuli appearing one-by-one. More evidence is needed in order to determine the differences between training regimen.

I also believe the lack of an effect may be due to different types of information being learned during different types of VSL training. In the training used in Experiment 4 and 5, the stimuli were spatially predictive of one another, while in Experiment 6 the stimuli were temporally predictive of one another. It may be the case that this predictive information is what drives the effect observed in the VWM block in Experiment 4 and 5. If the type of statistical information learned across stimuli dimensions is different, then it is possible that temporal relations between stimuli cannot generalize to spatial relationships. While I know that the transfer effects are present in the close context spatial training/test, I decided that my best chance at seeing transfer to VWM in the temporal domain would be to attempt to measure a benefit in a more temporally based VWM task. In order to examine this, in the next experiment I apply the same training to participants but this time participants are tasked with a temporal recall task, compared to the spatial recall task used previously.

Chapter 8

EXPERIMENT 7

8.1 Introduction

This experiment attempts to uncover the effect of VSL on VWM, but using temporal training and test. The motivation for this is that the null result of Experiment 6 might be due to the transfer distance between training and test being too great – I hypothesized that by making the test phase more similar to the training phase, I could improve the likelihood of generalization. The training was similar to that of Experiment 6, where the stimulus pairs were presented sequentially, allowing for temporally predictive information to be learned. I developed a new VWM test phase that would better match the characteristics of the temporal VSL training phase. During test, subjects were presented with a one by eight array of boxes. On each trial, stimuli appeared one at a time from right to left. The participants were then cued to recall which object appeared in a cued box within the array.

8.2 Methods

Experiment 7 is identical to Experiment 6 with the following changes. Preregistration of methods for this experiment can be viewed at: https://osf.io/f9jrq/

8.2.2 Participants

Based on the a priori power analysis of the significant pair-wise comparison of Experiment 4 after exclusion criteria were applied, a sample of 55 participants would yield 95% power and an alpha of .05, if the putative effect size is similar. We set an a priori collection goal of 60 participants. Data collection was terminated early due to high exclusion rates and no evidence of effects. One-hundred and nineteen students from the University of Delaware subject pool were recruited to participate in the study for course credit or pay. Eighty-nine subjects were excluded based on a priori criteria, leaving 30 viable subjects.

8.2.3 Stimuli

Stimuli in the training were consistent with Experiment 6. In the VWM task stimuli appeared one at a time, left to right, inside a one by eight array of reference boxes measuring 70 by 70 pixels (Figure 8.1). Stimuli themselves were 66 by 66 pixels in size.

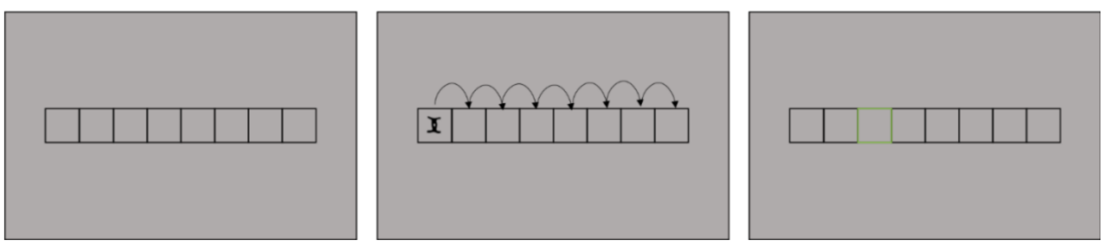

Figure 8.1: Depiction of the temporal VWM task. Stimuli appear one at a time from left to right within the array. Once all stimuli have appeared, one of the boxes is cued as the recall item.

8.2.4 Experimental Procedure

During the VWM test, on each trial, participants were presented with a one by eight box array. In each trial the stimuli appeared one by one within the array from right to left for 500 msec. One condition consisted of the paired stimuli preserved from the VSL training, while the other condition presented the unpaired VSL stimuli in consistent pairs, much like previous experiments. After the presentation of all 8 stimuli, one of the boxes is cued as the memory recall item. A memory array appeared below the boxes, and participants make an 8AFC response to the identity of the cued shape. Stimuli are presented in their corresponding pairs on 80% of trials, and scrambled on the remaining 20% of trials.

8.3 Results

8.3.1 VSL Training

One-back performance was monitored during the VSL training in order to ensure participants were actively participating in the cover task. Mean hit accuracy was 81.44% with 1.95% standard error. Mean false alarm rate was 1.95% with 0.42% standard error.

8.3.2 VWM test task

I applied 2x4 RM-ANOVA to the k-value data collected from the VWM task (Figure 8.2). The factors were defined by the two stimulus sets that were shown during the VWM task (paired during VSL and unpaired during VSL) and block (4 blocks of 32 paired trials each, 40 total). This analysis was only conducted on the trials in which the stimulus sets were appearing in their corresponding pairs, the randomized presentation trials were not included in the analysis.

The main effect of stimulus set was not significant, F(1,29) = 0.219, p = .643, η_p^2= .008. The main effect of block was significant, F(3,87) = 7.767, p = .001, η_p^2= .166. First block performance was significantly lower than last block performance marginally for the paired condition , t(29) = -1.964, p = .059, d = -0.359, and significantly in the unpaired conditions, t(29) = -4.038, p < .001, d = -0.737. The interaction between the two factors was not significant, F(3,87) = 1.566, p = .203, η_p^2= .051. The pair-wise t-test between the first block of the paired set and unpaired set was not significant t(29) = 0.607, p = .548, d = 0.111.

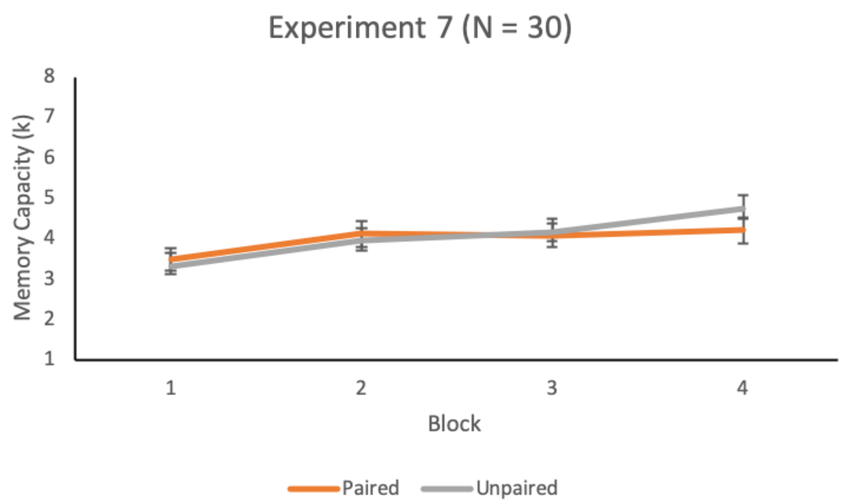

Figure 8.2: VWM results from Experiment 7. Accuracy scores are transformed into k values, representative of number of objects VWM can hold. Performance is plotted as a function of working memory task block and learning condition.

I observed no significant difference in VWM performance across the stimulus sets. I applied Bayesian ANOVA to the data in order to determine evidence for the null hypothesis (BF01). In Experiment 7 the main effect of pairing had a BF01 value of 6.591 with 1.633% error, showing strong evidence in support of the null hypothesis. BF01 values for the main effect of block was < .01, showing strong evidence for the alternate hypothesis. The interaction had a BF01 value of 0.020, showing moderate support for the alternate hypothesis.

8.4 Discussion

I was unable to elicit an effect on VWM through VSL training with the temporal VSL training, even when the training and test task were operating in the same stimulus dimension. The test task may have been too difficult for participants to perform, as the stimulus array was closer together than the spatial displays, possibly causing difficulty in determining the accurate position of the stimuli. It is also possible that these effects are subject to primacy and recency effects as they are similar to a serial position task (Jahnke, 1965). More exploration regarding the temporal test task is needed in order to understand if effects manifest in different ways other than general accuracy.

It seems that during the temporal VSL, the chunks formed during training are not equivalent to chunks formed within a spatial training paradigm. While the transfer of information was not present in either Experiment 6 or 7, the effect size of Experiment 6 was larger. This shows more promise for the potential that temporal contingencies can still effect working memory, but pursuit of this other type of VWM test seems less promising.

Chapter 9

GENERAL DISCUSSION

9.1 Introduction

Visual statistical learning refers to an ability we possess that allows for the quick and unintentional learning of statistical regularities. This ability has been demonstrated in numerous contexts and various experimental paradigms. Regardless of the number of demonstrations in the literature, little has been done to examine what this information is used for after we have achieved it. Within the visual domain, VSL is often indexed using basic familiarity or recognition judgments, with limited and sometimes controversial outcomes. I have argued that closer attention should be paid to the potential for VSL to transfer across training and testing contexts that differ, and particularly contexts that could be generally useful for cognition. Specifically, throughout the course of this dissertation I have examined one such situation – the capacity for VSL representations to benefit WM performance, and the limitations surrounding this transfer.

In my first experiment I replicated the effects shown by Brady et al. (2009), where statistically paired stimuli are recalled with better accuracy when items appear in statistically likely pairing configurations. I replicated this basic effect using Ndjuka stimuli in order to eliminate potential influence of semantic information on the chunked representations. In Experiments 2 and 3 I attempted to elicit a benefit to VWM task performance from Experiment 1 by training chunked representations via

VSL prior to the VWM test. I was unable to find a significant difference between the two pairing conditions of stimuli, even when I decreased the transfer distance between training and test. In my critical experiments 4 & 5 which controlled for explicit knowledge, I did find a significant difference in VWM performance between pairing conditions of stimuli (paired during VSL/unpaired during VSL). I argue that this is likely due to the formation of chunked representations during VSL training, which are then accessible by VWM, and thus result in an increased working memory capacity. This evidence lends support to claims that VSL could be broadly useful in cognition, because WM is ubiquitous in its importance to everyday tasks. At the same time, my research has presented important boundary conditions and limitations on when such transfer is likely to be observed. In Experiment 6 I attempted to elicit this transfer effect using a temporally based VSL training paradigm. I was unsuccessful at finding a significant difference between the pairing conditions within the spatially based VWM test task. Finally, in Experiment 7 I tried to see if the temporal VSL training would elicit a transfer effect using a more temporally based VWM task. Again, I found no significant difference between pairing conditions of the temporal VSL training.

Experiment	Training	Recognition	Testing	Transfer effect
1	N/A	No	Spatial	N/A
2A	Temporal	No	Spatial	No
2B	Spatial	No	Spatial	No
2C	Spatial	No	Spatial	No
3	Spatial	**Yes**	Spatial	No
4	Spatial	**Yes**	Spatial	**Yes**
4 Trimmed	Spatial	**Yes**	Spatial	**Yes**
5	Spatial	No	Spatial	**Yes**
6	Temporal	No	Spatial	No
7	Temporal	No	Temporal	No

Table 9.1: Summary of experimental designs and overall results of successful transfer between training and testing.

9.2 VSL supports VWM

I chose to look at how VSL memory representations could affect other cognitive systems outside of their initial learning context. VSL and VWM have been shown to utilize similar types of chunked memory representations (Brady et al., 2009; Burtis, 1982; Lengyel et al., 2021; Nassar et al., 2018; Slone & Johnson, 2015). Therefore I proposed that VWM would be a feasible candidate for observing transfer from VSL. I hypothesized that if participants were able to form chunked representation during the VSL training, then these representations could be later utilized by VWM, as evidenced by an increase in working memory capacity for the displays containing the paired stimuli. Chunked representations are thought to be formed in VSL and VWM due to the simultaneous retention of multiple stimuli in working memory. Chunked memory representations are believed to be supportive in holding more information in VWM with the exertion of less cognitive effort, compared to the same number of stimuli that were not recoded into chunks. This recoding of information allows for a greater number of stimuli to be stored in VWM at a single time (Brady et al., 2009; Brady, Konkle, & Alvarez, 2011b; Chekaf et al., 2016; Nassar et al., 2018). The formation of these chunked repetitions during the VWM task aid performance across the course of the experiment without any type of training (Experiment 1). Evidence from Brady et al. (2019) suggests that VWM capacity can increase it can depend on regularities within the memory display. Over the course of many trials of a high-load VWM experiment, participants learn to take advantage of statistical associations to increase effective WM capacity.

I hypothesized that if we pre-chunked object representations prior to the VWM task, that participants could use the chunks they learned in the VSL training to aid their performance in the VWM task. When I first attempted to demonstrate this, I was unsuccessful in showing transfer to the VWM task (Experiment 2), even when recognition of learned pairs was still significant (Experiment 3). During the VWM test task, stimuli appeared next to their paired associate 100% of the time. With this strong of a statistical relationship between the pairs, I hypothesized that the over learning of stimulus pairings was allowing for the formation of explicit representations of the stimulus contingencies, possibly overriding the beneficial nature of the more delicate VSL memory representations. I reduced the strength of the statistical pairings to only appear in their respective pairs on 80% of the VWM test trials (Experiments 4 and 5).

When I implemented this new VWM test task, I found a significant difference in the performance of the paired items during VSL compared to items that were unpaired during training. I interpret this boost in VWM performance towards the paired stimuli to be evidentiary of the successful formation of chunked memory representations during the VSL training, and their accessibility to VWM in the secondary test context. These chunked memory representations proceed to be further compressed during the VWM task as shown by the main effect of block significantly showing an increase of VWM capacity across the length of the experiment. This suggests that both VSL and VWM can utilize similar memory representations, allowing VSL to have potential influence on the VWM system.

This evidence is supportive of a contributory role of VSL in cognition through its influence on VWM and suggests that a practical role of VSL could potentially be to condense information from our environment into chunks, in order to reduce load on VWM prior to the stimuli entering explicit awareness. By providing evidence of said influence, VSL information could be further utilized outside of the already well-established improvements in the recognition of learned combinations of items. This evidence also supports previous studies that claim VSL recognition effects could be driven by the formation of chunked representations of the paired stimuli. These new findings allow for us to begin looking deeper into VSL, extending another avenue of study of VSL effects that may have more consequential effects on other cognitive systems.

9.3 Explicit knowledge may obscure VSL

VSL happens incidentally and without any instruction to learn relationships between stimuli (Fiser & Aslin, 2001, 2002b; Park et al., 2018). It is believed that this passive retention of information is one way in which we can begin to put structure to our perceptual environment without the need for explicit semantic information (Biederman, 1981; Chun & Jiang, 1998; Davenport & Potter, 2004; Nissen & Bullemer, 1987; Saffran et al., 1996). While not all this information may be important to perform the cover task, we still take in and retain this statistical information for later use. VSL occurs unintentionally and tends to be a more passive process in its formation of memory representations compared to the effortful processes of explicit learning.

Through the course of this dissertation I have found that in order to be able to observe the transfer of VSL information to VWM, there are a few requirements. Evidence from Experiments 2-3 suggests that explicit awareness of the associations between stimuli was possibly masking effects of the more delicate VSL representations. In Experiments 2-3, during the VWM test, stimuli were shown in their paired configurations on 100% of the trials. In both experiments I did not observe a difference in VWM performance between the two types of paired displays, even in Experiment 3 where I had found significantly above-chance recognition of the pairs. This was intriguing, as it seemed that participants were still learning the VSL regularities but were not exhibiting a behavioral difference in the VWM task. I hypothesized that participants were rapidly learning any of the remaining pairs of stimuli due to the explicit 100% chance of them appearing together. This over exposure to the learned pair may have made participants aware of the contingencies between stimuli, and thus changing their strategy for remembering the VWM displays. In this type of memory task, when individuals are equipped with the explicit associative information about the stimuli, they may be able to adopt a strategy of recreating the displays based on stimulus contingencies. With explicit knowledge of the contingencies, you can determine each stimulus's counterpart without having to actively retain the entire display in VWM. When participants are explicitly aware of the relationships between the stimuli, they have little to no use for the representations formed during VSL, and because of this they may be able to reach "ceiling" performance based on the information that they are explicitly aware of. Explicit knowledge of the pairs may have prevented expression of the chunked representations influence that was possibly still occurring in the VSL training. This leads me to believe that participants in Experiments 2-3 were either performing the VWM task at ceiling, and/or the measures of VWM capacity were confounded by explicit knowledge of stimulus contingencies.

To control for this explicit knowledge, I implemented a different ratio of trials in which the stimuli appeared in their paired configurations. In Experiments 4 and 5 during the VWM test task, instead of displaying the stimuli in their stereotypical pairs on 100% of trials, I displayed the stimuli in their pairs only 80% of the time, with the other 20% of trials displaying the stimuli in shuffled pairs. Reducing the statistically likelihood of the paired displays in the VWM task should obscure the formation of explicit knowledge, as stimuli can appear with different constituents within the shuffled displays. When I reduced the ratio of trials in which the paired stimuli appeared together, participants showed an effect of transfer from VSL to VWM. VWM performance was initially higher for the paired displays compared to the unpaired displays, even though the unpaired stimuli began to appear in pairs at the start of the VWM test. Participants seemed to be able to use the representations they had formed during the VSL training in order to aid their VSL performance. This remained the case even when the intermediate recognition test block was removed (Experiment 5). It seems that when we reduced the evidence of stimulus pairs during VWM, participants relied more on the representations formed during VSL, allowing for a difference in VWM capacity to be observed.

The ability to statistically learn does not require a set of prior rules or semantic knowledge, but is able to produce some form of structure from regularity within the perceptual experience (Biederman, 1981; Davenport & Potter, 2004; Nissen & Bullemer, 1987).While explicit knowledge tends to be an overall goal of learning, I believe that examining the role of VSL is still important as we cannot always directly engage in explicit learning. Our VSL ability is unique from explicit knowledge as we are able to maintain our ability to statistically learn structure when in a perceptually limited environment. While participants may be using explicit knowledge to perform the test task (Experiments 2-3), we can still learn contingencies with the more passive process of VSL when explicit knowledge in not available (Experiments 4-5).

9.4 Generalizability of VSL effects

VSL is characterized by many authors as an ability that has many applications within cognition. The claims of generalizability of VSL information have been well supported by recognition effects. However, when it comes to my transfer task, we see that there is very limited transfer across various contexts. One limiting factor of these new effects seems to be that the VSL training and VWM tasks may need to be contextually similar for transfer of the chunked representations to occur. I was only able to observe the effect when the training and test were contextually similar (Experiments 4 and 5), compared to the lack of the effect on VWM performance when training and test were contextually different (Experiment 6). It is not known if these transfer effect cannot occur across stimulus dimensions, or if the temporal VSL training was not strong enough to form the necessary chunked representations required for the spatial VWM task of Experiment 6. Studies looking at the formation of chunked representations in VSL have also used this type of temporal training presentation and found significant results during spatial recognition tasks. There is also evidence supporting the formation of chunked memory representations within perceptual sequence tasks (Chekaf et al., 2016), which is another VWM task. This evidence suggests that chunking can occur in both temporal and spatial tasks, however, how generalizable are these chunks to other memory contexts?

This limitation of cross context transfer is not observed in experiments where testing of VSL memory representations is done via recognition judgments, (Turk-Browne & Scholl, 2009). Studies looking at the formation of chunked representations in VSL have also used this type of temporal training presentation and found significant results during spatial recognition tasks (Park et al., 2018). The lack of transfer in my tasks suggests that the effects measured by recognition may be overestimating the generalizability of VSL representations. While task transfer may still be possible, my results suggest that there may be some critical difference between chunks formed between spatially predictive stimuli, compared to chunks formed from temporally predictive stimuli, at least when it comes to subsequent recruitment by VWM. Therefore, we need to be careful when making claims about VSL having a widely broad influence on cognition, as these effects seem to be more sheltered within their learned context than previously assumed.

Even though the transfer distance for these VSL/VWM effects to occur is limited by context, it can still occur across differences in task demand. Even though my experiments failed to show the type of transfer that occurs across spatial and temporal stimulus contexts, there are still some contextual differences between my spatial training and spatial test tasks in Experiments 4 and 5. During the training, participants are only having to store two pairs of stimuli in VMM in order to complete the 1-back judgment. Participants are also under a time constraint in making the 1-back response within a response window. The 1-back task is technically a VWM task, however, the speeded detection task is very different than the much slower cued memory recall task. In the VWM task participants are tasked to remember 8 items, well over the number during training. Participants are also allowed to take their time in responding to these stimuli and are presented with the stimuli during their response for reference. In the VWM task, it is evident how chunking aids VWM by reducing the memory load of the large array of stimuli. However, it is not as clear as to why chunking needs to occur during the VSL training, as the memory load of the items and stress on VWM during VSL training is much lower and VWM would not require stimuli be compressed together. Regardless, my results still suggest that the VSL items are being chunked prior to the VWM cued recall task. This transfer of knowledge from one task to another does cross some contextual barriers but is still limited in the ability to cross larger transfer distances.

9.5 Future directions

The revelation of a novel transfer effect opens the door for future investigation on VSL and VWM relationships and allows for us to begin defining a more functional role for VSL within a larger cognitive framework. These experiments have measured VSL in a different way that points directly to a purpose for VSL, rather than simply demonstrating an index that learning occurred. Measuring VSL in this way may be more advantageous than using recognition measures, as we are not relying on participants subjective judgments to measure responses. With this new paradigm we can see how well people VSL, as well as how much of that information is applied later. Instead of asking questions about how learning is affected by various factors, we can begin to examine how well the learned information is applied.

Using this more specific index of VSL through VWM may give us a chance to look at VSL in a more detailed manner. We can begin to break down learning by specific pairs to see which pairs are being successfully chunked based on their individual rates of recall, compared to the entire paired set of stimuli. Another way in which this design is more specific is that we use an eight-alternative forced choice compared to the 2AFC used in most recognition paradigms. There is less risk that participants are guessing which stimulus to choose as well as more opportunity to identify which specific pairs are remembered. Using this new method in order to observe VSL on a more individual item level is important for researchers looking at effects between stimulus groups, or for example, as a function of reward application during training (Rogers, Park, & Vickery, 2021). This new method of measuring VSL has a lot of potential in the fact that we can further break down data in terms of individual items, compared to looking at differences between conditional groups of stimuli.

In future studies examining transfer of VSL effects to VWM, it will be important to focus on issues of power. One potential target for future research is the training paradigm – some training paradigms are more effective in inducing VSL than others. Another possibility is extending the duration of the training paradigm. While we are aware that VSL effects can occur in a broad range of contexts, we do not know how strong they need to be in order to transfer to another task – one possibility is that some of my null results are due to subthreshold learning effects. In the face of extended training or an alternative training cover tasks, some transfer might be observable.

With the effects demonstrated in this dissertation, we can begin to understand more concrete ways in which VSL effects other aspects of cognition. One question that remains is if more VSL leads to more VWM compression. If we are able to learn more powerful stimulus contingencies, are these items more "chunked"? Looking at the strength of learning has been a major focus of the field, so it seems logical to see how increased learning could potentially benefit transfer. Another question is if the link between VSL and VWM that we have established is somehow mediated by recognition memory. Are participants able to show higher VWM capacity for recognizable pairs/triplets, or are we indexing a separate learning mechanism aside from recognition altogether? While the recognition effects have shown evidence of learning time and time again, are we measuring the same memory representations via recognition and recall, or are these two effects separable in terms of mechanistic makeup? The demonstration of this new way to measure VSL should be contrasted to the current evidence in order to determine if VWM and recognition are utilizing VSL representations in a similar manner.

While we see that VSL memory representations can be applied to VWM within similar contexts, we have also shown that these effects on VWM may not be as flexible when it comes to transfer distance across different stimulus dimensions. With various forms of recognition occurring across spatial and temporal domains (Turk-Browne & Scholl, 2009), we do not know if the recognition test task is sensitive enough in order to distinguish these effects from other possible confounds, (Rawal &

Tseng, 2021). Since we did not observe a transfer across a stimulus dimension boundary, it may be possible that the generalizability of VSL effects may be exaggerated due to a limited test task. While there is evidence that VSL is correlated with various other abilities such as language, we still need to be careful we are not overselling these effects as being universal or widespread throughout cognition. Moving forward in studying VSL, it is important that we continue to test effects using a variety of methods in order to reach converging evidence, before we claim such broad utility of VSL.

Previous studies of VSL have primarily looked at factors that influence the learning itself, but if this learning is not accessible during a later context, then that information may not serve much of a role outside of demands to explicitly recognize or judge familiarity. Focusing on the practical use of VSL knowledge allows for researchers to follow the chain of information past the initial exposure of the stimuli, to the actual formation memory representations themselves, to their subsequent utilization. I believe that the new ways I have demonstrated we can measure VSL allows for more questions to be asked about the mechanisms behind VSL as well as the application of various types of statistical learning information.

9.6 Conclusion

Overall, I found evidence that representations formed by VSL can be utilized by VWM, in order to increase memory capacity of statistically paired stimuli. This evidence of VSL influencing VWM provides a potential avenue in which VSL could have a wide influence on cognition. This effect demonstrates how the information that is learned in VSL can possibly be applied to scenarios where the learned information benefits us in some way. While these effects offer another functional explanation of VSL, they are also more sensitive than previous measures of VSL. This type of VSL effect is much more limited in transfer distance compared to previous recognition studies. It may be the case that the representations formed during various forms of VSL training result in different levels of learning or different memory representations that are not compatible across larger transfer distances, e.g., temporal training to spatial test. Since these effects are more limited than those of general recognition, this raises the possibility that the generalizability of VSL to contexts that are not strictly explicit recognition has been exaggerated. The results of successful transfer still shows promise for the role of VSL in ecological contexts that often rely on VWM. Regardless, these results provide evidence that, in principle, VSL representations can be accessed by VWM. Effects like these should be further investigated in order to explore more consequential influences of VSL on cognition.

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Appendix

CERTIFICATES OF INFORMED CONSENT

University of Delaware
Informed Consent Form

Title of Project: **Production and Perception of Patterns**
Principal Investigator:

Name: **Dr. Timothy Vickery**
Department/Center: **Department of Psychology, University of Delaware**
Contact Phone Number: **617-671-9079 (mobile); 302-831-1511 (office)**
Email Address: **tvickery@psych.udel.edu**

You are being asked to participate in a research study. This form tells you about the study, including its purpose, what you will do if you decide to participate, and any risks and benefits of being in the study. Please read the information below and ask the research team questions about anything we have not made clear before you decide whether to participate. Your participation is voluntary and you can refuse to participate or withdraw at any time without penalty or loss of benefits to which you are otherwise entitled. If you decide to participate, you will be asked to sign this form and a copy will be given to you to keep for your reference.

WHAT IS THE PURPOSE OF THIS STUDY?

The purpose of this study is to learn more about human learning and decision-making. We are interested in how people learn about events, such as decisions of other people, and how they use what they have learned to make better decisions.

You are being asked to take part in this study because we are interested in how normal adult humans make decisions and perceive the world. Our criteria for inclusion in this study are only that you are at least 18 years old, and that you have not previously participated in this study. We expect to test around 10000 people in this study.

WHAT WILL YOU BE ASKED TO DO?

The experiment will take place in the Perception and Learning Lab testing rooms. You will be seated in front of a computer for the duration of this experiment. You will view different questions and scenarios, and make simple responses to these questions using the keyboard and mouse. For instance, you may be asked to make a series of "random" choices, watch a movie and answer some questions about it, or complete a series of visual searches. You may complete several distinct tasks during your participation. Prior to completing each part of the task, you will be given simple instructions on how to complete the experiment. At the beginning of each stage of the task, you will be given further instructions. If any instructions are unclear, please ask the researcher to clarify. The experiment will take 0.5-1.5 hours to complete in one session, depending on the particular experiment. You will be told how long the current experiment is expected to take. You will be given frequent breaks (approximately every 5-10 minutes) to rest. Before the experiments, you will be asked to report your age and gender. You may additionally be asked to complete short personality questionnaires about motivation, competitiveness, aggressiveness, and a questionnaire about your sensitivity to risk and losses.

WHAT ARE THE POSSIBLE RISKS AND DISCOMFORTS?

The risks of participating in this experiment are minimal and the experimenters have taken precautions to ensure your well-being throughout the experimental session. The principal risks are boredom and eye fatigue, and thus frequent breaks are included.

WHAT ARE THE POTENTIAL BENEFITS?

You will not benefit directly from taking part in this research. However, the potential benefit of this study to society is an improved understanding of how humans learn and make decisions.

HOW WILL CONFIDENTIALITY BE MAINTAINED?

All information you provide in this study will be kept strictly confidential, no uniquely identifying information will be maintained, data will be associated with a code number, and any report will not identify you personally in any way. Data will be kept on record indefinitely and potentially posted on the Internet, but your identity will be strictly confidential and not linked in any way to this data.

The confidentiality of your records will be protected to the extent permitted by law. Your research records may be viewed by the University of Delaware Institutional Review Board, which is a committee formally designated to approve, monitor, and review biomedical and behavioral research involving humans. Records relating to this research will be kept for at least three years after the research study has been completed.

WILL THERE BE ANY COSTS RELATED TO THE RESEARCH?

There are no costs associated with participating in the study.

WILL THERE BE ANY COMPENSATION FOR PARTICIPATION?

If you were recruited for this experiment as part of the study pool at University of Delaware, you will receive 0.5 hours of course credit per half hour of participation on completion. If you were recruited via fliers or other public postings and are completing this experiment for payment, you will receive $8 per half hour of participation on completion of the study.

Additionally, some experiments involve monetary rewards on the basis of choices and chance outcomes in tasks. These rewards will vary based on performance, in the range of $0 to $20.

DO YOU HAVE TO TAKE PART IN THIS STUDY?

Taking part in this research study is entirely voluntary. You do not have to participate in this research. If you choose to take part, you have the right to stop at any time. If you decide not to participate or if you decide to stop taking part in the research at a later date, there will be no penalty or loss of benefits to which you are otherwise

entitled. Your refusal will not influence current or future relationships with the University of Delaware.
As a student, if you decide not to take part in this research, your choice will have no effect on your academic status or your grade in the class. If you choose not to participate or to terminate your participation before the study is over, you are free to go, but in place of this study your obligation will be to complete other research studies or papers to fulfill the Research Requirement for the course. Information regarding the Research Requirement, including specific details for its completion, was shared with you upon your registration in the subject pool and can be found in the Research Participation Document at the following internet address:
https://www.psych.udel.edu/undergraduate/psyc100-research-requirement

WHO SHOULD YOU CALL IF YOU HAVE QUESTIONS OR CONCERNS?

If you have any questions about this study, please contact the Principal Investigator, Dr. Timothy Vickery at 302-831-1511, or e-mail him at tvickery@psych.udel.edu.
If you have any questions or concerns about your rights as a research participant, you may contact the University of Delaware Institutional Review Board at 302-831-2137.

UNIVERSITY OF DELAWARE

CONSENT TO PARTICIPATE IN A RESEARCH STUDY

Title of Study: Studies of Human Cognition

Principal Investigator(s):

Timothy Vickery, Department of Psychological and brain sciences

Contact Phone Number: 302-831-1511 Email Address: tvickery@psych.udel.edu

Important aspects of the study you should know about:

- **Purpose:** The purpose of the study is to understand how people perceive and learn about the world and use that knowledge to guide behavior.
- **Procedures:** If you choose to participate, you will be asked to complete one or more simple tasks in a series of trials divided into blocks. Examples of tasks include simple categorization of images, short-term memory tasks, or searching through visually presented items. The tasks will be presented via computer and responses will be made using your keyboard, mouse, and/or eye movements monitored by a special camera that only records eye position. We will record your accuracy, choices, response times, and/or eye movements. We may also ask you basic demographics questions and questions about your experience in the experiment.
- **Duration:** This will take either ½ hour, 1 hour, or 1.5 hours, as described in experiment description or by experimenter.
- **Risks:** There are no known risks involved in this research.
- **Benefits:** There are no direct benefits to you for participation. Study results may benefit society by improving understanding of how human learning and performance works and improving understanding of human cognition.
- **Costs and Compensation:** e.g., If you decide to participate there will be no additional cost to you and you could be compensated up to 0.5 credits for a ½ hour experiment, 1 credit for an hour experiment, or 1.5 credits for a 1.5-hour experiment (see experiment description / experimenter for duration of this experiment), in satisfaction of course Research Requirements. Some studies involve additional potential monetary rewards that depend on luck and/or performance. Any potential rewards are presented in the experiment description.

  If you choose not to participate or to terminate your participation before the study is over, you are free to go, but in place of this study your obligation will be to complete other research studies or papers to fulfill the Research Requirement for the course. Information regarding the Research Requirement, including specific details for its completion, was shared with you upon your registration in the subject pool and can be found in the Research Participation Document at the following internet address: https://www.psych.udel.edu/undergraduate/psyc100-research-requirement
- **Participation:** Taking part or not in this research study is your decision. You can decide to participate and then change your mind at any point
- **Contact Information:** If you have any questions about the purpose, procedures, or any other issues related to this research study you may contact the Principal Investigator, Timothy Vickery, at (302) 831-1511 or tvickery@psych.udel.edu.

Press y to consent, escape to decline

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I/C Exempt Form Rev. 01/2019