Contributions of familiarity and chunking to visual working memory capacity

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Statement of originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Authorship attribution statement

Chapter 2 of this thesis contains material previously published in *Visual working memory for letters varies with familiarity but not complexity.* Ngiam, Khaw, Holcombe and Goodbourn (2018), published in *Journal of Experimental Psychology: Learning, Memory and Cognition.* I co-designed the study with the co-authors, collected the data, analysed the data and wrote the manuscript.

Chapter 3 of this thesis contains material that is currently under review at the *Journal of Experimental Psychology: General.* It was submitted under the title *"Memory compression" effects are contingent on explicit long-term memory*. I co-designed the study with the co-authors, collected the data, analysed the data and wrote the manuscript.

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ABSTRACT

Visual working memory (VWM) is responsible for the temporary storage of visual information required for perception and cognition. The capacity of VWM is surprisingly limited to three or four items. Despite decades of research, the nature of the capacity limit is still unclear, in part due to uncertainty about the main factors contributing to this limit. We approached this issue by exploring two instances in which memory performance is enhanced. Firstly, while controlling stimulus complexity and similarity, familiarity produced significant increases in both encoding rate and capacity. However, familiarity gained from training observers to simply recognise the stimuli did not produce any benefits for change detection. Secondly, the inclusion of statistical regularities in the displays produced significantly improved recall. However, only subjects with explicit awareness of the statistical regularities showed improvement, whereas unaware subjects showed no change in their recall performance. We extended this result by observing whether contralateral delay activity (CDA), a neural marker of the number of item-based representations held in VWM, reduces with explicit chunking. Although recall performance was significantly better, the CDA did not appear to index equivalent number of chunks, suggesting that online representations do not change with the use of explicit chunking. Instead, the behavioural benefit appears to rely on retrieval of a long-term memory representation (LTM) when recall is tested. These results indicate a major influence of LTM in guiding VWM performance. Behavioural data collected at the end of the trial, such as change detection or probed recall, appear inadequate for fully examining the nature of VWM. An embedded-process framework, in which activated LTM representations can fluidly shift into the focus of attention, is useful in interpreting these results and understanding the cognitive processes involved in memory.

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Chapter 1: Thesis Introduction

The visual system encounters an enormous amount of complex information, which must be processed to produce a smooth phenomenal experience of the world. This remarkable feat requires a memory store that encodes, retains and manipulates visual information. For example, an active memory store integrates the information between saccades (Irwin & Andrews, 1996), orients where attention should be deployed (Awh & Jonides, 2001), and retains information about objects during visual tracking and search (Carlisle, Arita, Pardo, & Woodman, 2011). The system responsible for actively storing visual information for perception has been termed *visual working memory* (VWM). Despite its necessity in everyday perception, the VWM system is surprisingly limited in the amount of information it can hold—approximately three to four items (Luck & Vogel, 1997). This thesis explores the processes that contribute to this capacity limit, and examines circumstances under which this limit might be circumvented. This chapter provides the background to the studies reported in the thesis by giving an overview of past VWM research.

1.1 The concept of working memory

Classical research separated memory into two distinct but interacting systems: short-term memory (STM) and long-term memory (LTM). The STM store, understood to have a highly limited capacity, held current information in awareness; whereas LTM was thought to be effectively unlimited in capacity, but requiring effort to retrieve stored information (Atkinson & Shiffrin, 1968). Atkinson and Shiffrin were among the first to consider the STM system as *working*: "a system in which decisions are made, problems are solved and information flow is directed" (*p.* 83). That is, working memory functions as a mental workspace for higher-level cognition (Nee & D'Esposito, 2018). However, this early conception of STM relied on an assumption that encoding of information into LTM—and therefore learning—required repeated maintenance in STM. This has since been demonstrated to be untrue (Baddeley & Hitch, 1974). The concept of STM was updated by Baddeley and Hitch in their highly influential multi-component working memory model. Their first iteration contained three subsystems: the central executive, the phonological loop and the visuospatial sketchpad (*Figure 1-1*). The phonological loop and the visuospatial sketchpad, collectively known as the *slave systems*, maintain verbal and visual information respectively. The visuospatial sketchpad is analogous to what researchers now refer to as the VWM system.

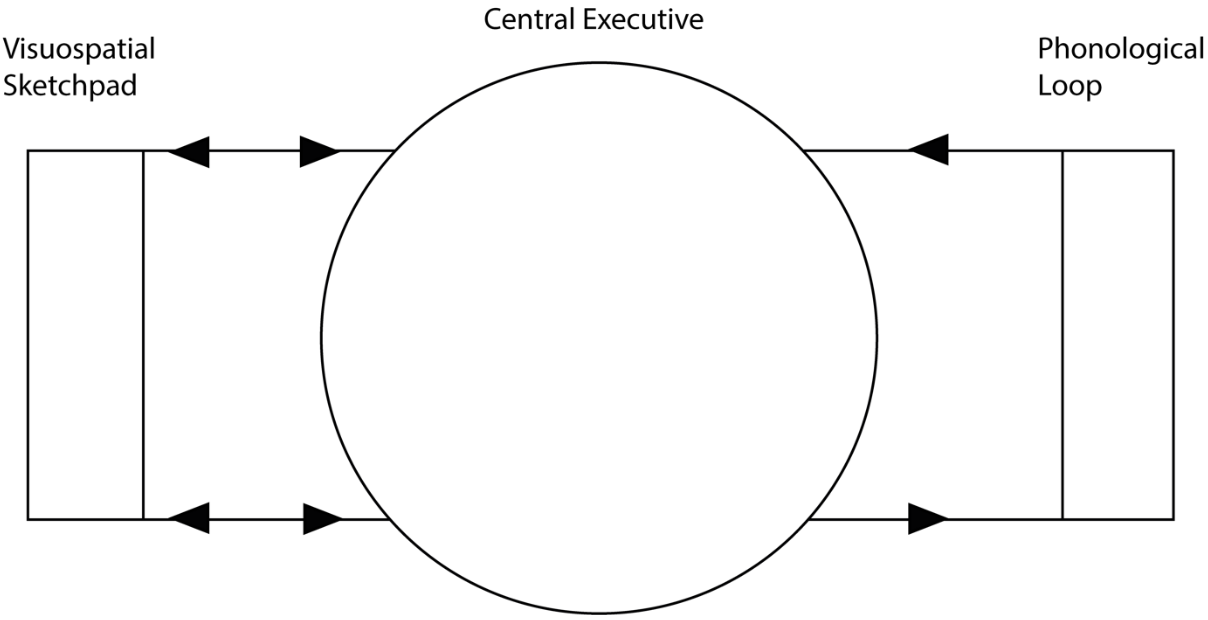

Figure 1-1. An early model of working memory proposed by Baddeley and Hitch. Figure adapted from Baddeley and Hitch (1974).

Baddeley and Hitch's (1974) model provided key foundations for a modern definition of working memory (Nee & D'Esposito, 2018). Firstly, the processes involved in the temporary maintenance of information are distinguishable from those involved in permanent transfer of information into long-term memory. Secondly, the processes that modulate and manipulate the retained information are dissociable from processes that only retain the information, such as those involved in iconic memory. Thirdly, memory processes are modal such that visual materials are represented differently from verbal materials.

Individual differences in VWM tasks have since been shown to predict cognitive ability and intelligence (Daneman & Carpenter, 1980; Unsworth, Fukuda, Awh, & Vogel, 2014a). In fact, estimates of an individual's VWM capacity—specifically the number of items that can be held in VWM—correlate robustly with measures of fluid intelligence (Cowan et al., 2005; Fukuda, Vogel, Mayr, & Awh, 2010; Unsworth et al., 2014a). VWM capacity estimates are significantly reduced in individuals with schizophrenia (Gold et al., 2010), and individuals with Parkinson's disease (Lee et al., 2010). An understanding of the factors that contribute to capacity limits in VWM is thus central to understanding the processes of perception and cognition, as well as the VWM deficits that accompany neuropsychiatric disorders.

1.2 Measuring visual working memory capacity

The term *visual working memory* is often used synonymously with *visual short-term memory*, which has led to some confusion. Luck and Vogel (2013) provide three defining aspects of VWM: (*i*) represented information is visual in nature; (*ii*) information is actively maintained; and (*iii*) information is accessed for cognitive use. In their seminal study, Luck and Vogel (1997) devised the change-detection paradigm for the measurement of VWM capacity. In this paradigm (*Figure 1-2*), an initial array of objects (*sample array* or *memory array*) is presented to the observer for a brief duration, usually no longer than a second, before disappearing. After a short delay, a second array (*test array*) appears; it may be identical to the sample array (*no-change* trials) or have one object replaced by another object (*change* trials). The observer has to indicate whether or not a change occurred.

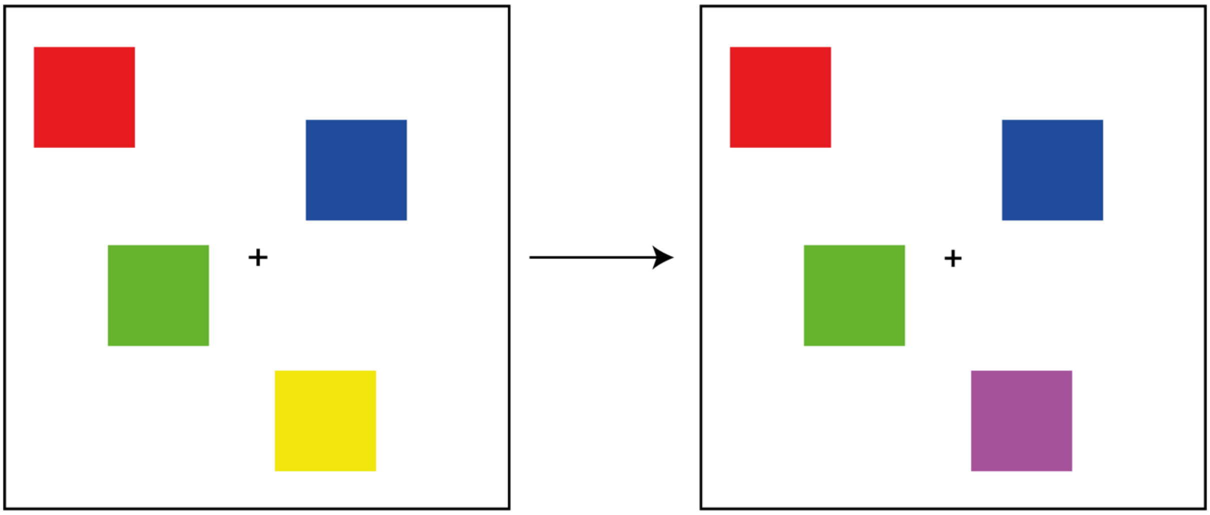

Figure 1-2. Example of the stimulus on a change trial in the change-detection paradigm. Here, the yellow square in the memory array changes to the purple square in the test array.

The proportion of trials on which a participant correctly indicates whether or not a change occurred can be used to estimate the number of items held in visual working memory. Assuming the observer has stored a certain number of objects (K) from the sample array, a correct response on a change trial (a *hit*) will occur whenever the changed item is one of those K objects. If an array contains N objects, on average this will occur on K out of N change trials. Additional hits will occur on a proportion (G) of the remaining ($N-K$) out of N change trials (when the changed object is not among those encoded) if the observer correctly guesses that a change has occurred. For an unbiased observer, this will occur on half of the remaining trials ($G = 0.5$), but G can be estimated directly from an observer's *false-alarm rate*, the overall number of trials in which a change is reported but no change occurred. This produces the formulation proposed by Pashler (1988):

$$H = \frac{K}{N} + \frac{N-K}{N} \times G, \qquad \text{(\textit{Equation 1-1})}$$

where H is the probability of a hit on a change trial. Rearranged to make K the subject:

$$K = \frac{N \times (H-G)}{1-G}. \qquad \text{(\textit{Equation 1-2})}$$

However, this equation assumes VWM has no bearing on a no-change trial (Cowan et al., 2005). On no-change trials, guesses may be limited to items *not* stored in VWM ($N-K$); thus the subject will guess that a change has *not* occurred with a probability of $1-G$, where G is the probability of guessing a change had occurred. Accordingly, Cowan (2001) estimates the *correct rejection rate* (CR):

$$CR = \frac{K}{N} + \frac{N-K}{N} \times (1-G). \qquad \text{(\textit{Equation 1-3})}$$

Adding this to Pashler's formulation (*Equation 1-1*):

$$H + CR = \frac{2K}{N} + \frac{N-K}{N} = \frac{K+N}{N}. \qquad \text{(\textit{Equation 1-4})}$$

Rearranging to make K the subject:

$$K = N \times (H + CR - 1). \qquad \text{(\textit{Equation 1-5})}$$

Using these equations, the capacity of VWM has been estimated to be limited to approximately 3–4 items' worth of information. Luck and Vogel (1997) presented sample arrays containing from 1 to 12 coloured squares for 100 ms, before showing a test array approximately a second later. They found performance was near perfect for arrays containing up to 3 colour blocks before gradually declining from 4 to 12 colour blocks. This pattern remained when observers were given two digits to rehearse aloud to suppress the influence of verbal working memory; when the sample array was displayed for a longer duration; and when observers were only required to make a decision about a single cued item in the array. Estimating VWM capacity from change-detection accuracy (*Equation 1-2*) indicated observers stored approximately four items in VWM.

1.3 Classic models of visual working memory

Despite agreement on this capacity limit for simple visual objects, there has been much debate regarding the architecture of VWM that produces this limit. In their experiments, Luck and Vogel (1997) increased the number of relevant features in the array items and found a pattern of memory performance identical to when they presented simple colours. For example, when items were defined by conjunctions of colour and orientation, VWM performance was no different when observers were instructed to detect changes only in colour, only in orientation, or in either feature. This pattern replicated with stimuli that were conjunctions of four features (colour, orientation, size, and the presence of a gap), and with conjunctions of the same feature type (such as two colours). Since increasing the number of relevant features in the stimuli did not influence memory performance, Luck and Vogel (1997) proposed that the architecture of VWM comprises 3 to 4 *slots*. Each slot stores a representation of the visual object with its features integrated, rather than the individual features of the object.

The *slots* model was directly challenged by the findings of Alvarez and Cavanagh (2004). In their study, participants completed the same change-detection task as in Luck and Vogel's experiments (1997) but with a range of stimulus sets. These sets included colour squares, but also Snodgrass line drawings, shaded cubes, random polygons, Chinese characters and English letters. VWM capacities differed significantly between the stimulus sets, contradicting straightforward predictions of the slots model. Critically, Alvarez and Cavanagh (2004) indexed the *complexity* of each stimulus set by conducting a visual-search task with the same stimulus sets. In this task, observers were presented with a target object before indicating whether or not the target was present in an array of objects from the same stimulus set. The arrays contained either 4, 8, or 12 objects and included the target object on half the trials. The *visual search rate*, their measure of stimulus complexity, was the increase in time to respond that the target was present with each additional item in the array. Estimating capacity as the number of objects for each stimulus set that would correspond to 75% accuracy on the change-detection task, visual search rate was very strongly correlated (r = .99) with the inverse of capacity. Alvarez and Cavanagh (2004) suggested VWM capacity is limited by total amount of visual information—rather than the number of objects, as Luck and Vogel's (1997) slots model suggests. They proposed a *resources* model, which suggests that more complex visual items (those with more features) require more resources for encoding and storage. Thus, as the visual stimuli get more complex, fewer items can be maintained in VWM.

The findings that inspired these influential models have failed to fully replicate. Hardman and Cowan (2015) attempted a direct replication of Luck and Vogel's (1997) finding whereby change-detection performance was no different when change could occur either in only one of four relevant features (size, orientation, colour or the presence of a gap) or in any of the four features. In eight replications, change-detection performance worsened when change was possible in all four features, suggesting a cost of encoding additional relevant features. Feature load alone, however, was insufficient to explain the drop in performance. Hardman and Cowan reported that there was still strong evidence for an item-based limit on VWM capacity, but not for a pure item-based account like the slots model. Eng, Chen and Jiang (2005) similarly failed to replicate Alvarez and Cavanagh's (2004) main finding, whereby visual search rates almost perfectly correlated with capacity estimates for increasingly complex stimuli. While they did reproduce a relationship, the magnitude was much weaker ($r^2 = .26$) when memory displays were presented for longer (3000 ms)[1]. This suggests that stimulus complexity does not explain all the variation in VWM capacity, as would be predicted under a strict resources model. Visual search rates were better predictors of VWM capacity at shorter memory display durations (500 and 1000 ms). Eng *et al.* (2005) suggest that as the relationship between visual search rates and VWM capacity estimates weakens with longer presentation, lower capacity estimates for more complex items are due to limits on perceptual encoding rather than storage capacity.

The *slots* versus *resources* debate has shaped the majority of VWM research, despite failures to fully replicate key findings that inspired each models (Eng et al., 2005; Hardman & Cowan, 2015). The situation is also reflected in quantitative models of VWM performance. On one side, some researchers report VWM capacity limits are best predicted when assuming object storage in three to four slots (Zhang & Luck, 2008). Opponents argue VWM performance is best considered as a limited resource that is divisible across any number of objects, such that representations become noisier with more information held in VWM (P. M. Bays & Husain, 2008). A hybrid *slots-plus-resources* model proposes a capacity limit determined by slots, but with unequal distribution of resources across them (Zhang & Luck,

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[1] Note, however, that Eng *et al.* (2005) tested the relationship between search rates and VWM capacity estimates, while Alvarez and Cavanagh (2004) tested the relationship between search rates and the inverse of VWM capacity estimates. This difference would have attenuated the relationship reported by Eng *et al.* if the inverse transformation produced a more linear relationship.

2008). Uncertainty surrounding the contribution to VWM capacity limits of various factors like stimulus complexity continues to hinder efforts to develop appropriate models.

1.4 Factors influencing capacity limits

Awh, Barton and Vogel (2007) have disputed the claim that stimulus complexity affects VWM capacity (Alvarez & Cavanagh, 2004). They suggest that variation in VWM performance is due to an increase in comparison errors made when an object stored in memory is visually similar to the changed object in the test array. Awh *et al.* (2007) gave participants a change-detection task with memory arrays containing 4 or 8 items selected from a stimulus set of 6 shaded cubes and 6 Chinese characters. This meant that either a *within-category* change would occur, where a shaded cube changed to another shaded cube or a Chinese character changed to another Chinese character, or a *cross-category* change would occur, where a shaded cube would change to a Chinese character or vice versa. A within-category change is more likely to produce a confusion error as the to-be compared items come from the same stimulus set, whereas the to-be compared items in a cross-category change come from different stimulus sets and are therefore relatively dissimilar. If stimulus complexity is the key determinant of the number of items that can be stored in VWM, then there should be no benefit for a cross-category change compared to a within-category change. However, if stimulus complexity simply makes the comparison decision more difficult, there should be an improvement in performance for cross-category changes relative to within-category changes. Awh *et al.* (2007) indeed found that performance for within-category changes was significantly worse than for cross-category changes, and significantly worse for Chinese characters compared to a shaded cubes. Change-detection performance for cross-category changes was equivalent to change-detection performance for colours. From this, Awh *et al.* concluded that the number of items represented in visual working memory is fixed, regardless of the complexity of those items. Of course, their findings did not invalidate the basic conclusion that stimulus complexity influences change-detection performance. A key insight from Awh *et al.* is that rather than the number of stored items, it may be the resolution with which objects can be stored in visual working memory that is the key limiting factor in change-detection performance. That is, limited resolution means that changes among complex objects are more difficult to detect, leading to poorer overall change-detection performance at the same set size.

Stimulus familiarity is another factor that appears to influence VWM processes. Change-detection performance is better for famous faces compared to unfamiliar faces

(Buttle & Raymond, 2003; Jackson & Raymond, 2008), and better for the original, canonical generation of Pokémon (a popular cartoon during the childhood of the university student sample) over a recent generation, only for those reporting familiarity with the characters (Xie & Zhang, 2017a). However, Xie and Zhang (2017b, 2018) suggest that capacities for familiar stimuli are not in fact larger, but that familiar stimuli are consolidated into VWM *faster*. They observed significant differences in change-detection performance between familiar and unfamiliar stimuli only with limited stimulus durations, which were presumably insufficient for VWM capacity to be saturated. It is unclear whether these effects of familiarity occur independently of the effects of stimulus complexity. Familiarity may allow the observer to encode only the distinguishing features of the stimuli, enhancing the rate of consolidation into VWM and reducing any influence of stimulus complexity. Having knowledge of the distinguishing features of the stimuli may also reduce the sample–test similarity that Awh *et al.* (2007) contend produces the effect of stimulus complexity on VWM capacity.

Training has the potential to alleviate potential confounds by controlling an observer's *fluency* with a stimulus set—a combination of how familiar, complex and similar the stimuli appear to the observer. While expertise or familiarity from extended experience appears to produce profound differences in VWM, attempts to increase VWM capacity through shorter periods of training has had mixed results. An hour of change-detection trials with over 20 repeats of the same sample arrays produced no improvements, despite observers recognition of the repeated displays following training (Olson & Jiang, 2004). Only when each display was consistently associated with the same changed location did change-detection performance significantly improve (Olson, Jiang, & Moore, 2005). This improvement did not transfer to novel displays, or to displays in which changes occurred in the non-associated locations. Similarly, Chen *et al.* (2006) trained observers to recognise a subset of eight polygons through repeated presentations of those polygons in a change-detection task. Observers were consequently able to distinguish a trained polygon from a novel polygon, but this learned recognition did not produce any significant improvements in change detection for trained polygons over novel polygons. As both of these studies produced no overall increases in VWM capacity, learning appeared only to modulate how information is encoded into VWM (Olson et al., 2005). However, a recent study by Blalock (2015) found a positive effect of familiarity training on VWM capacity. Rather than training with the change-detection task itself, Blalock (2015) used a recognition task in which observers were presented a target polygon before being asked to select the target from a test array of four polygons. This recognition training produced improved change-detection performance for trained polygons over novel polygons, where Chen *et al.* (2006) had not observed improvements. This might suggest that to increase VWM capacity, training must occur outside of the change-detection task. However, another cause for this discrepancy may be the difference in the statistical power of experiments: While Chen *et al.* (2006) used only 12 participants in each of their experiments, Blalock (2015) used considerably larger sample sizes of 102 and 70 participants in separate experiments. We resolve the discrepancy between Chen *et al.* (2006) and Blalock (2015) in *Chapter 2* by observing whether familiarity training produces changes to VWM performance while controlling stimulus complexity and similarity.

1.5 Units of storage in VWM

Apparent increases in capacity limits, like those observed for familiar stimuli over unfamiliar stimuli, have been explained by *chunking*—the combining of disparate elements for efficient storage in VWM. Chunking mechanisms often have been invoked to explain capacity limits in the verbal working memory domain. Miller (1956) famously reported recall was “magically” limited to seven *chunks*, which could take the form of individual letters, digits or words. Further, he suggested that learning allowed more efficient storage of information in a chunk, even though the number of chunks remained limited to about seven. Chen and Cowan (2009) precisely examined chunking with learned knowledge. They had subjects learn lists of words that appeared as singletons or in pairs until they could perfectly recall all word partners (or no partner in the case of singletons). Quantifying a learned pair as one unit and singletons as one unit, subjects only remembered approximately 3 units when required to reproduce the list. While prominent in the study of verbal working memory, factors such as chunking that influence the units of representation and storage are less well understood in the visual domain.

Statistical learning is thought to augment VWM capacity limits by changing how information is represented in VWM (Brady, Konkle, & Alvarez, 2009). Brady *et al.* required observers to memorise the locations of eight colours, presented as four pairs; however, certain pairs were more likely to appear, giving statistical regularity to the displays. Observers were able to take advantage of the statistical regularity, with a significant increase in recall accuracy compared to when all colour pairs were equally likely, and well beyond an accuracy expected with a capacity limit of three to four objects. Brady *et al.* argued that this improvement was produced by visual statistical learning, the learning of associations between elements through automatic, unconscious statistical computations (Fiser & Aslin, 2001, 2002;

Perruchet & Pacton, 2006; Turk-Browne, Jungé, & Scholl, 2005; Turk-Browne, Scholl, Chun, & Johnson, 2008). Learning the statistical redundancies allows the efficient compression of information, enabling an apparent increase in VWM capacity. This advantage of *implicit* knowledge in VWM contrasts with Chen and Cowan's (2009) finding of an advantage for *explicit* knowledge in verbal working memory. We explore how this memory compression effect might occur by scrutinizing the nature of learning produced by the Brady *et al.* (2009) paradigm in *Chapter 3*.

Perceptual cues that govern the grouping of objects in complex scenes, known as Gestalt cues, are also thought to affect the units of storage in VWM (Wagemans et al., 2012). Woodman, Vecera and Luck (2003) examined how the Gestalt cues of *proximity* and *connectedness* influenced change-detection performance (see *Figure 1-3*). To do this, they cued a corner location prior to the memory display and tested change detection at the equidistant uncued corners. When items in displays were grouped by proximity, change detection was more accurate for the grouped item than for the ungrouped item. For example, in *Figure1-3a*, after pre-cueing the top-left corner, change-detection was significantly better for the bottom-left corner than the top-right corner. However, when displays had opposing proximity and grouping cues (*Figure 1-3b*), change-detection was more accurate at the connected corner than the proximally grouped corner. That is, in *Figure1-3b*, after pre-cueing the top-left corner, change-detection was now significantly better for the top-right corner than for the bottom-left corner. Electrophysiological studies measuring the neural correlates of VWM capacity provide further evidence that perceptual grouping cues influence representation in VWM (Balaban & Luria, 2016; Luria & Vogel, 2014; Peterson, Gözenman, Arciniega, & Berryhill, 2015).

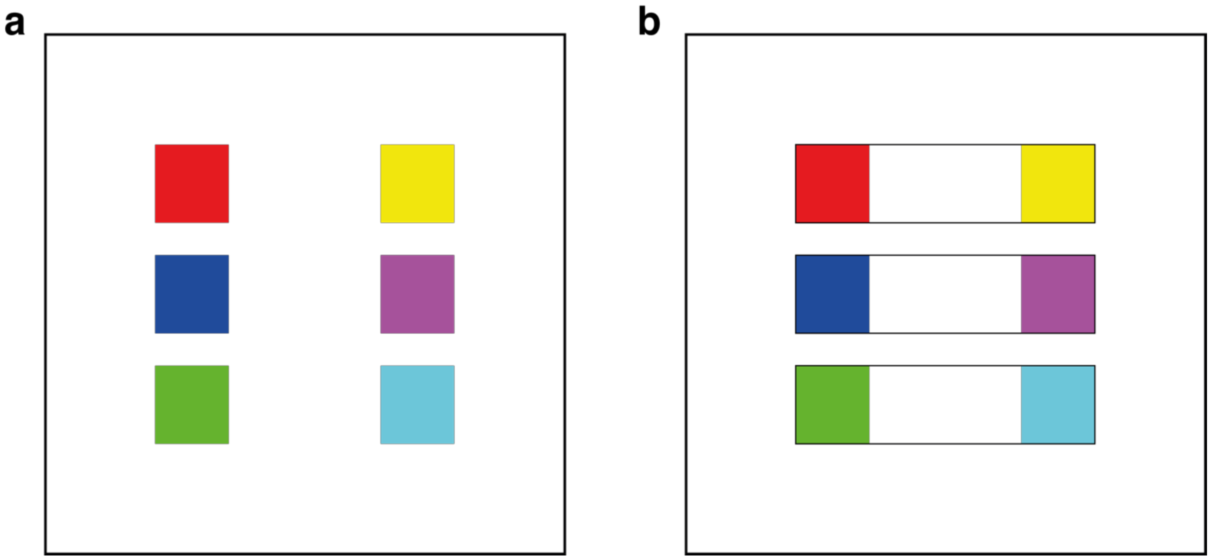


Figure 1-3. Adapted examples of memory displays from Woodman *et al.* (2003). (a) Colour squares are grouped vertically due to proximity. (b) Colour squares are grouped horizontally by a connectedness cue, as well as grouped vertically due to proximity.

1.6 Neural correlates of VWM capacity

The majority of VWM research relies on responses made at the end of a trial, such as a decision on whether a change occurred or the delayed recall of a probed item. This makes it hard to discern what occurs during consolidation and retrieval in a typical VWM task and, as such, researchers have begun to examine neural measures during the retention periods. An electrophysiological component tightly associated with VWM load is the *contralateral delay activity* (CDA), discovered by Vogel and Machizawa (2004). Measured with electroencephalography (EEG), the CDA is the sustained negative activity on parietal–occipital electrodes of the target side on a lateralized VWM task. The mean amplitude of this sustained activity has been shown to increase with memory load before plateauing at the typical 3–4 item capacity limit of VWM (Vogel & Machizawa, 2004) and is correlated (r = .57) with an individual's behaviourally estimated VWM capacity (Unsworth et al., 2014a; Vogel, McCollough, & Machizawa, 2005). It appears the CDA tracks the number of chunks in VWM, as its amplitude drops with the inclusion of Gestalt grouping cues in a display (Balaban & Luria, 2016; Peterson et al., 2015), and rises when a single object splits into two discrete halves (Balaban & Luria, 2016). We use the CDA to examine whether explicit chunking produces changes to encoding and storage of objects in VWM as observed with perceptual grouping in *Chapter 4*.

1.7 Overview of Studies

The studies reported in the following chapters use three different approaches to investigate factors that appear to augment VWM capacity. The empirical chapters include experiments that have been either submitted or accepted for publication in peer-reviewed journals. *Chapter 2* isolates the benefit in VWM performance due to familiarity, controlling stimulus complexity and similarity, before examining whether familiarity training can generate this benefit. *Chapter 3* examines whether statistical learning augments VWM capacity through memory compression or other means. Finally, *Chapter 4* examines whether chunking processes influence storage in the same manner as perceptual grouping using known neural correlates of VWM capacity. Where a chapter includes experiments that have either been submitted or accepted for publication in a peer-reviewed journal, this is indicated at the start of the chapter.

Chapter 2: The Influence of Familiarity on the Encoding Rate and Capacity of Visual Working Memory

Experiment 1 of this chapter was included as Experiment 3 in Ngiam, Khaw, Holcombe and Goodbourn (2018), "Visual working memory for letters varies with familiarity but not complexity. *Journal of Experimental Psychology: Learning, Memory and Cognition*.

2.1 Abstract

A point of contention for two prominent models of visual working memory (VWM) is whether the capacity limit is systematically influenced by stimulus complexity. An often-ignored factor influencing VWM performance, which could be intertwined with the perceived complexity of a stimulus, is stimulus familiarity. It is unclear how stimulus complexity, familiarity and similarity interact and contribute to VWM performance. In this chapter, we isolate the influence of familiarity by controlling for stimulus complexity and similarity. We find familiarity with a stimulus is associated with increased encoding rates and higher capacity limits. In Experiments 2 and 3, we examine whether training recognition familiarity can increase the encoding rate or capacity of VWM performance. Despite gaining recognition, observers did not improve in change-detection for those stimuli. While there is clearly a benefit of extensive familiarity to VWM processing, the lower level of familiarity needed for successful recognition apparently does not provide any benefit.

2.2 Introduction

A common method employed by visual working memory (VWM) researchers is to manipulate the stimuli used in a change-detection task and examine the resulting effect on memory performance. For example, a major point of contention central to the current debate over the architecture of VWM is the influence of stimulus complexity on VWM processes. Contrasting findings from different manipulations of the stimuli, targeting the stimulus complexity, brought about two conflicting models of VWM architecture that have shaped much of the research—the *slots* model and the *resources* model. Defining complexity is difficult and different metrics of complexity have likely led to different results. However, a less examined influence on the VWM system, and even on the perceived complexity of a stimulus, is the observer's familiarity with the stimulus. This chapter examines the influence of stimulus complexity and familiarity on two parameters of VWM: encoding rate and capacity.

2.2.1 Classic models of VWM architecture

Proponents of the *slots* model suggest the information capacity limit of VWM is defined strictly by the number of *objects* to be stored, regardless of the complexity of the objects. In their seminal paper, Luck and Vogel (1997) increased the stimulus complexity by adding features in which change could occur in the to-be-remembered stimuli. They found change-detection accuracy was unchanged despite the increase in the number of relevant features. This result suggests the items are stored into VWM with their features integrated, filling up a limited number of slots.

On the other hand, proponents of the *resources* model suggest storing more complex objects expends additional limited resources, lowering the number of complex objects that can be stored. Alvarez and Cavanagh (2004) manipulated complexity by employing various stimulus sets, ranging from complex random polygons and Chinese characters to simpler colour squares, in a change-detection task. They found different capacities for the different stimulus sets, a finding at odds with the strict slots model. Critically, they indexed each stimulus' complexity by conducting a visual-search task with those stimuli. Alvarez and Cavanagh (2004) found that the visual search rate was almost perfectly correlated with the inverse of working memory capacity ($r^2 = 0.99$). This finding that stimulus complexity not only influences but almost perfectly accounts for VWM performance motivated Alvarez and Cavanagh (2004) to propose the *resources* model, which suggests that the VWM system allocates a finite pool of resources to storing stimuli. As more complex items require more resources, fewer items can be stored in VWM.

Although the object-based *slots* model (Luck & Vogel, 1997) and the feature-based *resources* model (Alvarez & Cavanagh, 2004) have been influential in VWM research, the manner in which object complexity influences VWM processes—that is, the main difference between these two models—is still disputed. Firstly, the results upon which these models are based have not been perfectly replicated. In their direct replication, Hardman and Cowan (2015) were unable to reproduce Luck and Vogel's (1997) most striking result by which change-detection accuracy for objects possessing features from four different dimensions was equal, regardless of which feature or the number of features participants were required to remember. However, they suggested that despite an effect of feature load on VWM performance, significant evidence supported the claim that VWM capacity was predominantly constrained by object load. This rules out the pure *slots* account according to which the number of items is the sole factor limiting VWM performance, but retains the notion that the number of items is a significant contributor to the capacity limit of VWM. Attempts at perfectly reproducing the findings of Alvarez and Cavanagh (2004) have been similarly unsuccessful. Eng, Chen and Jiang (2005) were able to replicate the overall finding that visual search rate was related to VWM capacity at various memory display presentations (500, 1000 ms and 3000 ms). However, they did not replicate the near perfect inverse relationship found by Alvarez and Cavanagh (2004), finding a weaker magnitude correlation ($r^2 = .26$) with 3000 ms memory display presentations. This suggests that complexity explains approximately 25% of the variation in VWM capacity, rather than all the variation as posited by the *resources* model. Eng *et al.* (2005) suggests that rather than affecting overall VWM capacity, complexity limits perceptual encoding during consolidation into VWM.

2.2.2 Similarity

The stimulus sets used to manipulate complexity likely had other differences that can influence VWM performance. Awh, Barton and Vogel (2007) suggest the differences in VWM capacity found by Alvarez and Cavanagh (2004) are not due to stimulus complexity *per se,* or perceptual encoding as suggested by Eng *et al.* (2005), but rather arise from confusion at the comparison stage in change detection. In their own experiments, they manipulated whether the changed object in the test array came from the same stimulus set (*within-category*) or from a different stimulus set (*cross-category*). Change-detection accuracy for *within-category* changes, such as a shaded cube changing to another shaded cube, decreased with increasing stimulus complexity, replicating the finding of Alvarez and Cavanagh (2004). When changes were *cross-category*, such as a shaded cube changing to a Chinese character, change-detection accuracy was equivalent to change-detection accuracy for simple colours. Awh *et al.* (2007) posited that an effect of complexity only manifests with *within-category* changes because of the similarity between the target item in memory and the test item. Direct manipulations of the visual similarity of the test object support this interpretation (Jackson, Linden, Roberts, Kriegeskorte, & Haenschel, 2015). Jackson *et al.* used sets of simple polygons and complex polygons and asked participants for subjective similarity ratings of polygon pairs within each set. They found change detection was worse for complex polygons when test objects were subjectively rated as similar, but no difference between simple and complex polygons when the test items were rated as dissimilar. As objects that were more complex were more visually similar (high *sample–test similarity*), within-category changes produced more change-detection errors, lowering estimates of VWM capacity. The visual comparison of highly similar stimuli leading to lower estimates of VWM capacity is likely to contribute to slower visual search rates (Duncan & Humphreys, 1989), explaining the significant correlations found by Alvarez and Cavanagh (2004) and Eng *et al.* (2005).

It is still unclear whether effects of stimulus complexity on VWM are entirely attributable to sample–test similarity. The conclusions of Jackson *et al.* (2015) rely on matched subjective ratings of simple and complex polygon pairs. Yet, despite being matched in subjective similarity, it is not evident that two simple polygons are as visually confusable as two complex polygons. Furthermore, Jackson *et al.* (2015) report capacity estimates for both simple and complex polygons using *dissimilar* test items (approximately 1.5 items) that are far lower than estimates reported by Awh *et al.* (2007) for other stimulus sets with low sample–test similarity (3.5 Chinese characters, 3.6 colours, 4.2 shaded cubes). These findings in themselves do not completely contradict Alvarez and Cavanagh's basic claim that VWM performance is influenced by stimulus complexity. For example, a more complex object may be represented at a lower resolution, with fewer intact features. A degraded representation of a complex object, such as a Chinese character, might then be easily distinguishable from a coloured square, but not from another character with similar features. Prolonging encoding time may allow VWM representations of complex objects to achieve equivalent resolution and produce comparable estimates of VWM capacity for simple objects.

2.2.3 Familiarity

Stimulus familiarity is intertwined with stimulus complexity, and has been shown to influence consolidation and storage in VWM. Chess experts show improved memory performance for chess game positions compared to novices (Chase & Simon, 1973). Similarly, higher VWM capacities have been found for famous faces over unfamiliar faces (Buttle & Raymond, 2003; Jackson & Raymond, 2008) as well as for Pokémon (characters from a popular childhood cartoon) from an original generation over a recent generation among those reporting familiarity with the characters (Xie & Zhang, 2017a). Additionally, participants familiar with Pokémon showed a higher encoding rate for the characters (Xie & Zhang, 2017b, 2018). These studies do not directly control stimulus complexity and it is unknown whether these effects of familiarity or expertise are independent of stimulus complexity.

Confounds caused by differences in familiarity between stimuli might be alleviated with training. While expertise with stimuli has consistently been shown to produce improvements in VWM performance, the results of training have been mixed. Detection of changes in spatial locations or shapes showed no improvement following an hour of training that included over 20 repeats of the same stimulus arrays, despite recognition of the displays in a recognition task following training (Olson & Jiang, 2004). Only when the repeated displays were associated with changes at a specific location did change-detection performance significantly improve (Olson et al., 2005). This came without improvement in overall VWM capacity, as performance was unchanged for novel displays and when change occurred at a non-associated location. This suggests following learning of the association between a display and a target location, that target location can be prioritized during encoding in VWM. It appears that the actual capacity of VWM is very difficult to change, whereas the information encoded into VWM is easily modulated through learning (Olson et al., 2005).

Two noteworthy studies directly training stimulus familiarity were conducted by Chen, Eng and Jiang (2006) and Blalock (2015). Chen *et al.* (2006) trained observers to recognise a subset of eight polygons using a change-detection task. On each of 320 trials, these observers were briefly presented with a display containing four polygons from the training subset. After a short blank delay, a new display containing a polygon at each of two previously occupied locations was presented. At one location the polygon remained unchanged, while at the other location, the polygon had changed to one of the remaining four in the training set. Observers were required to select the location at which they believed the polygon had changed. While they were near perfect at distinguishing a trained polygon from a novel polygon, this learned recognition did not improve change-detection with the trained polygons compared to novel polygons. Chen *et al.* suggest that improvements in VWM produced by familiarity—such as for faces or Pokémon (Buttle & Raymond, 2003; Jackson & Raymond, 2008; Xie & Zhang, 2017a) —require LTM representations that have been built over extended periods of experience with stimuli.

In a similar study, Blalock (2015) found improvements in change detection following recognition training. Observers were trained to recognise a subset of twelve polygons in a different manner from Chen *et al.* (2006). On each of 240 trials, observers were shown a target polygon before the onset of a backward mask, which interrupted further consolidation. In a subsequent display, observers were required to recognise the target amongst three distractors. Following recognition training, change-detection performance was significantly better for the trained polygons compared to novel polygons. The benefit of the recognition training was very small (83% vs 81%), although statistically significant. Change-detection performance did not differ across various stimulus onset asynchronies (SOA) for trained polygons, but did vary across these intervals for novel polygons. This raises the possibility that recognition training protects visual information from impairment by backward masking, possibly by producing faster encoding into VWM.

2.2.4 Encoding rate

The encoding rate corresponds to the speed at which early VWM processes create durable memory representations. However, it is often ignored by researchers, despite the possibility that influences on early VWM processing might systematically limit VWM capacity estimates. Typically the time between memory and mask is kept constant within an experiment but limiting encoding to brief durations may lead to underestimation of VWM capacity. Increasing object complexity may slow the rate of encoding into VWM, such that complex objects will require more time to saturate VWM capacity. This would confound conclusions made from comparisons of VWM capacity for objects of different complexity with the same memory array durations, such as those reported by Alvarez and Cavanagh (2004).

The encoding rate was first quantified by Vogel, Woodman and Luck (2006), who presented four colours to observers in a change-detection task for a fixed duration (100 ms) before interrupting encoding with a backward mask. They varied the *stimulus onset* *asynchrony* (SOA), the duration during which stimuli are available to encode their durable representations into VWM before the onset of the backward mask. They found change-detection performance improved with longer encoding durations up to 200 ms, before plateauing. From the initial slope of the encoding function, they estimated it took approximately 50 ms to encode each colour block, (assuming serial encoding), prior to reaching an asymptote of approximately 2.5 objects.

In a previous study, we examined whether stimulus complexity influences the encoding rate. We adapted Vogel, Woodman and Luck's (2006) paradigm, but employed English letters in four different fonts as well as characters from four alphabets that were unfamiliar to our participants (Ngiam, Khaw, Holcombe, & Goodbourn, 2018). These stimuli varied in *perimetric complexity*, the square of the combined inside and outside perimeters of a letter, divided by its area (Attneave & Arnoult, 1956). Compared to previous measures, there are many advantages to using perimetric complexity to define stimulus. Perimetric complexity has a nearly perfect negative linear relationship with letter identification efficiency, such that as letters increase in perimetric complexity, they are identified increasingly inefficiently (Pelli, Burns, Farell, & Moore-Page, 2006). Pelli *et al.* suggest this relationship occurs because complex letters require more features to be bound together, and perimetric complexity indexes the number of basic visual features in a letter. Perimetric complexity also provides an objective, quantitative measure of complexity derived from the stimulus, that corresponds well to subjective figural goodness (Attneave, 1957) and apparent information load (Jiang, Shim, & Makovski, 2008; Makovski & Jiang, 2008). An increase in perimetric complexity reflects an increase in stimulus complexity without the addition of extra feature dimensions, unlike typical manipulations of stimulus complexity. In our study, encoding rate and capacity estimates did not vary as a function of perimetric complexity in the familiar or unfamiliar alphabets. Model fitting confirmed this, showing performance was better explained by an item-based account of VWM like the *slots* model (Luck & Vogel, 1997) rather than a feature-based account of VWM like the *resources* model (Alvarez & Cavanagh, 2004). However, across experiments, both encoding rate and capacity differed according to the familiarity of the stimulus to the observer (*Figure 2-1*). A *slots* model does not inherently predict or provide an explanation for the relatively higher capacity for familiar stimuli compared to unfamiliar stimuli. A *resources* model may account for these results by positing that familiar stimuli requires less resources for VWM encoding.

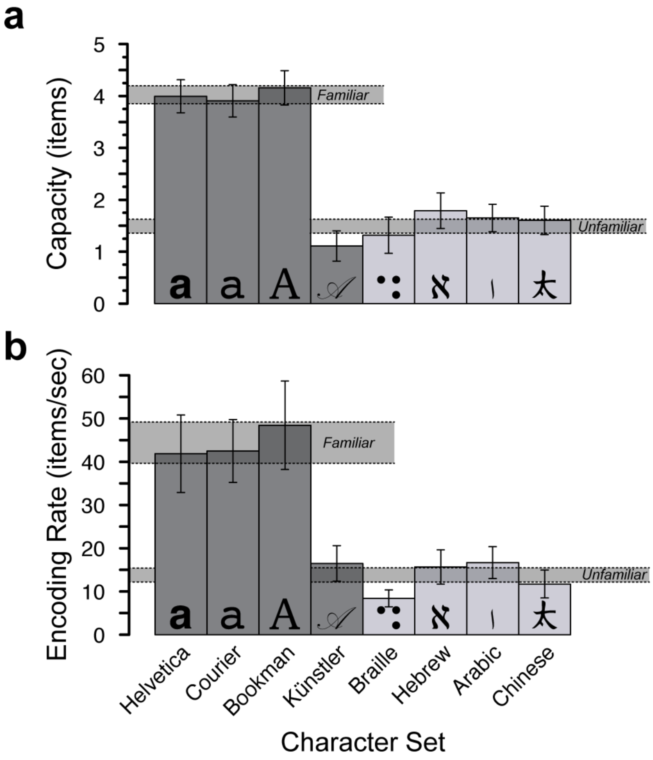


Figure 2-1. Mean capacity and encoding rate for alphabets used by Ngiam, Khaw, Holcombe and Goodbourn (2018). (a) Mean capacity shows two distinct clusters, one for familiar letters and the other for unfamiliar letters. (b) Mean encoding rate shows the same two distinct clusters. Error bars show ±1 SEM. Horizontal bars represent the range of ±1 SEM for the mean across individuals, separately for familiar and unfamiliar stimuli.

Here, we isolate the effect of familiarity on VWM performance. We controlled stimulus complexity by comparing the Brussels Artificial Character Set (BACS; Vidal, Content, & Chetail, 2017) to an equivalent English font matched in perimetric complexity. The BACS is designed to have the same number of junctions, strokes and terminations as English letters but was unfamiliar to our observers. BACS characters and English letters are also matched with respect to the similarity between characters (Vidal et al., 2017).

2.3 Experiment 1

2.3.1 Method

2.3.1.1 Participants

Ten subjects (six males) recruited from the University of Sydney with normal or corrected-to-normal vision completed the experiment. All were native English speakers naïve to the aims of the experiment.

2.3.1.2 Apparatus

The stimuli were generated using the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) in MATLAB (The Mathworks, Natick, MA) and presented on a 40.5 by 30.35 cm Trinitron G520 CRT monitor (Sony Corporation, Tokyo, Japan) on a uniform grey background. The spatial resolution of the monitor was set to 1024 by 768 pixels, and the refresh rate was 100 Hz. Subjects were seated in a dark room, with a chin rest to maintain a viewing distance of 57 cm from the monitor.

2.3.1.3 Stimuli

Each letter was drawn in black within a white circular aperture. The aperture for each letter subtended 1.8°, and a letter subtended a maximum of 1.5° on vertical and horizontal axes. Each aperture was positioned on the circumference of an imaginary circle, with each aperture centred 4.0°from the fixation point. Apertures were equally spaced around the circle, with a random rotation applied to the circle of apertures on each trial.

The English letters were Courier New lowercase, generated using TrueType fonts from Apple OSX 10.7.5. The artificial letters were the serif BACS-2 character set. The most commonly confused English letters according to our pilot experiments (C, F, I, N, V and W) and their BACS equivalents were excluded, leaving 20 matched characters (*Figure 2-2)*. The items in each array were selected randomly without replacement from the set of 20 for each alphabet.

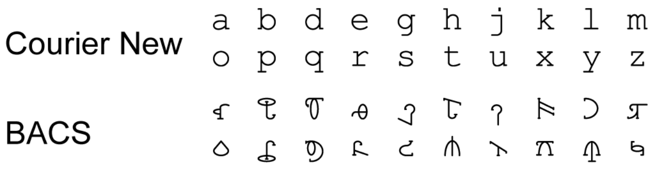


Figure 2-2. Courier New and BACS characters used in Experiment 1.

2.3.1.4 Procedure

The procedure for each trial is shown in *Figure 2-3*. A warning tone sounded at the beginning of each trial. At the same time, a fixation point appeared with two randomly selected digits (1-9) on either side (centred 3.2° to the left and right). Participants were instructed to repeat these numbers aloud throughout the trial. This articulatory suppression procedure is used to interrupt verbal encoding of the letter stimuli (Besner, Davies, & Daniels, 1981), which might otherwise allow participants to rely on systems other than VWM to perform the task.

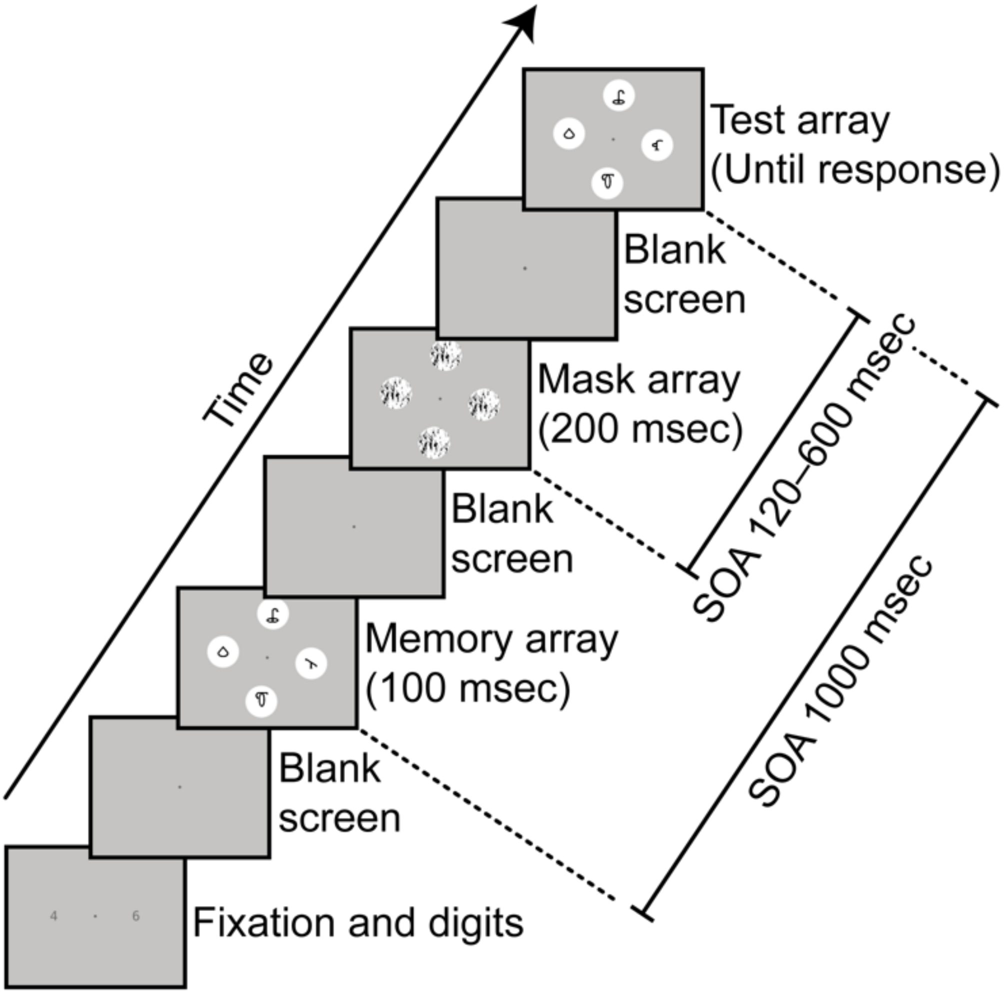


Figure 2-3. Stimulus sequence on a single trial. At the beginning of the trial, two digits were shown to either side of the fixation point. The memory array, containing different characters from the same stimulus set, was presented for 100 ms and followed by a blank screen. The dynamic mask contained phase-scrambled transformations of all letters from that stimulus set, presented for 200 ms. The SOA for the memory array and mask array was 120, 130, 160, 200, 270, 390, or 600 ms on each trial. The test array, which was identical to the memory array except for a change in letter at one position, was presented 1000 ms after the memory array. The test array remained on the screen until the participant made a response. The participant responded to each trial by selecting the aperture in which they believed the change had occurred. For illustrative purposes, the stimuli shown here have been enlarged. This figure depicts an example of a trial with BACS characters, in which the right-most character changes on the test array.

The numbers disappeared after 1000 ms, leaving a blank screen with the fixation point for 1000 ms, after which the memory array was shown for 100 ms. Finally a dynamic mask array was presented for 200 ms. Mask onset occurred 20, 30, 60, 100, 170, 290 or 500 ms after offset of the memory array. It contained phase-scrambled transformations of all letters in the set, displayed in each circular aperture. Scrambling the Fourier phase spectrum of an image retains the spatial-frequency content while destroying overall form information. On each trial, ten different transformations were randomly selected and displayed for 20 ms each. The stimulus onset asynchronies (SOAs)—that is, the set of delays between the onset of the memory array and the onset of the mask—were therefore 120, 130, 160, 200, 270, 390 or 600 ms. We expected that concentrating SOAs at the lower end of the range would yield more precise measurement of encoding rate by increasing the number of SOAs below ceiling capacity.

The test array was presented 1000 ms after onset of the memory array. In each test array, one letter was randomly changed to one of the other letters in the set. Participants were required to identify where the change had occurred by using the computer mouse to click on the circular aperture of the changed letter. Feedback was provided: A high tone was played after a correct response, or a low tone after an incorrect response. The next trial commenced 1000 ms following feedback.

Each participant completed eight blocks, four blocks for each of the two alphabets. Each block lasted approximately 20 minutes, and contained 210 trials in total (30 trials at each of seven SOAs). Within each block, participants were prompted to take a short break after completing each set of 70 trials. In total, each participant completed 1680 trials: 120 at each of the seven SOAs, for each of the two alphabets.

2.3.1.5 Estimating perimetric complexity

We used perimetric complexity to quantify stimulus complexity as we had done in our previous studies. Perimetric complexity (κ) was defined as the sum of the inside and outside perimeter of the stimuli (P_{total}) squared, divided by the area (A) and 4π,

$$\kappa = \frac{{P_{total}}^2}{4\pi A}. \qquad (Equation\ 2\text{-}1)$$

Because the perimetric complexity of a stimulus depends on the effective resolution of the display (Watson, 2011), perimetric complexity estimates will vary with different screens. We therefore calculated values for this experiment using a MATLAB program based on the algorithm specified by Pelli *et al.* (2006). These estimates of perimetric complexity allowed us to assess the number of *features* stored in VWM. Using κ as a proxy for the average number of features (up to a proportionality constant) contained within letters of an alphabet (Pelli et al., 2006), the number of stored features is the product of the number of stored items and complexity,

$$\text{Number of features} = K \times \kappa \qquad (\textit{Equation 2-2})$$

2.3.1.6 Estimating items stored in VWM

Pashler's (1988) formula for estimating the number of stimuli in VWM was adapted for our forced-choice change-detection task, as we asked participants to identify the location of the change rather than whether or not a change occurred. If the participant encodes, on average, a given number of objects in VWM (*K*) out of the total number of objects in the array (*N*), we make the straightforward assumption that they will detect the location on *K* out of *N* trials. On the remaining (*K–N)* trials, when they do not detect the location of change, the participants will have to guess from the array. When guessing, participants may randomly select one target from the array, such that they will have a 1 out of *N* probability of selecting the correct letter. Thus, the proportion of correct responses (*P*) will be

$$P = \frac{K}{N} + \frac{1}{N}\left(1 - \frac{K}{N}\right) \qquad (\textit{Equation 2-3})$$

Rearranged to estimate *K*,

$$K = \frac{PN-1}{\left(1-\frac{1}{N}\right)} \qquad (\textit{Equation 2-4})$$

We refer to *Equation 4* as the *random-guessing* formulation. This assumes that when a participant, cannot identify the location of the change, they select randomly from the array. If a participant is able to inform their guess by inferring that it did not occur at any of the successfully encoded locations, they will have a 1 out of (*N–K)* probability of selecting the correct letter, such that

$$P = \frac{K}{N} + \left(\frac{1}{N-K}\right)\left(1 - \frac{K}{N}\right) \qquad (\textit{Equation 2-5})$$

When rearranged to estimate K,

$$K = PN - 1 \qquad (\textit{Equation 2-6})$$

We refer to this equation as the *informed-guessing* formulation. For simplicity, the analyses presented here have been conducted with the random guessing formulation. The two formulations produce very similar estimates of *K* and the conclusions do not change when the informed guessing formulation is used.

2.3.1.7 Estimating encoding rate and capacity limits

For each alphabet, we measured *K* as a function of SOA. The slope of the initial part of this function was taken to be the encoding rate (Vogel et al., 2006). The function was expected to reach a ceiling at longer SOAs; this ceiling is interpreted as the capacity of VWM. We estimated encoding rate and capacity by fitting a combination of two lines using least-squares (*Figure 2-4*). The intercept of the first line was set to zero so it passed through the origin, with only its gradient (encoding rate) as a free parameter. The second line was the ceiling (capacity), a horizontal line whose *y*-value was its free parameter. The domain of the first line was restricted to *x*-values below where the two lines interested; the domain of the second was restricted to *x*-values above that point.

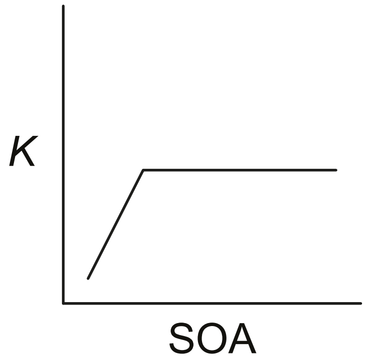


Figure 2-4. The two-line function fit to the data of each individual for each alphabet to estimate encoding rate and capacity. The slope of the first line, representing the encoding rate, was allowed to vary as a free parameter. The second line, representing the capacity, was a horizontal line with its *y*-value as a free parameter.

2.3.2 Results

2.3.2.1 Perimetric complexity

The perimetric complexity of the set of Courier New letters (*M* = 11.6, *SD* = 1.7) was very similar to the perimetric complexity of the BACS letters (*M* = 10.8, *SD* = 2.4), *t*(38) = 1.22, *p* = 0.23.

2.3.2.2 Change-detection performance

Figure 2-5a shows mean accuracy (percentage correct) as a function of the SOA for each alphabet. *Figure 2-5b* shows *K* as a function of SOA for each alphabet and *Figure 2-5c* shows the estimate number of features ($K\kappa$) as a function of SOA for each alphabet. A combination of two lines was fitted to estimate the encoding rate and capacity for each alphabet, separately for each participant. Mean encoding rate (in items per second) was significantly faster for Courier New letters (*M* = 22.8, *SD* = 6.1) than for BACS letters (*M* = 15.7, *SD* = 6.5). *t*(9) = 3.76, *p* < .01. Additionally, capacity was significantly higher for Courier New letters (*M* = 2.5, *SD* = 0.5) than for BACS letters (*M* = 1.9, *SD* = 0.3), *t*(9) = 5.17, *p* < .01.

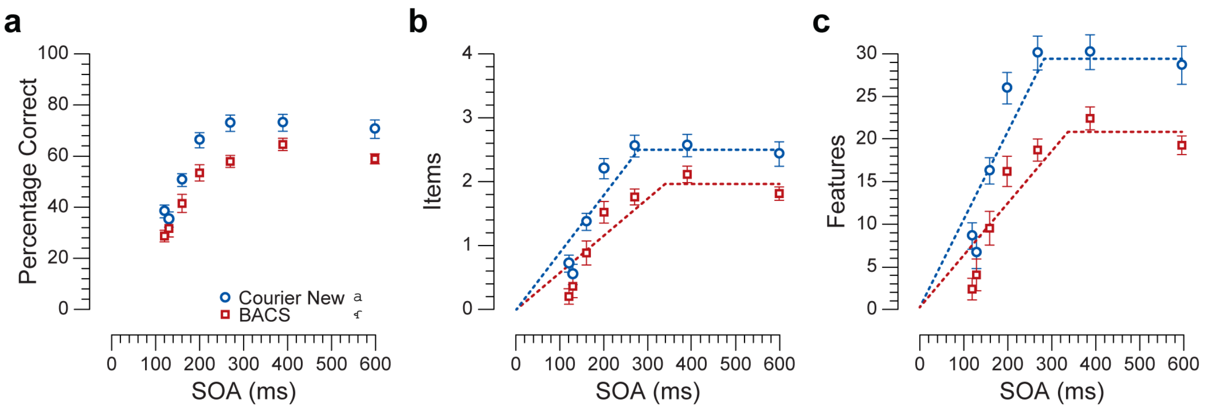


Figure 2-5. Results from Experiment 1. (a) Mean percentage correct on the change-detection task as a function of stimulus onset asynchrony (SOA) and alphabet. (b) Number of items encoded (K) as a function of SOA and alphabet. (c) Number of features encoded ($K\kappa$) as a function of SOA and alphabet. Error bars show ±1 SEM across observers.

2.3.3 Discussion

In Experiment 1, we examined the influence of familiarity on the encoding rate and capacity of VWM for alphabetic stimuli, while controlling for visual complexity and similarity by comparing performance for English letters and the Brussels Artificial Character Set (Vidal et al., 2017). We matched the perimetric complexity of the letters—an objective, intrinsic measure of stimulus complexity that estimates the number of basic visual features it contains (as validated by recognition efficiency). The two sets of letters were also equivalent in between-letter similarity, and matched on the number of strokes, junctions and terminations. We found the familiar English font to have a significantly faster encoding rate and higher VWM capacity than the unfamiliar BACS font.

2.4 Experiment 2

It has been shown previously that training subjects to recognise polygons increases VWM capacity for those polygons (Blalock, 2015). In Experiment 2, we examined whether training subjects to recognise the BACS letters with the same training procedure would increase VWM capacity.

2.4.1 Method

2.4.1.1 Participants

Twenty-seven first–year psychology students at the University of Sydney (23 female) completed this experiment in exchange for course credit. Three participants were excluded from analyses due to chance–level performance. All participants reported normal or corrected–to–normal vision.

2.4.1.2 Stimuli

The stimuli were as in Experiment 1.

2.4.1.3 Procedure

The experiment procedure involved three phases: a training phase, an immediate recognition test, and a change-detection task. It took approximately an hour to complete all phases.

2.4.1.4 Recognition training

Each participant was trained to recognise ten randomly selected BACS letters using a an adaptation of Blalock's (2015) procedure, which produced recognition for polygons that resulting in improved VWM capacity. The procedure for a trial of recognition training is shown in *Figure 2-6*. One target character was presented in the centre of the screen for 200 ms at the beginning of each trial. A dynamic mask was shown for 200 ms to interrupt any further encoding. The mask contained ten randomly selected and phase scrambled characters, each shown for 20 ms. Participants were then shown a test array containing three distractor characters and the target character. They were instructed to select the target character. The three distractor letters were randomly selected from the subset of ten letters on which subjects were being trained. Audio feedback was provided after every trial, where a high-pitched tone indicated a correct response and a low-pitched tone indicated an incorrect response. Each participant completed 210 training trials.

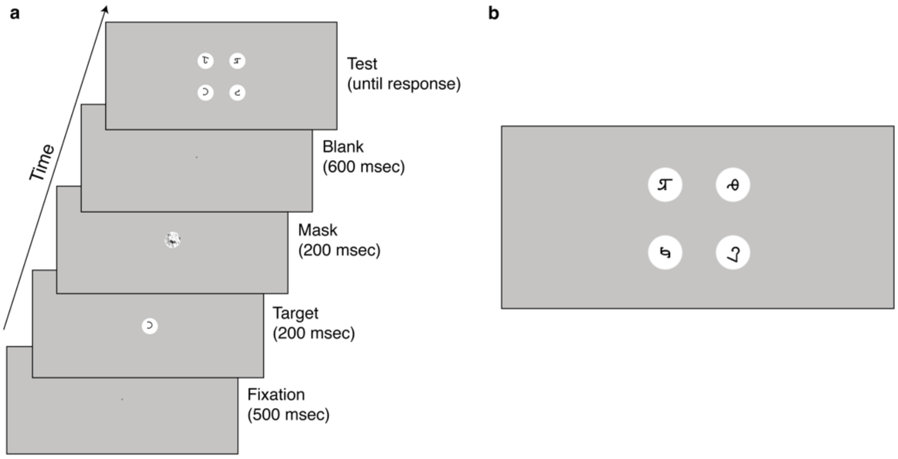


Figure 2-6. (a) Procedure on one trial of recognition training. After a 500 ms fixation, a target BACS character was shown for 200 ms before a dynamic backward mask followed for 200 ms. After a blank screen was presented for 600 ms, a test array was shown with four BACS characters including the target. The participant was required to click on the target. (b) An example of a display from the recognition test. Of the four BACS characters shown, only one was from the set that had been used during training.

2.4.1.5 Recognition test

A surprise recognition test was administered immediately following training. On each test trial, one of the BACS characters on which subjects had been trained and three of the untrained BACS characters were shown. Participants were asked to click on the letter that they had seen in the previous session. Each participant completed 40 trials (four trials for each BACS letter on which they had been trained). An example of a test display is shown in *Figure 2-6b*.

2.4.1.6 Change detection

Following the recognition test, subjects completed a change-detection task similar to that in Experiment 1. The SOAs used were set at 200, 270, 390 and 600 ms to achieve stable estimates of VWM capacity. There were three sets of stimuli: trained BACS characters, novel BACS characters and English letters. Subjects completed four blocks of 40 trials with each stimulus set.

2.4.2 Results

2.4.2.1 Recognition

Accuracy in the training task was near ceiling (*M* = .98, *SD* = .02) and accuracy in the surprise recognition test following was also near perfect (*M* = .98, *SD* = .03). This suggests that subjects had been trained to recognise and distinguish a subset of BACS characters from novel BACS characters.

2.4.2.1 Change-detection performance

Figure 2-7 shows VWM capacity estimates (K) derived from change-detection accuracy as a function of SOA, for each of the three character sets: English letters, trained BACS characters and novel BACS characters. A repeated-measures ANOVA revealed a significant main effect of stimulus set, $F(2, 46) = 89.72$, $p < .001$, but no significant main effect of SOA, $F(3, 69) = 1.22$, $p = .31$. There was no significant interaction between stimulus set and SOA, $F(6, 138) = 1.14$, $p = .35$. Planned contrasts revealed the capacity for English letters ($K = 3.0$) was significantly higher than the capacity for BACS letters ($K = 1.7$), $F(1, 23) = 138.09$, $p < .001$. There was no significant difference in capacity between the trained and novel BACS characters (both $K = 1.7$), $F(1, 23) = .08$, $p = . 78$.

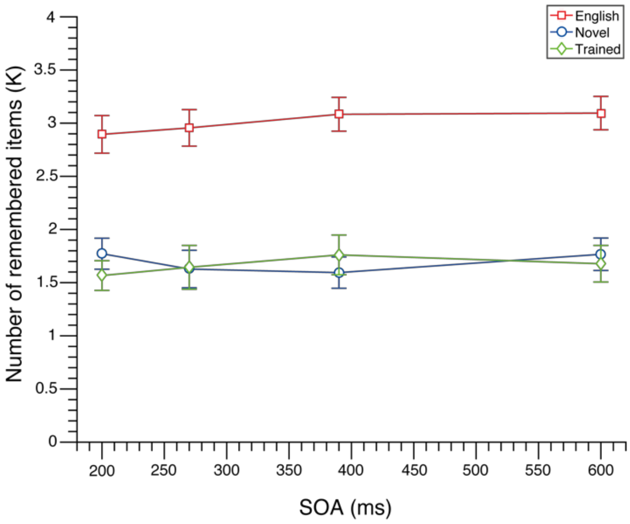


Figure 2-7. VWM capacity estimates at each SOA for each of the three character sets in Experiment 2: English letters are shown in red, novel BACS characters in blue and trained BACS characters in green. Error bars show ±1 SEM across subjects.

2.4.3 Discussion

Following training to recognise random polygons, participants showed improved change-detection performance with those trained stimuli (Blalock, 2015). Our participants completed the same training procedure with a subset of BACS characters. Despite successfully learning to recognise and distinguish the trained BACS characters from novel BACS characters, change-detection performance was not statistically different between trained and untrained stimulus sets. Change-detection performance for BACS characters was significantly worse than change-detection with English letters. Because we found no effect of SOA, it appears that the SOAs used were sufficiently long enough to capture change-detection performance with saturated VWM capacity. While recognition training did not increase VWM capacity limits for the trained stimuli, there was still an overall effect of familiarity as indicated by the higher capacity estimates for English letters over BACS characters.

2.5 Experiment 3

While Experiment 2 showed learned recognition of the BACS characters did not increase VWM capacity, recognition training may still influence encoding into VWM. Familiarity with Pokémon characters accelerated consolidation into VWM (Xie & Zhang, 2017b, 2018), and we found encoding rate was faster for English letters than for BACS characters in Experiment 1. In Experiment 3, we examined whether training recognition influences the rate of encoding into VWM.

2.5.1 Method

2.5.1.1 Participants

Twenty-five first-year psychology students at the University of Sydney completed the experiment in exchange for course credit. No participants took part in the previous experiments reported here. All participants reported normal or corrected-to-normal visual acuity.

2.5.1.2 Stimuli

The stimuli were identical to those used in Experiment 2.

2.5.1.3 Procedure

The experiment procedure was identical to that of Experiment 2 with one exception. SOAs for the change-detection task were lowered to 120, 130, 160 and 200 ms to better capture encoding into VWM. We estimated encoding rate by calculating the slope of the line of best fit through VWM capacity estimates across every SOA, separately for each participants and stimulus set. The line was not required to pass through the origin.

2.5.2 Results

2.5.2.1 Training

No participants were excluded from analyses. Accuracy was near perfect on the training task (*M* = .99, *SD* = .01) and in the following surprise recognition (*M* = .98, *SD* = .04). This suggests participants learned to recognise the subset of BACS characters following the training.

2.5.2.2 Change Detection

Figure 2-8 shows estimated VWM capacity for each of the stimulus sets (English letters, trained BACS characters and novel BACS characters) as a function of SOA. A repeated-measures ANOVA revealed VWM capacity estimates were significantly different across the stimulus sets, $F(2, 48) = 63.26$, $p < .001$ and varied across SOA, $F(3, 72) = 28.99$, $p < .001$. However, there was no interaction between SOA and stimulus set, $F(6, 144) = .52$, $p = .80$. Planned contrasts were conducted to further investigate the differences between stimulus sets. VWM capacity across all SOAs, were 2.8 for English letters, 1.8 for trained BACS characters and 1.6 for novel BACS characters. VWM capacity was significantly higher for English letters than the average of the BACS characters, F(1, 24) = 134.34, $p < .001$. However, capacity estimates were not significantly different between the trained and novel BACS characters, $F(1, 24) = 1.07$, $p = .31$. Capacity estimates across all stimuli, were 1.9, 1.9, 2.0 and 2.4 at 120 ms, 130 ms, 160 ms and 200 ms respectively. Follow-up contrasts were conducted to investigate the differences between capacity estimates for the various SOAs. Estimates were significant lower at the two shortest SOAs (120 ms and 130 ms) than at the two longest SOAs (160 and 200 ms), $F(1, 24) = 30.50$, $p < .001$. The capacity estimates were not significantly different between the two shortest SOAs (120 ms and 130 ms), $F(1, 24) = .004$, $p = .95$, but were significantly higher at 200 ms than at 160 ms, $F(1, 24) = 51.18$, $p < .001$.

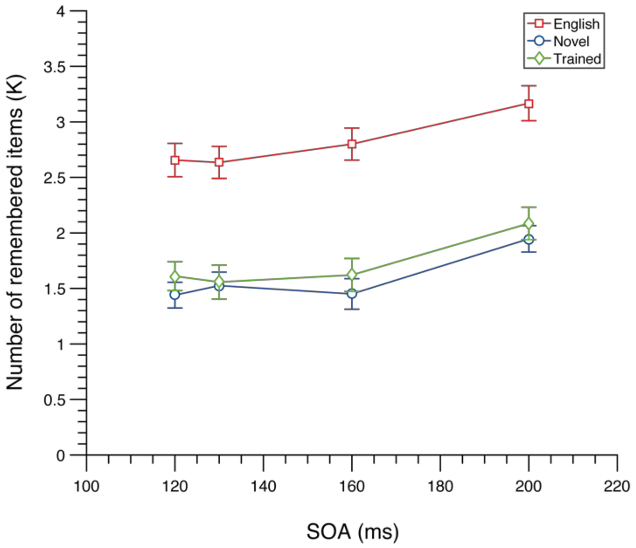


Figure 2-8. VWM capacity estimates at each SOA for each of the three character sets in Experiment 3: English letters are shown in red, novel BACS characters in blue and trained BACS characters in green. Error bars show ±1 SEM across subjects.

2.5.2.3 Encoding rate

To estimate each participant's encoding rate for each stimulus set, we found the best-fitting line through the VWM capacity estimates (*K*) as a function of SOA. The mean encoding rate was 6.7 items per second for English letters, 6.2 items per second for trained BACS letters and 5.8 items per second for novel BACS letters (*Figure 2-9*). Encoding rate did not vary significantly across the three stimulus sets, *F*(2, 48) = .19, *p* = .83. This is consistent with the non-significant interaction of stimulus set and SOA in change-detection performance.

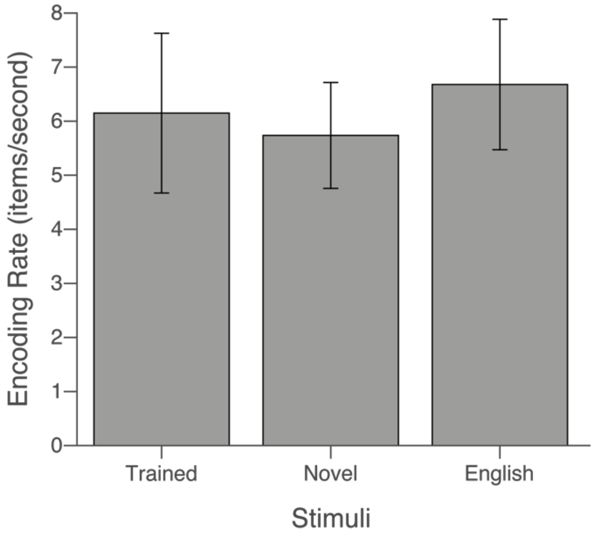


Figure 2-9. Mean encoding rate for trained BACS characters, novel BACS characters and English letters. The encoding rates were estimated by taking the slope of the line of best fit through each individual's *K* estimates as a function of SOA. Error bars show ±1 SEM.

This result is at odds with the findings of Experiment 1, in which we found a faster encoding rate of English letters compared to BACS characters. However, this may be due to differences in modelling methods: In Experiment 1, we fixed the intercept of the initial 'encoding' line to the origin, whereas we applied no such restriction for the intercept to the line of best fit in Experiment 3. We re-modelled the current data, requiring the line of best fit to pass through the origin. Mean encoding rate for English (*M* = 7.3, *SD* = 2.0) was significantly faster than BACS characters (*M* = 4.8, *SD* = 1.6), *t*(24) = 6.50, *p* < .001. The encoding rate did not differ significantly between trained BACS characters (*M* = 4.9, *SD* = 2.1) and novel BACS characters (*M* = 4.6, *SD* = 1.6), *t*(24) = .87, *p* = .39. *Figure 2-10* shows the mean encoding rates for the three stimulus sets. This alternative analysis replicates the finding of Experiment 1 that encoding rate was significantly faster for familiar English characters than for BACS characters.

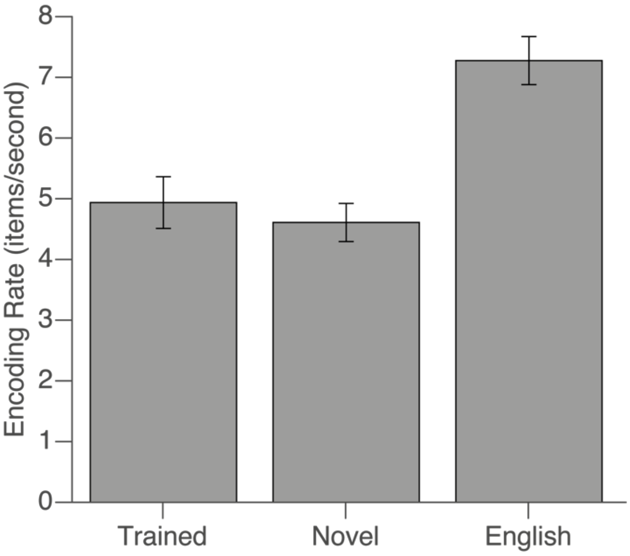


Figure 2-10. Mean encoding rate for trained BACS characters, novel BACS characters and English letters using an alternative modelling procedure. Encoding rate for each stimulus set and participant was estimated by taking the slope of the line of best fit through *K* as a function of SOA, with the line constrained to pass through the origin. Error bars show ±1 SEM.

2.5.3 Discussion

In Experiment 3, we examined whether recognition training would influence VWM encoding rate by examining change-detection performance at very short stimulus durations. We found that change-detection performance, across all SOAs, was significantly higher for English letters compared to BACS characters. There was no statistically discernible difference between the novel and trained BACS characters, suggesting there was no influence (or a negligible influence) of training. There was a significant effect of SOA on change-detection performance, suggesting improvement with increased time allowed for encoding. We computed the line of best fit to the change in *K* across these short SOAs, using its slope to estimate the encoding rate. There were no significant differences in encoding rate between all three stimulus sets, suggesting English letters produced an overall advantage independent of stimulus presentation times. However, this was inconsistent with our findings from Experiment 1. After fixing the line of best fit to the origin (i.e., assuming that encoding begins at stimulus onset), we replicated the finding of Experiment 1 that encoding rates were significantly higher for English characters than for BACS characters.

2.6 General Discussion

VWM is limited to storing approximately three to four items at a time. Researchers have scrutinised factors influencing this capacity limit—particularly stimulus complexity and item similarity. A less-researched factor is stimulus familiarity, despite its potential influence on the perceived complexity and similarity of the stimuli. Stimulus familiarity also appears to improve VWM performance, although there have been mixed findings with respect to the effects of training. The goal of the present study was to isolate the influence of familiarity on two aspects of VWM, the encoding rate and capacity limit.

2.6.1 Familiarity

In the present study, we compared change-detection performance for familiar English letters to the unfamiliar Brussels Artificial Character Set (BACS). BACS characters match the number of strokes, junctions and terminations of each English letter, and similarity ratings between these characters is equivalent to ratings between English letters (Vidal et al., 2017). Additionally, we controlled stimulus complexity by selecting a font for English letters that matched the perimetric complexity of the BACS characters. Change-detection performance for English letters was significantly better than for BACS characters across multiple experiments. At longer SOAs, allowing sufficient encoding time to saturate VWM, we observed significantly higher estimates for the English letters over BACS characters, suggesting familiarity produces robust increases to VWM storage capacity.

The effect of familiarity at shorter SOAs is less clear. In Experiment 3, although we observed an overall advantage for English letters compared to BACS characters, we did not observe a difference in encoding rate; this was inconsistent with the faster encoding rate for English letters we observed using the same SOAs in Experiment 1. However, in Experiment 1, we estimated encoding rates from the line of best fit passing through the origin, whereas we allowed the intercept to vary freely in Experiment 3. By fixing the intercept of the fit line to the origin as in Experiment 1, we replicated the original finding. Modelling with a fixed intercept at the origin produces more reliable estimates for at least two reasons. First, allowing a freely varying intercept produces unreliable encoding rate estimates for some participants in Experiment 1, because they relied on only one or two data points at the shortest SOAs. Second, because only short SOAs were used in Experiment 3, we were unable to determine if capacity had or had not been saturated. For observers who reached their capacity limit prior to our longest SOA (200 ms), the resulting horizontal section of the function would have a greater influence on an unconstrained line of best fit and lead to underestimated encoding rates. In any case, it is clear there is an advantage in change-detection performance for English letters compared to BACS characters.

2.6.2 Training

Having identified benefits of familiarity for English letters compared to BACS characters, we examined whether training observers to become familiar with BACS characters would generate similar improvements to VWM performance. Previous research regarding newly acquired familiarity with stimuli has produced mixed results, with some finding subsequent improvements in change-detection (Blalock, 2015), while others have not (Chen et al., 2006). We replicated a training procedure that had produced increased capacity for trained random polygons (Blalock, 2015) and examined subsequent change-detection performance at both short SOAs (targeting consolidation into VWM) and long SOAs (targeting VWM capacity). Observers successfully learned to recognise the BACS characters, but there was no difference in subsequent change-detection performance compared to novel BACS characters at either short or long SOAs. As such, encoding rates and capacity were not increased for trained versus novel BACS characters. These results suggest recognition familiarity was insufficient to produce improvements to VWM processes. Our results mirror those reported by Chen *et al.* who found no improvement in change-detection performance for random polygons trained to perfect recognition. This also converges with the finding that observers who are trained to identify English letters with the same efficiency as native readers do not obtain the same memory span for those letters. Native readers have a memory span of approximately four to five letters, whereas trained observers have a memory span closer to two letters (Pelli et al., 2006).

The mechanism driving the influence of familiarity on VWM processing appears to be more complex than simply invoking LTM representations. While we found significantly better change-detection performance for familiar English letters compared to BACS characters, we found no effect of recognition training on change-detection performance. This is despite—in the case of recognition training in the present study— the fact that some form of LTM representation has been built that allowed observers to distinguish between trained and untrained stimuli. These results suggest improvement in VWM performance with familiarity requires extended experience with the stimuli, such as previously shown with Pokémon (Xie & Zhang, 2017a, 2017b), famous faces (Buttle & Raymond, 2003; Jackson & Raymond, 2008), and in the present study with English letters. On the other hand, newly-acquired familiarity, such as from recognition training (as in the current study) or procedural training (Olson & Jiang, 2004), does not seem to produce robust improvements in change-detection performance. This discrepancy calls for a revision of ideas about the mechanism by which LTM representations produce improvements in VWM. One possibility is that familiarity allows participants to selectively attend to the distinguishing features of stimuli, effectively reducing subjective stimulus complexity, for encoding and storage, or reducing stimulus similarity at the comparison stage. That is, observers are better equipped at distinguishing stimuli between memory and test using an accessible LTM representation for familiar stimuli. Observers may also be faster to encode familiar stimuli into VWM by prioritizing the distinguishing features (Xie & Zhang, 2017b, 2018), such that VWM representations durable to interruption from backward masking are created earlier. For example, consider the familiar English letters used in the present study. Dehaene, Cohen, Sigman and Vinckier propose (2005) extensive experience with English letters produces dedicated shape detectors specific in the visual system. These letter detectors then provide an efficient neural pathway for encoding English letters. Neuroimaging studies have identified the *visual word form area*, a region in the left inferior occipitotemporal cortex, which shows specific activation in response to words and consonant strings but not line drawings or digit strings (Dehaene, Le Clec'H, Poline, Le Bihan, & Cohen, 2002). Moore, Cohen and Ranganath (2006) trained observers to become experts in a set of random polygons during several training sessions totalling over 10 hours. This extensive training was associated with increased activity in the aforementioned occipitotemporal cortex, as well as in the dorsolateral prefrontal cortex and intraparietal sulcus, during encoding and maintenance on a VWM task. These areas were not recruited for the same task with novel polygons, nor for polygons that had been trained to familiarity using a match-to-sample task (similar to our recognition training), just prior to the neuroimaging session. This parallels our findings with the familiar English letters, trained and novel BACS characters. Our recognition training may thus have been insufficient to develop the efficient neural pathways required for improved VWM processing, that exist already for the familiar English letters.

2.6.3 Conclusion

We found an influence of familiarity on VWM processes, demonstrating improvements in change-detection performance for English letters compared to BACS characters. Although observers learned to recognise and distinguish trained BACS characters from novel BACS characters, change-detection performance for trained BACS characters was no better than for novel ones. We conclude that recognition training is insufficient to produce the improvements in VWM performance observed for expertly familiar stimuli such as English letters. We suggest that efficient neural pathways may be recruited to improve

VWM performance for familiar letters. Although recognition training did produce some form of LTM for novel stimuli, this in itself was insufficient to generate such efficient neural pathways. The role of LTM representations should be clearly formalised to elucidate how familiarity improves VWM performance.

Chapter 3: "Memory Compression" Effects are Contingent on Explicit Awareness Of Statistical Regularities

This is an edited version of a manuscript currently under review at the *Journal of Experimental Psychology: General*.

3.1 Abstract

In Chapter 2, we examined the influence of familiarity on two measures of visual working memory (VWM) and found significantly higher encoding rate and capacity for familiar English letters than for unfamiliar BACS characters. Training observers to recognise the unfamiliar characters, which match English letters in similarity and complexity, did not produce improvements. Here, we investigated another example of apparently increased VWM capacity reported by Brady, Konkle and Alvarez (2009). They argued observers were able to expand their VWM capacity via visual statistical learning. In a task requiring WM recall, they found robust performance enhancements when specific colours were more likely to appear together. However, this is inconsistent with previous findings showing no improvement in VWM performance following repetitions of specific displays. Here. we replicated this effect in two experiments, but only observed the effect in subjects that could perfectly and explicitly recall the repeated colour pairs at the end of the study. These findings argue against the hypothesis that statistical regularities elicit automatic compression of information in visual working memory. Instead, improved recall may rely on paired associate learning at retrieval.

3.2 Introduction

The visual working memory (VWM) system is responsible for the maintenance and manipulation of online information that is required for perception and cognition. Despite its importance, the system has a surprisingly severe capacity limit of approximately 3-4 items (Luck & Vogel, 1997). Given that measures of an individual's VWM capacity strongly correlate with measures of cognitive ability such as fluid intelligence and scholastic achievement (Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Cowan, Chen, & Rouder, 2004; Fukuda et al., 2010; Unsworth et al., 2014a; Xu, Adam, Fang, & Vogel, 2017), there is sustained interest in how VWM capacity might be enhanced to overcome this capacity limit. An influential paper by Brady, Konkle and Alvarez (2009) reported apparent increases in VWM capacity with statistical learning. They demonstrated that when specific pairs of colours were more likely to appear in the memory display, observers were able to use this to their advantage and improve recall accuracy. Brady *et al.* (2009) argued that this improvement comes from an increase in the amount of information that can be held concurrently in VWM via the compression of information. However, this contradicts previous research suggesting that the VWM system is inelastic. For example, VWM performance is unchanged by repetitions of the same display (Olson & Jiang, 2004). This current pair of experiments investigated the mechanism of learning that produces enhanced memory performance, and how any changes would be reflected in the architecture of VWM.

3.2.1 Chunking

Working memory limits have classically been explained using *chunking.* Miller (1956) proposed learning allowed greater amounts of information to be stored more efficiently as chunks, with the absolute number of chunks stored into memory remaining constant. For example, experts recall chess positions from real matches significantly more accurately than novices (Chase & Simon, 1973). It is believed chess experts do not have a larger overall VWM capacity than novices but instead use their expertise to efficiently chunk game positions, which novices cannot do.

3.2.2 Embedded process models

Embedded process models of WM provide a more nuanced framework to evaluate how the VWM system changes to yield improvements in memory recall performance. These models hypothesise WM is a collection of memory processes engaging both offline and online representations (e.g. Cowan, 1999; Ericsson & Delaney, 1999; Jonides et al., 2008; Oberauer, 2002). For example, Cowan's (1999) embedded process model proposes a base layer containing the entire long-term memory (LTM) content. Within this layer, a specific subdivision of LTM maintains content that is still offline but readily accessible due to priming or recent activation of the content. The highest layer includes only the representations that can be maintained online or in the "focus of attention". It is this highest layer that is typically addressed when researchers examine the highly limited capacity of VWM. Various conceptions of embedded process models may differ in the number of layers and the capacity limit within each layer, but all acknowledge that complex tasks engage interactions between LTM and WM.

3.2.3 Effects of training and learning on visual working memory

Findings regarding whether training can improve VWM have been mixed. Olson and Jiang (2004) examined whether VWM could improve in the absence of chunking cues. Participants were required to memorise the locations of either six, nine or twelve squares before being shown a probe. On half of the trials the probed location was not in the previous display (a change trial), and on the other half the probed location had been shown in the previous display (a no-change trial). Across 24 blocks of 12 trials each, a subset of six displays was kept identical and presented once in every block, intermixed with six displays newly generated for each block. Participants showed above-chance recognition of the repeated displays but were surprisingly no better at change-detection for those displays. Having above-chance recognition suggests participants had encoded the repeated displays into LTM, but could not use these LTM traces to assist VWM performance. Olson, Jiang and Moore (2005) were only able to produce improvement in change-detection accuracy once the changed location was consistently associated with the repeated display. This improvement disappeared when the association between change location and display was removed, suggesting that participants were prioritising the associated location for encoding into VWM, rather than any overall increase in VWM capacity.

A recent demonstration that explicit associate learning can boost performance in a WM task comes from Chen and Cowan (2009). Participants were trained on word lists of various lengths such that they would perfectly recognise whether a cued word was a singleton, or explicitly recall the associated word partner if the word belonged to a word-pair. Assuming learned word pairs effectively became two-word chunks, Chen and Cowan (2009) showed WM capacity was constant at approximately 3 chunks, suggesting that training enabled subjects to retrieve the learned word partner from LTM and doubling the number of individual words recalled. Critically, this account does not require any change to capacity of VWM, as the associated knowledge can be retrieved at the time of test. Further evidence for this explanation of memory compression effects come from a study that measured the time to access colours stored in VWM with and without the benefits of statistical regularities (Huang & Awh, 2018). Huang and Awh replicated the benefits of statistical regularities observed by Brady *et al.* (2009), but showed these manifest only when subjects have a relatively long period of time (~1 sec) to respond following the test probe. Thus, contrary to what might be expected if the additional information was held online in WM, access to the associated information was quite sluggish. A natural explanation for this finding is that subjects exploited statistical regularities by encoding the colour pairs in LTM, and then retrieved the needed information when the test probes were presented. Here again, this explanation does not require any change in the number of representations that can be maintained in the focus of attention.

3.2.4 Visual statistical learning

In contrast to the interpretation offered by Huang and Awh (2018), Brady *et al.* (2009) argued statistical learning enabled the compression of information held in WM. In this way, a larger number of colours was concurrently maintained online during the WM task. This interpretation was motivated by past studies of *visual statistical learning* (Fiser & Aslin, 2001, 2002; Turk-Browne et al., 2005, 2008) suggesting that observers can learn subtle statistical relationships automatically and without awareness of those regularities (Chun & Jiang, 1999; Turk-Browne et al., 2005, 2008). For example, observers gained knowledge of the structure of the base shapes that made up a complex visual scene even though this was irrelevant to the task (Fiser & Aslin, 2001). Visual statistical learning is often thought to involve unconscious statistical computations, forming the required associations between elements for the efficient chunking of information (Perruchet & Pacton, 2006). In fact, statistical learning bears so much similarity to implicit learning that some believe they are produced by the same general mechanisms (Perruchet & Pacton, 2006; Turk-Browne et al., 2008). The fact that statistical learning can occur in the absence of awareness also implies that such learning may help to optimise processing in familiar contexts while minimizing the load on limited-capacity systems for perception and selection. In line with this interpretation, Brady *et al.* (2009) reported that subjects who reported noticing the regularities did not show a larger memory compression effect than the subjects who did not report explicit awareness of the colour pairs. That said, there were very few subjects who did not report awareness of the regularities in Brady *et al.*'s study. Thus, a more sensitive test of this key question is required.

3.3 Experiment 1

We replicated Brady *et al.*'s (2009) study but included a task explicitly testing subjects' awareness for the colour pairs. Brady *et al*. also queried subjects about whether they had noticed the pairings, and found that the benefit was not reliably different between subjects who reported noticing the pairs and those who did not. An important caveat for this conclusion, however, is that there were only ten subjects in the relevant condition of the studies reported by Brady *et al*. Thus, the null result in question—equivalent compression effects in subjects who did and did not notice—included only three (Experiment 1) and two (Experiment 2) subjects who did not notice the regularities. Here, we collected data from a total of 64 subjects (32 in each of Experiments 1 and 2), each of whom participated in both patterned (i.e., with statistical regularity) and the uniform (i.e., without statistical regularity) conditions. This within-subjects design, combined with an objective test of subjects' knowledge of the colour pairings, provided a more sensitive test of whether memory compression effects were linked to explicit knowledge of the colour pairs.

3.3.1 Method

3.3.1.1 Participants

Thirty-two subjects (19 females) were recruited from the local University of Chicago community and received monetary compensation (US$10 per hour) for their participation. All subjects provided informed consent to procedures approved by the University of Chicago Institutional Review Board. All reported normal or corrected-to-normal vision and no impairment to colour vision.

3.3.1.2 Apparatus

Stimuli were generated using the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) in MATLAB and presented on a 24-inch BenQ XL2430T LCD monitor with spatial resolution set to 1920 × 1080 and a 120 Hz refresh rate. Observers viewed stimuli in a dark room from a distance of approximately 70cm.

3.3.1.3 Stimuli

Stimulus displays contained eight colours (red, green, blue, magenta, cyan, yellow, black and white) arranged in four pairs around a fixation point (*Figure 3-1b*). All colours were presented as squares with side length of 1.8° of visual angle or as circles with diameter 1.8°of visual angle (see *Manipulation*). The four pairs were presented in fixed, equidistant locations 1.7° of visual angle from the central fixation point. Items within a pair were separated by a centre-to-centre distance of 2.0°.

3.3.1.4 Manipulation

Observers completed a set of blocks for each condition, a *patterned* set and a *uniform* set. A different shape was used in each set of blocks in an attempt to reduce carryover effects from completing the first set. That is, if observers completed the first set of blocks with colour squares, the second set was completed with colour circles (or vice versa). Both starting shape and condition were counter-balanced across observers.

In the uniform condition, colours were chosen randomly such that it was equally likely for a colour to be paired with any other colour. In the patterned condition, colours were not chosen randomly. A joint probability matrix was constructed containing the probabilities of each possible colour pair being selected. The diagonal of this matrix was set to zero to prevent pairs of the same colour. Each observer was assigned four high-probability pairs (probability = 80/372) randomly with the constraint that a colour could only be assigned once to a high-probability pair. The fifty-two remaining possible colour pair combinations were given an equal probability (probability = 1/372). On each trial, four pairs were randomly drawn from this probability matrix without replacement, with the restriction that a colour could not be drawn more than once.

In the final block of the patterned condition, the regularities in colour pairings were removed, such that it was identical to a block in the uniform condition. This allowed us to quantify the amount of learning that had occurred, by taking the difference in performance between the average of the first nine blocks and the final block. This also allowed us to compare performance in the final block of both conditions, to check any improvements in recall performance were a function of the statistical regularity and not generalised improvements in recall.

3.3.1.5 Procedure

Observers completed a total of 20 blocks (10 from each of the two conditions) of 60 trials each. Observers completed all blocks within a condition prior to starting the other condition.

The general procedure for each trial is shown in *Figure 3-1a*. At the beginning of each trial, a fixation point was displayed for 750 ms. Four colour pairs were presented surrounding the fixation for 1000 ms. Observers were instructed to remember the colour of each item. After a delay period for 1000 ms, observers were probed to recall a colour from a randomly selected location, outlined with a thicker black line (*Figure 3-1b*). Below the probe display, an array of all colours was presented. The observer was instructed to click on the colour below the display they thought was presented previously at the probed location.

After completing both sets of blocks, observers were tested on their ability to recall the colour pairs. Observers were presented a colour in the middle of the screen and asked to click on the colour they thought was most likely to appear with the presented colour (*Figure 3-2*).

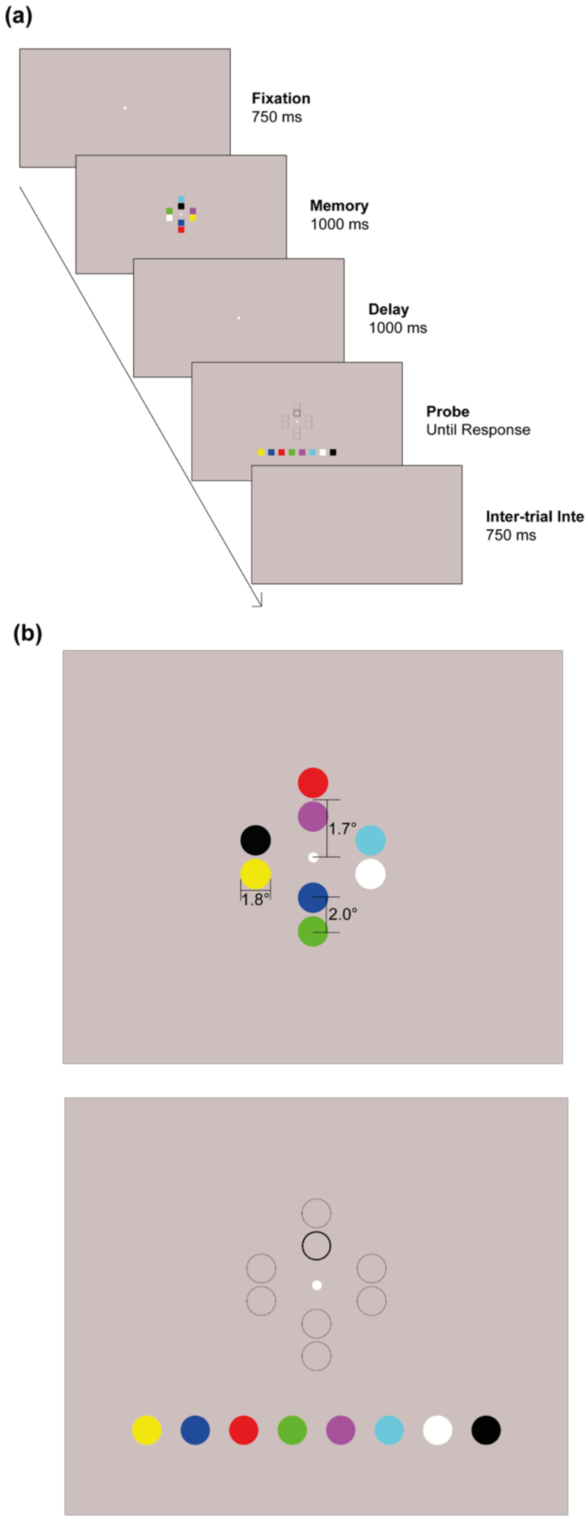
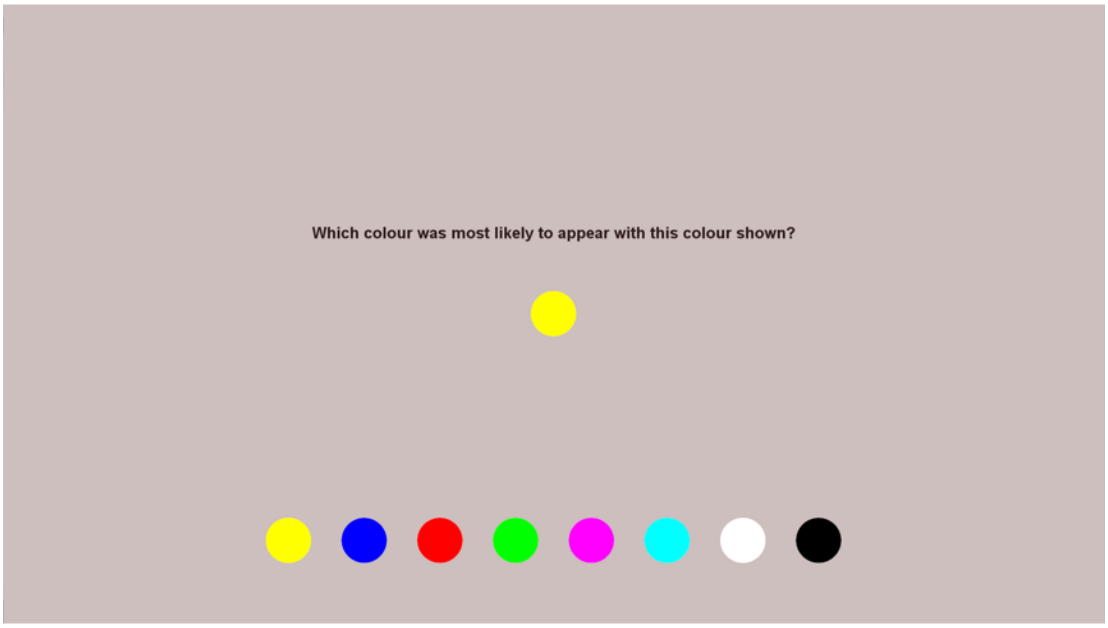


Figure 3-1. Procedure and stimuli for the experiments in the present chapter. (a) Example of the procedure for a single trial of the experiment. A fixation dot was presented for 750 ms before eight colours appeared arranged in four pairs around the fixation point for 1000 ms.

After a 1000 ms delay, observers were instructed to click on the colour of the item probed with the thicker border. A 750 ms inter-trial interval with a blank screen followed the response. (b) Examples of the stimuli (top) display and probe (bottom) displays. Distance are shown in degrees of visual angle.



Which colour was most likely to appear with this colour shown?

Figure 3-2. Test for awareness of statistical regularities. Observers were shown each colour in the middle of the screen and asked to click on the colour that was most likely to appear with the colour shown.

3.3.2 Results

We measured VWM performance using the proportion of correct responses (*PC*) for each block. These were used to estimate the number of colours observers could recall (*K*) using the following formula from Brady *et al.* (2009) (see *Appendix* for derivation):

$$K = \frac{[(PC \times 8 \times 8) - 8]}{7} \qquad (\textit{Equation 3-1})$$

3.3.2.1 Performance across conditions

We replicated the advantage Brady *et al.* (2009) reported in the patterned condition (*Figure 3-3*). We observed a statistically significant effect of condition (patterned vs. uniform), $F(1,31) = 41.30$, $p < .001$ and a statistically significant effect of block, $F(8, 248) = 8.96$, $p < .001$. There was a significant interaction between condition and block, $F(8,248) = 8.66$, $p < .001$. Capacity for colours increased significantly across blocks in the patterned condition, $F(8,248) = 13.33$, $p < .001$, whereas performance did not change across blocks in the uniform condition, $F(8,248) = 1.04$, $p = .40$. There was no significant difference in performance in the first block across conditions, $t(31) = 1.04$, $p = .31$, but performance in following blocks was significantly higher in the patterned condition, all $t(31) > 2.39$, all $p < .02$. In the last block, in which regularities were removed in the patterned condition, performance was not significantly different from performance in the uniform condition, $t(31) = 1.79$, $p = .08$.

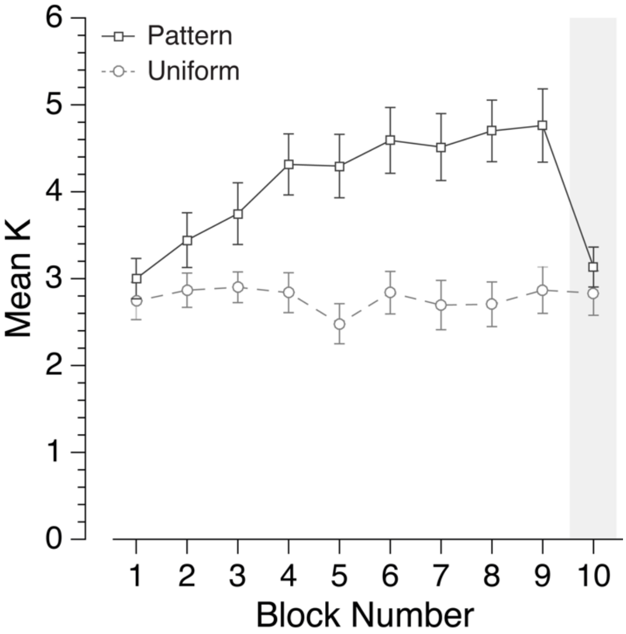


Figure 3-3. Mean number of items remembered (*K*) in each block for both patterned (dark squares) and uniform (light circles) conditions. The shaded bar marks the last block in which statistical regularities were removed from the patterned condition. Error bars indicate ±1 S.E.M.

Observers remembered 2.8 colours on average in the uniform condition. This is consistent with Brady *et al.*'s (2009) study, in which average *K* was 2.7 and 3.4 in Experiment 1 and 2 respectively. Observers remembered 4.8 colours on average after viewing the regularities in the stimulus displays (Block 9 of the patterned condition). This was significantly higher than the 3.1 colours remembered on average when the regularities were removed from the displays (Block 10 of the patterned condition), $t(31) = 5.29$, $p < .001$. Thus, we replicated the learning effects observed by Brady *et al.*

3.3.2.2 Postperceptual inference

To test whether observers stored a single colour from each pair, and then inferred the identity of the other colour at the end of the trial, Brady et al. (2009) examined whether observers were more likely to erroneously report the high-probability colour associate of the adjacent item. Given such a strategy, observers would guess incorrectly on trials in which a low-probability pair was probed, systematically guessing the typical partner of the adjacent colour. For example, if the observers had learned a blue–green colour pairing, this kind of postperceptual inference would bias them to report green when blue was paired with a low probability partner. Brady *et al.* (2009) found no such effect and concluded that postperceptual inference did not play a role in the memory compression effect. We observed the same result. On average, 76 trials per observer (2427 trials across 32 observers, 14% of total trials) tested a low-probability pair. If observers were inferring the colours of the display using the high-probability pairings, their responses would more often be the high-probability colour of the adjacent item. However, observers reported the high-probability colour of the adjacent item only 11% of the time (where chance is 1/7 or 14%). In addition, we found that observers' performance improved over blocks when considering only trials in which the low-probability pair was probed (*Figure 3-4*). *K* when low-probability pairs were probed (*M* = 3.8) was significantly greater in Block 9 of the patterned condition than in Block 10 of the patterned condition, when all pairs were low-probability (*M* = 3.1), *t*(31) = 2.66, *p* = .012. These findings suggest that high probability pairs required a smaller portion of limited mnemonic resources, thereby enhancing performance for other items in the display.

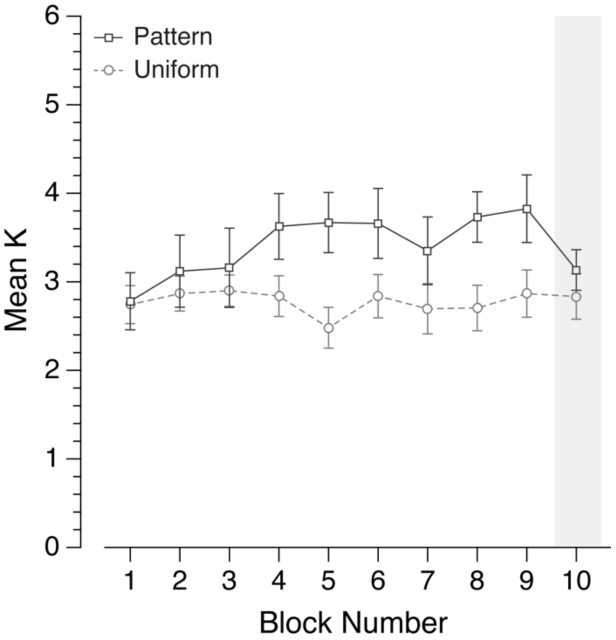


Figure 3-4. Mean number of items remembered (*K*) for each block, including only trials in which a low-probability pair was probed. The shaded area marks the last block, in which statistical regularities were removed from the patterned condition. Error bars indicate ±1 S.E.M.

Thus, our findings support the conclusion of Brady *et al.* that subjects were not encoding a single item from each pair, and then using postperceptual inference to boost performance with high probability pairs. However, we note that this analysis does not rule out the possibility that subjects selectively stored a subset of colours after they recognised familiar pairs during encoding.

3.3.2.3 Primacy effects

Because we employed a within-subjects design, in which subjects participated in both the patterned and uniform conditions, we looked for possible carryover effects between conditions. Indeed, the order of conditions affected the size of the memory compression effect. A mixed three-way ANOVA revealed a statistically significant between-subject effect of condition order on performance, $F(1, 30) = 9.88$, $p = .004$. There were significant two-way interactions between condition order and the main effect of condition, $F(1, 30) = 8.22$, $p = .008$, and between condition order and the main effect of blocks, $F(8,240) = 2.08$, $p = .04$. There was a statistically significant three-way interaction between the condition order, the main effect of condition and the main effect of blocks, $F(8,240) = 3.02$, $p = .003$, suggesting that the difference in performance across blocks in the patterned and uniform conditions was significantly greater for observers that started with the patterned condition than observers that started with the uniform condition (*Figure 3-5*). Thus, the advantage in the patterned condition was reduced for subjects who experienced the uniform condition first (Jungé, Scholl, & Chun, 2007).

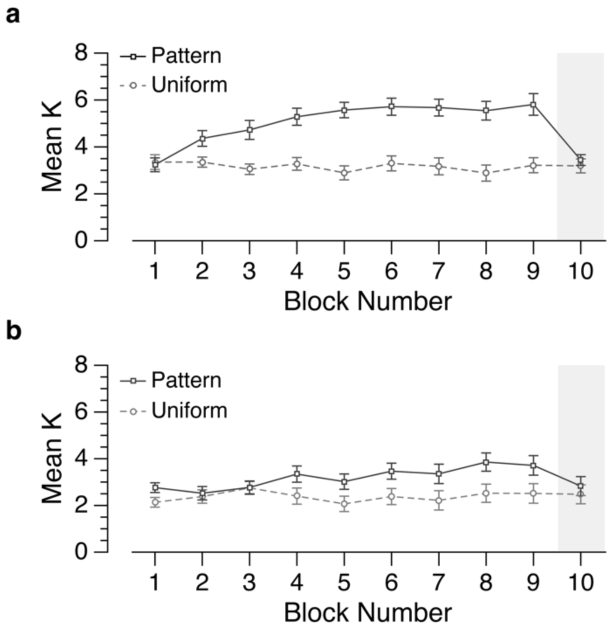


Figure 3-5. Mean number of items remembered (*K*) in each block as a function of within-subject block order (a) Subjects who completed the patterned condition first showed a larger improvement than (b) subjects who completed the uniform condition first. Error bars indicate ±1 S.E.M.

3.3.2.4 Are memory compression effects contingent on awareness?

The results thus far have provided a close replication of those reported by Brady *et al.* (2009). The central question, however, is whether memory compression effects are contingent on subjects' explicit knowledge of the colour pairings. We classified subjects as *aware* according to the strict criterion that they recalled all high probability pairs at the end of the study. While subjects with less-than-perfect performance may still have substantial awareness, the results show that subjects falling below this stringent criterion showed no evidence of the memory compression effect. Nineteen of the 32 observers were aware of the statistical regularities at the end of the experiment (5 out of the 16 observers who completed the uniform condition first and 14 out of the 16 observers who completed the patterned condition first).

A mixed three-way ANOVA (awareness; block; condition) revealed a main effect of awareness, with higher accuracy in the aware group (M = 57%) than in the unaware group (M = 40%), $F(1,30) = 17.59$, $p < .001$. There was a significant interaction between awareness and condition, $F(1,30) = 41.80$, $p < .001$, and between awareness and block, $F(8,240) = 2.08$, $p = .039$. Finally, there was a statistically significant three-way interaction between awareness, block and condition, $F(8,240) = 2.25$, $p = .025$ (*Figure 3-6*). For aware subjects, performance improved across patterned blocks while performance in the uniform condition did not change; thus, for these subjects there was a significant interaction between condition and block, $F(8,144) = 10.83$, $p < .001$. By contrast, for unaware subjects (those who could not report all the colour pairings at the end of the study), performance in the patterned and uniform conditions remained stable and equivalent throughout the study; thus, for these subjects there was no significant main effect of condition and no significant interaction between condition and block, $F(8,96) = 1.27$, $p = .27$. Therefore, the increase in the number of items remembered in the patterned condition was contingent on explicit awareness of the colour pairings.

We computed an effect size by subtracting performance in the 10th block from average performance in the first 9 blocks of the patterned condition to capture the amount of learning that occurred (see *Figure 3-7*). Mean effect size for aware observers was 17.9% whereas mean effect size for unaware observers was 1.3% (see *Figure 3-8*). A regression analysis showed that the number of correct responses on the awareness test was a significant predictor of effect size, $b = 2.68$, $SE_b = .68$, $t(31) = 3.92$, $p < .001$. Aware observers showed a significant difference in performance between the 9th and 10th blocks of the patterned condition, $t(18) = 6.82$, $p < .001$ whereas unaware observers showed no significant difference, $t(12) = .62$, $p = .55$. Thus, only aware observers remembered a reliably larger number of colours in the patterned condition.

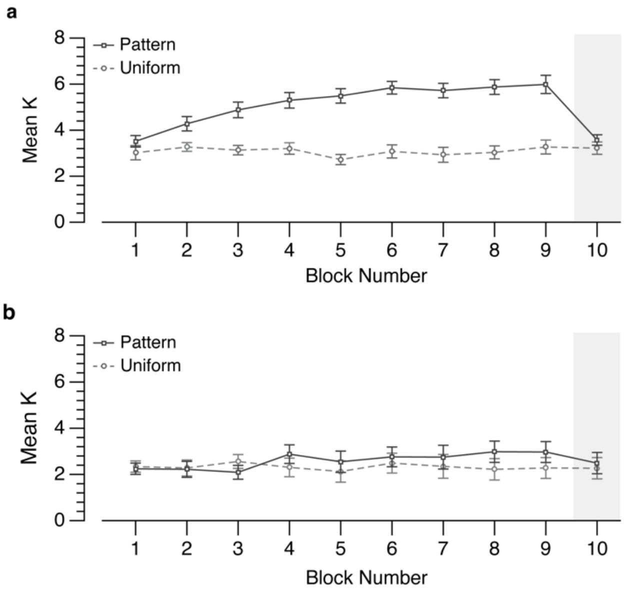


Figure 3-6. Average number of items remembered (*K*) in each block in Experiment 1 as a function of subject awareness. (a) Aware subjects, who correctly reported all colour pairings at the end of the study, showed improvement in the patterned condition. (b) Unaware subjects, who did not report all colour pairings correctly, did not show improvement. Error bars indicate ±1 S.E.M.

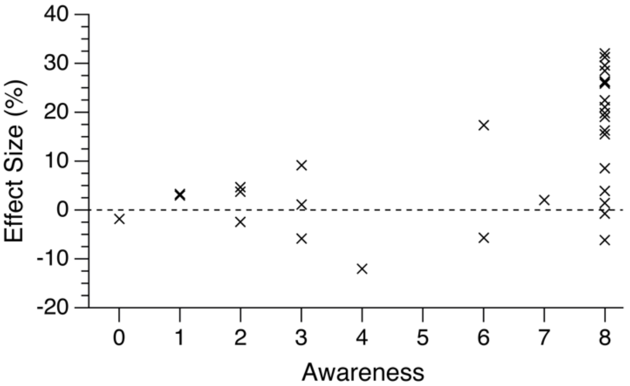


Figure 3-7. Effect size as a function of the number of items correct in the explicit awareness test of Experiment 1. Effect size was calculated by taking the difference in percentage correct between the final block and the average of the first nine blocks in the patterned condition.

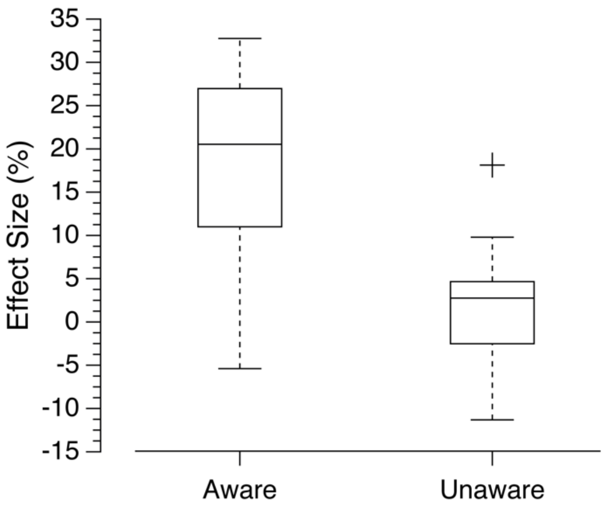


Figure 3-8. Box plot of effect size as a function of participant awareness in Experiment 1. Aware observers correctly reported all colour pairings in the explicit awareness test, while unaware observers did not. Effect size was calculated by taking the difference in percentage correct between the average of the first nine blocks and the ultimate block in the patterned condition.

3.4 Experiment 2

Most observers completing the patterned condition first were explicitly aware of the statistical regularities in the display, whereas observers completing the uniform condition first were mostly unaware of these regularities. Due to numerous trials without statistical regularities, observers who completed the uniform condition first may be primed to believe that no statistical regularities are present in the patterned condition. In Experiment 2, observers completed blocks of each condition in an alternating order, in an attempt to reduce the primacy effect observed in the blocked design of Experiment 1.

3.4.1 Method

The method was identical to Experiment 1 except for those aspects noted below.

3.4.1.1 Observers

Thirty-two observers were tested in total. Sixteen observers (9 females) were recruited from the local University of Chicago community and completed the experiment for monetary compensation (US$10/hour), and 16 observers (7 females) were recruited from the undergraduate psychology student population from the University of Sydney and completed the experiment for course credit. None of these subjects participated in Experiment 1. All reported normal or corrected-to-normal visual acuity and colour vision, and all gave informed consent.

3.4.1.2 Procedure

Observers completed a total of 20 blocks containing 60 trials each. Observers alternated between blocks of the two conditions: a *patterned* condition block followed by a *uniform* condition block, or vice versa. The stimulus shape (circles or squares) also alternated to be consistent with condition throughout the experiment. The starting condition and shape was counterbalanced across observers. Participants completed an awareness test after completing all trials.

3.4.2 Results

3.4.2.1 Performance across conditions

We observed a statistically significant main effect of condition (patterned vs. uniform), $F(1,31) = 36.72$, $p < .001$ but no significant main effect of block, $F(8,248) = 0.69$, $p = .70$. There was a significant interaction between condition and block, $F(8,248) = 4.42$, $p < .001$. Capacity significantly increased across blocks in the patterned condition, $F(8,248) = 2.15$, $p = .03$, whereas there was no change across blocks in the uniform condition, $F(8,248) = .93$, $p = .49$. There was no effect of condition in the first block, $t(31) = .70$, $p = .49$, but performance was significantly higher in the patterned condition in all subsequent blocks prior to the last, all $t(31) > 2.59$, all $p < .02$. In the last block, in which regularities were removed from the patterned condition, performance was not significantly different between conditions, $t(31) = .56$, $p = .58$.

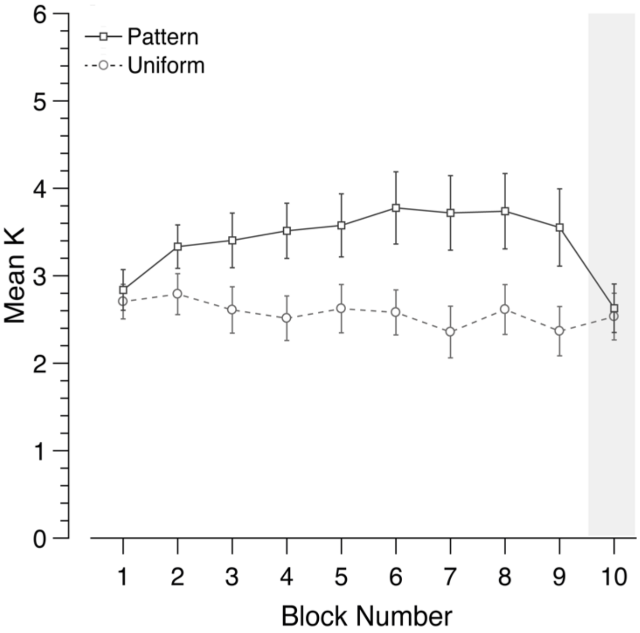


Figure 3-9. Mean number of items remembered (*K*) across blocks in Experiment 2. The shaded area indicates the last block, in which statistical regularities were removed from the

patterned condition. Error bars indicate ±1 S.E.M.

Observers remembered 2.6 colours on average in the uniform condition, consistent with mean performance reported by Brady *et al.* (2009) and Experiment 1 of the present study. Observers remembered 3.6 colours on average after viewing the regularities in the stimulus displays (Block 9 of the patterned condition). This was significantly higher than the 2.6 colours remembered on average when the regularities were removed from the displays (Block 10 of the patterned condition), $t(31) = 3.10$, $p = .004$.

3.4.2.2 Postperceptual inference

On average, 76 trials per observer (2419 trials across 32 observers, 14% of total trials) tested a low-probability pair. Observers reported the high-probability colour of the adjacent item only 11% of the time (where chance is 1/7 or 14%). As in Experiment 1, observers' performance varied significantly as a function of the number of high-probability pairs in the display ($K = 2.4, 2.8, 3.1, 3.3, 3.7$ for 0, 1, 2, 3, and 4 high-probability pairs respectively in the display, averaged across the entire experiment), $F(4,124) = 3.5$, $p = .01$.

3.4.2.3 Primacy effects

There was no significant interaction between condition order and the main effect of condition, $F(1,30) = .55$, $p = .46$, and there was no three-way interaction between condition order, the main effect of condition and the main effect of block, $F(8,240) = 0.65$, $p = .73$. This suggests that alternating between conditions every block eliminated the primacy effect observed in Experiment 1.

3.4.2.4 Awareness

Sixteen out of the 32 observers correctly identified all high-probability colour pairs. A mixed three-way ANOVA revealed a statistically significant main effect of awareness, $F(1,30) = 7.87$, $p = .01$. There was a significant two-way interaction between awareness and condition, $F(1,30) = 21.46$, $p < .001$, but not between awareness and block, $F(8,240) = 1.95$, $p = .054$. However, there was a significant three-way interaction between awareness, block and condition, $F(8,240) = 2.74$, $p = .007$.

To characterise the interactions between awareness and performance, we examined aware and unaware observers separately, as we did in Experiment 1. Among unaware participants, average performance was statistically higher in the patterned condition compared to the uniform condition, $F(1,15) = 19.76$, $p < .01$, but this effect was very small and did not change across blocks, $F(8,120) = 0.82$, $p = .59$. Moreover, there was no significant interaction between condition and block suggesting the trajectory for performance did not differ between the uniform and patterned conditions, $F(8,120) = .58$, $p = .79$. Indeed, the advantage in the patterned condition was over 30 times larger for aware (19.6%) compared to unaware (0.6%) participants, based on the difference between performance in the penultimate and final blocks in the patterned condition. The difference between the patterned and uniform conditions had a different trajectory across blocks, such that the learning effect grew with additional exposures in the aware subjects, but showed no such interaction with block in the unaware subjects. Among aware participants, K was significantly higher in the patterned condition, $F(1,15) = 155.10$, $p < .001$ but there was no main effect of block, $F(8,120) = 1.77$, $p = .09$. Importantly, there was a significant interaction between condition and block, $F(8,120) = 3.48$, $p = .001$, suggesting the change in performance across blocks was different between conditions (see *Figure 3-10*). That is, performance significantly improved in the patterned condition compared to the uniform condition for aware participants, but there was no improvement in either the patterned or the uniform condition for unaware participants.

To summarise, Experiment 2 replicated the finding that the advantage in the patterned condition was largely restricted to subjects with perfect explicit knowledge of the colour pairings (see *Figure 3-11*). Although there was a statistically reliable advantage in the patterned condition for unaware subjects, this effect does not appear to provide evidence for the cumulative effects of statistical learning: The effect was extremely small, and did not show the monotonic increase in number of items remembered across blocks observed by Brady *et al.* (2009) and in Experiment 1. The number of correct responses on the explicit awareness test was a significant predictor of the effect size, $b = 1.57$, $SE_b = .61$, $t(31) = 2.56$, $p = 0.016$ (*Figure 3-12*). Thus, Experiment 2 replicated the finding that the benefits of statistical regularities were strongly dependent on the degree to which observers acquired explicit knowledge of the colour pairings. Aware observers showed a significant difference in performance between the penultimate and last block of the patterned condition, $t(15) = 3.82$, $p = .002$, whereas unaware observers showed no significant difference, $t(15) = .26$, $p = .79$.

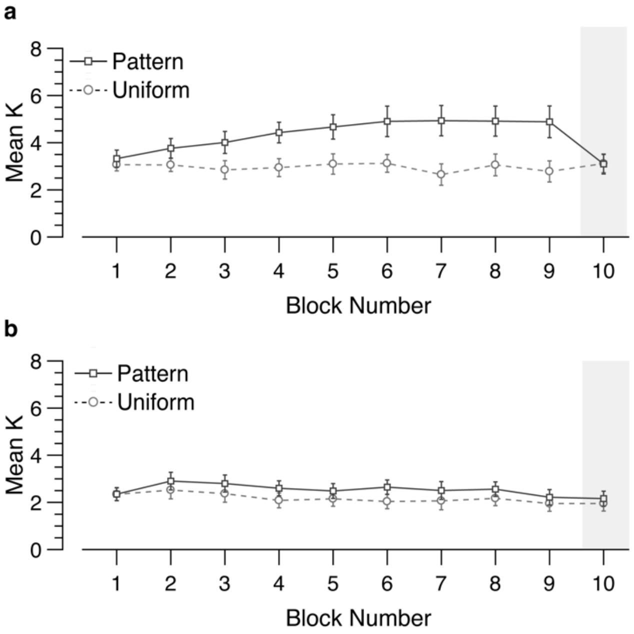


Figure 3-10. Average number of items remembered (*K*) in each block of Experiment 2 as a function of subject awareness. (a) Aware subjects, who correctly reported all colour pairings at the end of the study, showed improvement in the patterned condition. (b) Unaware subjects, who did not report all colour pairings correctly, did not show improvement. The shaded area indicates the last block, in which statistical regularities were removed from the patterned condition. Error bars indicate ±1 S.E.M.

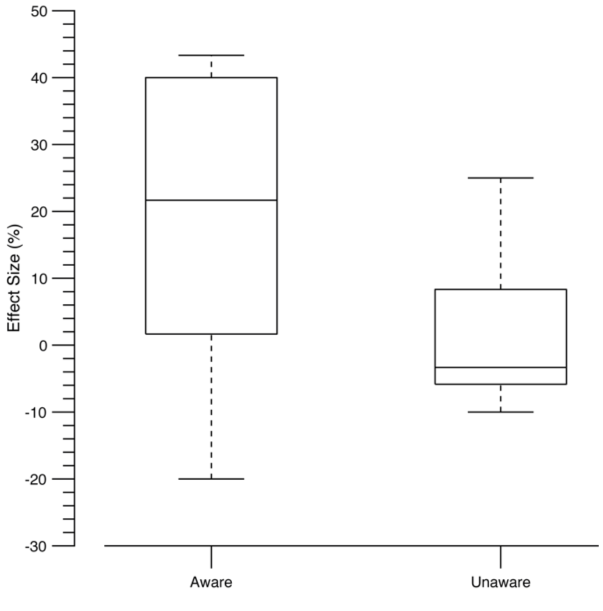


Figure 3-11. Box plot of effect size as a function of participant awareness in Experiment 2. Aware observers correctly reported all colour pairings in the explicit awareness test, while unaware observers did not.

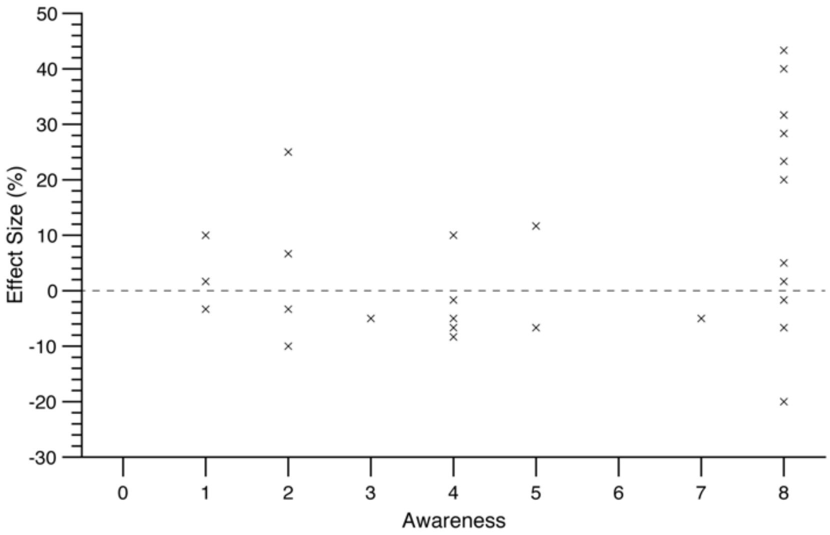


Figure 3-12. Effect size as a function of the number of items correct in the explicit awareness test of Experiment 2. Effect size. Effect size was calculated by taking the difference in percentage correct between the final block and the average of the first nine blocks in the patterned condition.

3.5 Aggregated results

We compared the data across experiments to check for significant differences in results, and aggregated the data across experiments to increase sensitivity. In Experiment 1, participants completed all the blocks within one condition (*patterned* blocks or *uniform* blocks) before the other, whereas in Experiment 2, participants completed the blocks from each condition in alternating fashion. We expected any significant differences would likely be due to this difference in block order.

3.5.1 Comparison between experiments

We conducted a mixed ANOVA with three factors: condition, block and experiment. The effect of condition on memory performance was not significantly different between experiments, $F(1,62) = 3.06$, $p = .09$, nor was the effect of block between experiments, $F(8, 496) = 1.90$, $p = .06$. Additionally, the interaction between the condition and block was not significantly different between experiments, $F(8,496) = 1.32$, $p = .23$. To further investigate the difference in performance across blocks, we analysed the patterned blocks and uniform blocks separately. Memory performance significantly increased across blocks in the patterned condition, $F(8,496) = 11.72$, $p < .001$, and this increase was significantly different between experiments, $F(8,496) = 2.07$, $p = .037$, indicating that the learning effect was significantly larger in Experiment 1 than in Experiment 2. There was no main effect of block in the uniform condition, *F*(8,496) = .96, *p* = .46, and performance was not significantly different between experiments, *F*(8,496) = 1.00, *p* = .44.

These results indicate that the improvement in memory performance in the patterned condition was significantly larger in Experiment 1, in which blocks containing statistical regularities were grouped together than in Experiment 2, in which patterned blocks alternated with blocks that did not contain statistical regularities.

3.5.2 Overall effects

Collapsing the data across both experiments, memory performance was significantly better in the patterned condition compared to the uniform condition, *F*(1,63) = 74.07, *p* < .001, and significantly changed across blocks, *F*(8,504) = 4.73, *p* < .001. The change in memory performance across blocks was significantly different between the conditions, *F*(8,504) = 12.49, *p* < .001. Consistent with our previous analyses, memory performance significantly increased in the patterned condition, *F*(8,504) = 11.52, *p* < .001, but did not change across blocks in the uniform condition *F*(8,504) = .96, *p* =.46.

3.5.3 Effect of awareness

Across both experiments, there were 35 aware participants (19 from Experiment 1 and 16 from Experiment 2), and 29 unaware participants (13 from Experiment 1 and 16 from Experiment 2). The difference in memory performance between conditions (see *Figure 3-14)* was significantly different between aware and unaware participants, *F*(1,62) = 60.65, *p* < .001. The memory advantage in the patterned condition over the uniform condition was significantly different between aware and unaware participants, *F*(8,496) = 4.59, *p* < .001. This is consistent with the pattern of findings in both Experiment 1 and 2.

In unaware participants, memory performance was significantly higher in the patterned condition than in the uniform condition, *F*(1,28) = 7.71, *p* = .01, but did not change across blocks, *F*(8,224) = .31, *p* = .96. Additionally, the interaction between condition and block was not significant, *F*(8,224) = 1.17, *p* = .32. By contrast, aware participants showed a significant difference in memory performance between conditions, *F*(1,34) = 159.98, *p* < .001, and a significant change across blocks, *F*(8,272) = 8.46, *p* < .001. Critically, aware participants showed a significant interaction between block and condition, *F*(8,272) = 16.17, *p* < .001, indicating that only aware participants show significant improvement in the patterned condition compared to the uniform condition. Unsurprisingly, this pattern of findings was consistent with the results of both Experiment 1 and 2.

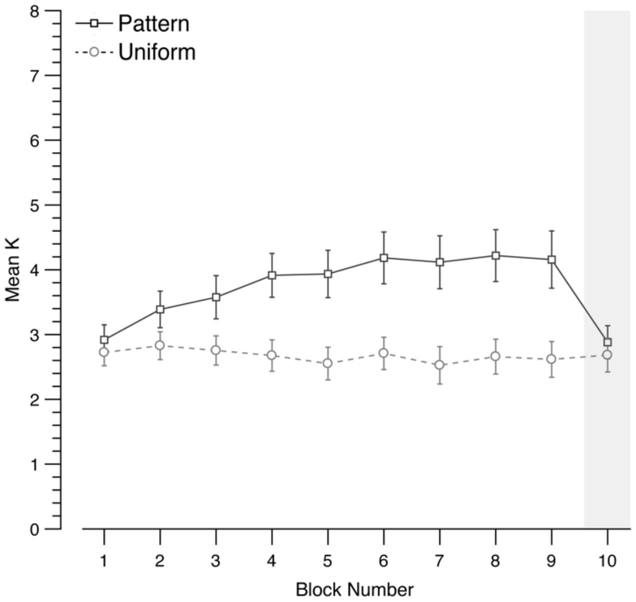


Figure 3-13. Mean number of items remembered (*K*) across blocks, with data aggregated across Experiment 1 and 2. The shaded area indicates the last block, in which statistical regularities were removed from the patterned condition. Error bars indicate ±1 S.E.M.

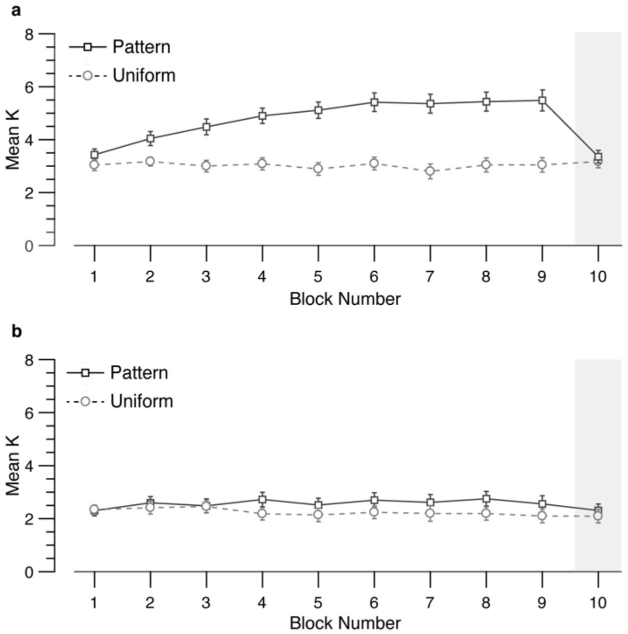


Figure 3-14. Average number of items (*K*) remembered in each block as a function of subject awareness, with data aggregated across Experiments 1 and 2. (a) Aware subjects, who correctly reported all colour pairings at the end of the study, showed improvement in the patterned condition. (b) Unaware observers, who did not report all colour pairings correctly, did not show improvement. The shaded area indicates the last block where statistical regularities were removed from the patterned condition. Error bars indicate ±1 S.E.M.

3.6 General discussion

We replicated the results of Brady *et al*. (2009), finding substantially better VWM performance when displays contained consistent colour pairings. This effect was either completely absent (Experiment 1) or negligible (Experiment 2) in subjects who did not achieve *perfect* explicit recall of the colour pairs at the end of the study. The fact that compression effects were contingent on subjects' explicit recall of the colour pairs is inconsistent with the hypothesis that visual statistical learning, an automatic process that is disconnected from explicit awareness (Perruchet & Pacton, 2006; Turk-Browne et al., 2008), was responsible for improved performance in the patterned condition. Moreover, the statistical learning hypothesis fails to explain multiple published studies that did not observe improved performance after repetitions of memory displays similar to those used by Brady *et al*. (Logie, Brockmole, & Vandenbroucke, 2009; Olson & Jiang, 2004). For example, Olson and Jiang (2004) reported change detection performance was unaffected by 24 exact repetitions of the sample display. Thus, both our findings and others call for a different explanation of this "memory compression" effect.

The embedded process model of WM provides a framework for explaining the advantage in the patterned condition in terms of dynamic interactions between WM and LTM. We propose that a subset of subjects developed highly accessible long-term representations of the colour pairs, evidenced by their explicit recall of the pairings at the end of the study. These subjects could then retrieve this information at the time of test to boost recall. This explanation does not require a change in the number of representations held online in the focus of attention. This is precisely what Chen and Cowan (2009) observed when they trained subjects to encode word pairs into LTM. In a subsequent WM task, participants could remember the same number of learned pairs of words as they could learned individual words.

Our alternative explanation may also illuminate why other studies found no advantage of memory displays repeated up to 24 times (Logie et al., 2009; Olson & Jiang, 2004). Both the present study and that of Brady *et al.* (2009) used a recall procedure to test WM performance, while Logie *et al.* and Olson and Jiang employed a two-alternative choice response (same versus different). It is possible that this relatively rapid mode of responding was not conducive to the effortful retrieval of long-term memories for the repeated displays. This explanation dovetails with the findings of Huang and Awh (2018), who found that the improved recall performance in the Brady *et al.*'s task only emerged after approximately a full second had elapsed after the onset of the test display, in line with sluggish retrieval of information from LTM. Consistent with this possibility, Logie et al. (2009) found benefits for repeated displays when they used a probed recall procedure (similar to that in the present work), but not when they used a change-detection procedure. Thus, the robust benefits of statistical regularities in the Brady *et al.* (2009) procedure can be reconciled with several null effects (Logie et al., 2009; Olson & Jiang, 2004) by positing that different methods for testing working memory are more or less conducive to the retrieval of related information from LTM.

In both of our experiments, observers who were unaware of the statistical regularities showed either negligible or no improvement in recall accuracy. Thus, it appears that this procedure does not elicit the same kind of visual statistical learning that has been highlighted in past studies (Fiser & Aslin, 2001, 2002; Turk-Browne et al., 2005, 2008) in which subjects apprehended statistical regularities in the absence of explicit awareness of those regularities (Chun & Jiang, 1999; Turk-Browne et al., 2005, 2008). However, this result does not rule out that visual statistical learning may shape performance in a VWM task. For instance, Umemoto et al. (2010) measured change detection performance when one quadrant of the display—unbeknownst to subjects—was more likely to contain the changed item. They found that memory encoding was biased towards the quadrant most likely to contain the changes, and subsequent measures of explicit knowledge showed no difference in effect size between subjects who could and could not identify the dominant quadrant. This result and others (Beck, Angelone, Levin, Peterson, & Varakin, 2008; Jiang, Swallow, & Rosenbaum, 2013) suggest that implicit knowledge of likely target positions can elicit useful biases in the items that are encoded into WM.

Interestingly, there is at least some evidence that location information may have a special status in implicit learning. Beck *et al.* (2008) found that unlike location, equally predictive cues in the shape and colour dimensions were ineffective at eliciting useful encoding biases. Likewise, subjects did not benefit when an item of a specific colour was most likely to change its orientation during a change detection procedure (Umemoto and Awh, unpublished). The notion that location may have a privileged status in visual processing is a longstanding one. Some have argued that location is automatically attended and stored in WM (e.g. Foster, Bsales, Jaffe, & Awh, 2017; Rajsic & Wilson, 2014; Schneegans & Bays, 2017; Tsal & Lavie, 1988) and that spatial attention is a fundamental component of feature integration (Treisman & Gelade, 1980). That said, Beck et al. (2008) noted that the nonspatial cues in their study were not explicitly task relevant, and this alone may have precluded apprehension of the relevant probabilities. Further work is needed to determine the boundary conditions under which implicit knowledge can guide performance of VWM.

In conclusion, while many studies have shown that statistical regularities can be automatically apprehended and exploited in the absence of conscious awareness of those regularities, this may not be an accurate framing of the memory compression effects in the Brady *et al.*'s (2009) procedure. Instead, the benefits of statistical regularities in this procedure may be best characterised as an example of paired-associate learning, given that only subjects with perfect explicit knowledge of those pairs were able to benefit from those regularities. Thus, while there will surely be continued interest in any manipulation that may boost online memory capacity, the memory compression effect examined here provides no evidence for such an effect.

3.7 Appendix

Derivation of formula for calculating K

The task in the current study is an eight-alternative forced choice, and observers may choose the correct answer if they know it or guess it by chance. Therefore, to estimate capacity (*K*), we need to estimate the number of correct answers from knowing the colours and the number of correct answers from guessing. We use the same formulation derived by Brady *et al.* (2009).

If an observer remembers *K* items, a remembered item will be probed (and observers will consequently be correct) on an average of *K* in 8 trials. On the remaining trials, the observer will guess correctly 1/8th of the time. Therefore, percent correct (*PC*) in terms of *K* will be:

$$\mathrm{PC} = \frac{\mathrm{K}}{8} + \left[\frac{8 - \mathrm{K}}{8} \times \frac{1}{8}\right]$$

Making *K* the subject:

$$\mathrm{PC} = \frac{\mathrm{K} \times 8}{8 \times 8} + \frac{8 - \mathrm{K}}{8 \times 8}$$

$$\mathrm{PC} \times 8 \times 8 = \mathrm{K} \times 8 + 8 - \mathrm{K}$$

$$\mathrm{PC} \times 8 \times 8 = 7 \times \mathrm{K} + 8$$

$$PC \times 8 \times 8 - 8 = 7 \times K$$

$$K = \frac{PC \times 8 \times 8 - 8}{7}$$

Chapter 4: Explicit Chunking Does Not Reduce the Contralateral Delay Activity

4.1 Abstract

The previous chapters suggest that VWM performance can be enhanced with learning in at least two ways. Firstly, we observed a faster encoding rate and higher capacity for familiar English letters over unfamiliar alphabets even when matched on similarity and complexity. Secondly, we observed improved VWM recall when statistical regularities were included in displays, but only for those participants who gained explicit knowledge of the pairings. These findings highlight the complex interactions between LTM and VWM in those tasks, as can be understood through the framework of embedded process models. However, the findings rely on behavioural responses at the end of a trial, which are not ideal for disentangling storage and retrieval processes. In Chapter 4, we attempt to overcome this by measuring the contralateral delay activity (CDA)—a neural index of the number of objects held in VWM—in the same paradigms. Despite significantly improved recall in a patterned condition containing statistical regularities, the CDA was no different from that observed in a uniform condition containing random stimulus pairings. These results favour an account by which improved recall comes not from a change to online representations, but from a late retrieval of a LTM representation after the probe.

4.2 Introduction

The visual working memory (VWM) system is responsible for holding temporary representations of visual information for perception and cognition. Despite this important function, VWM is limited to a surprisingly low capacity of approximately three or four items (Luck & Vogel, 1997). The factors that produce this striking result have been a topic of intense debate for researchers in recent decades. Luck and Vogel proposed a *slots* model, in which VWM holds integrated object representations. They found that change-detection performance was equivalent whether those three or four objects in VWM were simple colour squares or multifaceted shapes varying in colour, orientation, size and the presence or absence of a gap (Vogel, Woodman, & Luck, 2001, but see also Hardman and Cowan, 2015). In contrast, Alvarez and Cavanagh (2004) found lower VWM capacity estimates for more complex stimuli, where complexity was indexed by visual search slopes. This led them to propose an alternative *resources* model, wherein more complex objects require a larger proportion of a finite pool of resources to be stored in VWM (but see Eng, Chen and Jiang, 2005). Some researchers modelling VWM performance have fallen on the extremes of this debate, with some conceiving of VWM storing object-like representations as in a pure slot model (Zhang & Luck, 2008) and others taking VWM to act as an infinitely divisible limited resource as in a pure resource model (Bays, 2008). Still others have adopted intermediate variants, such as a *slots plus resources* model (Zhang & Luck, 2008). This range of perspectives reveals the current uncertainty regarding the nature of the units of storage in VWM.

4.2.1 Embedded process models

A less examined issue pertinent to the capacity limitation of VWM is that higher-order *chunking* of visual information can influence the unit representation in VWM (Miller, 1956). Take the finding that experts recall real chess positions significantly more accurately than novices, but show less of an advantage when the chess pieces were randomly placed (Chase & Simon, 1973; Gobet & Simon, 1996). Rather than revealing a higher VWM capacity, this finding can be taken to indicate that expert knowledge allows efficient chunking of real game positions in a way that novices are unable to. Gestalt grouping cues (Woodman et al., 2003) and statistical learning of relationships between elements (Brady et al., 2009) have also been shown to influence the representation of information in VWM. This interaction between storage in VWM and cognitive mechanisms can be described by *embedded process models* of WM. These models posit that the WM system comprises a set of memory processes engaging both offline and online representations. For example, Cowan (1999) proposed three distinct layers of memory. The highest layer contains all of the representations stored in long-term memory (LTM) and is effectively unlimited in capacity. The second layer includes 'activated' LTM; representations that are offline but readily accessible due to recent access or priming. These 'activated' representations can be shifted into the third layer of online memory representations of which a limited number can be maintained in what Cowan calls the 'focus of attention'. While other variants of embedded process models distinguish different numbers of layers, they all acknowledge the complex interaction of various levels of memory in any task that requires visual cognition.

The assumption that VWM architecture is accurately reflected in embedded process models presents a significant challenge in pinning down capacity limits. If activated LTM representations can fluidly shift into the focus of attention, the units maintained in VWM cannot be assumed simply to be the objects present in memory displays. The behavioural responses typically employed at the end of trials, such as recall or change detection, are then not ideally suited to disentangling whether the behavioural responses is guided by an activated LTM representation or an online VWM representation held throughout the trial. Some researchers have turned to neural markers in dissociating contributions of WM and LTM. Sustained patterns of neural activity have been associated with representations in VWM (Vogel & Machizawa, 2004), whereas storage in LTM is thought to be mediated by lasting changes in synaptic connectivity. In the present study, we examine the *contralateral delay activity* (CDA), an electrophysiological component associated with the storage of information in VWM (Vogel & Machizawa, 2004).

4.2.2 Contralateral delay activity

The CDA was first isolated by Vogel and Machizawa (2004), who developed a lateralised change-detection task. In this task, stimuli are presented to both hemifields, but subjects are instructed to remember the stimuli on only one side. The task proceeds the same way as a typical change-detection task, requiring observers to identify whether or not a change occurred on an ensuing test display. During the retention interval prior to test, a sustained negative slow wave manifests across the parietal-occipital electrodes contralateral to the side of the visual display that was to be remembered. Subtracting the activity from corresponding ipsilateral electrodes from the contralateral signal cancels bilateral activity linked to the sensory processing of the visual stimuli. In this way, activity specific to the storage of visual information in working memory can be isolated. The mean amplitude of the difference wave during the retention period is referred to as the CDA. Vogel and Machizawa (2004) showed that the CDA increases with the number of items held in memory and plateaus when VWM capacity is reached at 3-4 items. Additionally, the CDA is correlated with individual differences in subjects' behavioural measures of VWM capacity ($r = -.37$, Unsworth, Fukuda, Awh, & Vogel, 2014b; Vogel et al., 2005).

Recent research suggests the CDA tracks the number of individuated representations held in the focus of attention. The CDA is the same whether a change-detection task involves oriented bars or coloured oriented bars, and polygons or coloured polygons. However, when an oriented bar and colour square are presented as two separate objects, the CDA increases despite the amount of task-relevant information being equivalent to a coloured polygon (Luria & Vogel, 2011; Woodman & Vogel, 2008). This parallels the behavioural findings of Luck and Vogel (1997) that change-detection performance is unchanged with the addition of relevant features to the stimuli. Similarly, Gestalt grouping cues, such as similarity and common fate, reduce CDA amplitude presumably because the number of 'chunks' to be remembered is reduced (Balaban & Luria, 2016; Peterson et al., 2015). Further evidence for the CDA reflecting the number of representations in VWM comes from tasks requiring changes to the online representations showing these perceptual grouping cues do not appear to automatically influence the objecthood in VWM. Luria and Vogel (2014) found that the initial independence of colour squares overrode the strong grouping cue when they subsequently came together to form a conjunction as there was no corresponding reduction in CDA. When a single object splits into two separate objects, the CDA changes to match the increased set size—presumably because separate representations are then required to successfully detect changes in those stimuli (Balaban & Luria, 2016). The CDA changes similarly when subjects are cued to add or remove objects from attention (Drew, Horowitz, Wolfe, & Vogel, 2011). Taken together, these findings suggest the CDA amplitude can be interpreted as indexing the number of individuated objects held in the focus of attention. While Gestalt grouping cues have been shown to reduce the CDA, it is unclear whether higher-order chunking processes will produce similar changes. Researchers do not mention any involvement of LTM as Gestalt grouping cues are thought not to require any specialized knowledge and thus, primarily be bottom-up, stimulus-driven factors driving perception.

4.2.3 Memory compression

Brady *et al.* (2009) reported an example of improvement in VWM performance from higher-order cognitive processes. In their task, observers were required to memorise the location of eight colours, shown in pairs around a fixation point. Colours were more likely to be paired with a specific other colour, adding statistical regularity to these memory displays. Observers were able to use the regularity to their advantage and showed increased recall accuracy beyond the typical capacity limit of three to four objects. Brady *et al.* (2009) argued that this improvement occurred via efficient compression in the online representations of VWM, affording an increase in the amount of concurrent information. We have suggested, however, this improved recall may actually occur without any changes to the online representations of VWM (see Chapter 3). Taking an embedded process perspective, observers may instead rely on activated LTM representations which are retrieved at time of recall. For example, during consolidation, individuated representations of the colours may be held in VWM prior to any chunking process. Only during retrieval is a LTM representation of the chunk accessed to assist recall.

These perspectives make opposite predictions about the behaviour of the CDA during statistical learning. If learning produces efficient memory compression—the storage of information in fewer VWM representations—as Brady *et al.* (2009) argue, the CDA should reduce to the number of pairs in the display. In contrast, the embedded process perspective suggests the CDA should remain unchanged as the focus of attention is unchanged. That is, an unchanged number of item representations are produced during encoding into VWM, tracked by the CDA, before activating retrieval of LTM representations at test. Note that capacity estimates calculated from the improved recall are often beyond the capacity limit of 3-4 items. If learning produces an increase in the number of representations in VWM corresponding to these capacity estimates, the CDA would then be expected to be significantly higher with the inclusion of regularities, contradicting both the embedded process perspective and Brady *et al.* (2009).

4.2.4 The present study

We implemented the paradigm of Brady *et al.* (2009), with adjustments to allow the measurement of the lateralised CDA. Improved recall is contingent on observers' explicit knowledge of high-probability colour pairs (see Chapter 3). Observers were therefore informed of the colour pairings to speed their acquisition of this knowledge.

4.3 Method

4.3.1 Participants

Twenty-two members of the university community (8 females), aged 22 to 41 (mean age of 27.9 years) were recruited from the University of Sydney. All subjects were naïve to the aims of the study, and provided informed consent to procedures approved by the University of Sydney Human Research Ethics Committee. Subjects were recruited until a sample size of 18 subjects was achieved (following exclusions due to excessive eye movement and muscular artifacts). All subjects reported normal or corrected-to-normal vision and no impairment to colour vision.

4.3.2 Apparatus

Stimuli were generated using MATLAB (The MathWorks, Natick, MA) and PsychToolbox (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). They were presented on a 24 inch ASUS VG248QE LED backlit LCD monitor with spatial resolution set to 1920 × 1080 and 120 Hz nominal refresh rate. Observers were seated in a dark room with a viewing distance of approximately 70 cm. Responses were recorded with clicks on a standard mouse placed in front of the subject.

EEG was recorded using Ag–AgCl active electrodes (BrainProducts actiCAP) from 64 channels based on the modified International 10/20 System: Fp1/2, Fz, AF3/4, AF7/8, AFz, F1/2, F3/4, F5/6, F7/8, Fz, FC1/2, FC3/4, FC5/6, FT7/8, FT9/10, FCz, C1/2, C3/4, C5/6, Cz, T7/8, CP1/2, CP3/4, CP5/6, CPz, TP7/8, TP9/10, P1/2, P3/4, P5/6, P7/8, Pz, PO3/4, PO7/8, POz, O1/2, Oz. The ground electrode was Fpz and all electrodes were referenced to FCz, and re-referenced offline to the average of all electrodes. Impedances for active electrodes were kept below 10kΩ. The sample rate was 1000 Hz with a high cutoff filter of 250 Hz and a low cutoff filter of 0.01 Hz. EEG activity was recorded using the BrainVision Recorder software and analysed using MATLAB and the EEGLAB toolbox (Delorme & Makeig, 2004).

4.3.3 Stimuli

All stimuli were presented on a grey background. They were either squares with a side length of 2° of visual angle, or circles with diameter of 2° of visual angle. Each item could be one of eight colours: red, green, blue, magenta, cyan, yellow, black or white. Stimuli were presented in two imaginary regions, one in each hemifield. These regions were 3.9° in width and 4.3° in length, centred 2.9° to either side of the central fixation diamond (0.5° × 0.5°). On each trial, two locations were randomly selected in each region with the constraints that one location was above the fixation point and the other below, and that any presented stimuli would not overlap. In the 2-item condition, items were centred on the selected locations. In the 4-item and 2-pair conditions, the items were presented as pairs, equidistant above and below the selected locations such that the centre-to-centre distance within the pair was 2.5°.

4.3.4 Procedure

The general procedure for each trial is shown in *Figure 4-1*. Observers were required to click on a fixation diamond to initiate each trial and instructed to hold fixation on this point until they were probed for a response. Two hundred ms after the trial was initiated, an arrow cue informing the observer the side to which to direct their attention was shown above the fixation diamond for 500 ms. The cued side was equally likely to be left or right. After a 500 ms delay, stimuli were presented for 1000 ms. Observers were instructed to remember the colour of each item. After a retention period of 1000 ms with a blank screen, observers were probed to recall a colour from a randomly selected location, outlined with a thicker black line. Other locations where stimuli were presented were outlined with a thinner black line. Below the probe display, an array of all possible colours was presented. The observer was instructed to click on the colour they thought had been presented at the probed location.

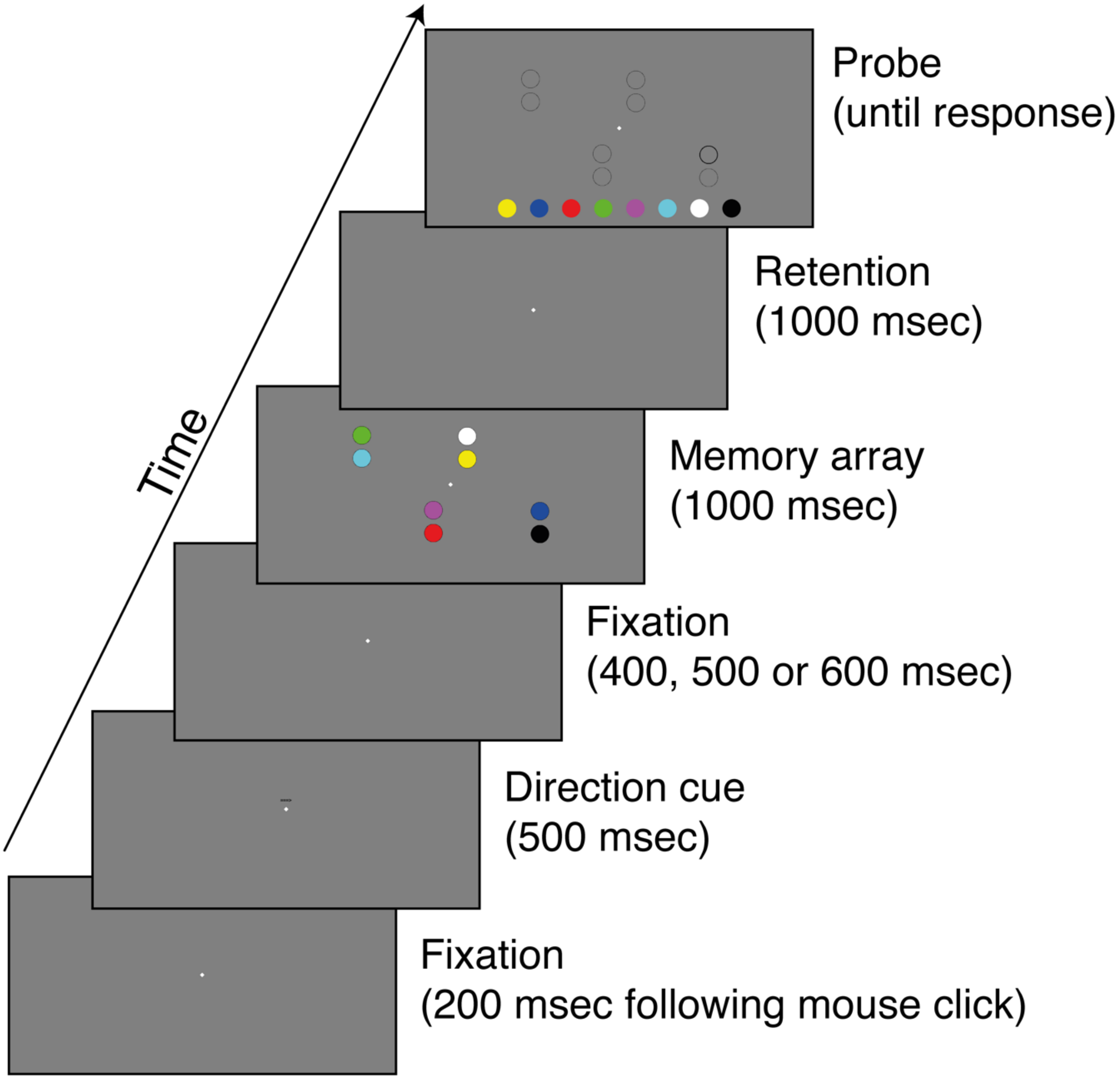
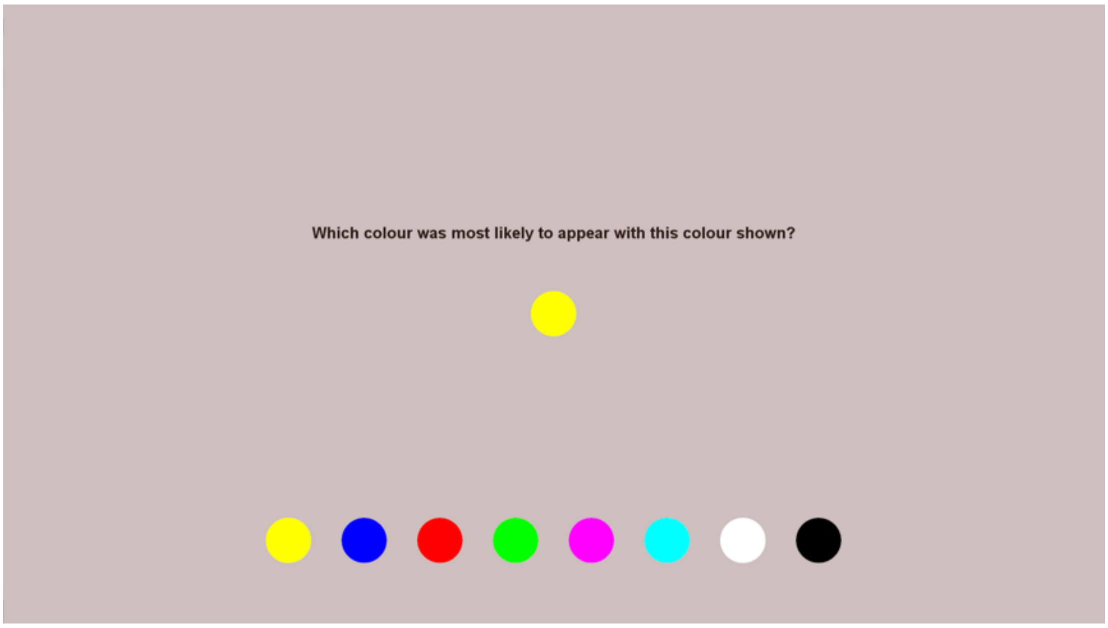


Figure 4-1. Procedure on one trial of the experiment. Durations for each frame are shown in brackets. Subjects initiated the trial by clicking the fixation point. An arrow was presented above the fixation point to indicate to the observer the side to which they should attend. After a variable interval, the memory array was shown for 1000 ms, before a blank retention period for 1000 ms. Subjects were required to keep fixation from the mouse click until the end of the retention period. Subjects were then shown a test array, in which one location was marked with a thicker outline. Subjects were required to select the colour they thought had been presented at that location.

Subjects completed 4 blocks of 30 trials in each of three conditions: 2-items, 4-items, and 2-pair. Subjects completed all trials of one condition before moving to the next, and were given breaks after every block. The order of conditions was counterbalanced across subjects. In the 2-item condition, two colours were selected randomly on each trial, such that it was equally likely for any colour to be selected on each trial. Similarly, in the 4-item condition, two colour pairs were randomly selected on each trial. However, in the 2-pair condition, each observer was randomly assigned four colour pairs for the duration of the condition, with the constraint that each colour could only be assigned to one of those pairs. Prior to completing the 2-pair condition, subjects were shown their assigned colour pairs and informed that only these pairs would be presented throughout. They were afforded a brief moment to study the colour pairs, with the expectation this would facilitate the rapid development of explicit LTM representations. A different shape was assigned to the 2-pair condition to help distinguish it from the random conditions (2-item and 4-item). Two of the subject's four assigned pairs were randomly selected on each trial, such that a particular colour would only ever appear with its assigned partner.

After completing all three conditions, observers were tested on their knowledge of the colour pairs. Improved recall performance was previously shown to be contingent on having perfect accuracy on this awareness test (see Chapter 3). Observers were presented each colour in the middle of the screen and asked to click on the assigned partner of that colour (*Figure 4-2*).



Which colour was most likely to appear with this colour shown?

Figure 4-2. Example display from the awareness test participants completed at the end of the experiment. Each colour was shown in the middle of the screen and participants were asked to click on its paired colour in the 2-pair condition.

4.3.5 Data analysis

4.3.5.1 Behavioural data

To estimate capacity (*K*) in each condition, we used the following formula (derivation in Appendix):

$$K = \frac{N(8P-1)}{7} \qquad (\textit{Equation 4-1})$$

where *P* is the porportion correct and *N* is the set size for that condition.

4.3.5.2 EEG data

Unfiltered EEG data were divided into epochs beginning 200 ms before stimulus onset and ending 2000 ms after stimulus onset. The data were then baseline corrected by subtracting the mean voltage of the 200 ms preceding the memory array. Trials with a peak-to-peak amplitude greater than 200 µV within a sliding 20 ms time window were excluded for excessive noise. To detect blocking, a 200 ms time window was shifted in steps of 50 ms and the trial was excluded if any EEG electrode had at least 60 consecutive time points (60 ms) within 1 µV of each other. Finally, all trials were visually inspected to confirm automatic rejection and to exclude trials with eye blinks or saccades detected by the Fp1 and Fp2 electrodes. Subjects with more than 35% of trials rejected were excluded from further analyses. Mean contralateral and ipsilateral activity across the P3/P4, P5/P6, P7/P8, PO3/PO4, and PO7/PO8 electrode pairs was calculated for each participant in each of the conditions separately. The CDA was calculated as the mean difference between contralateral and ipsilateral waveforms from 1000 to 1900 ms after stimulus onset. We also replicated analyses conducted by Xie and Zhang (2018) to examine the influence of familiarity on consolidation and storage in VWM. They separated the CDA into an early-window CDA, measured from 300 ms to 800 ms after stimulus onset, and a late-window CDA, measured from 1500 ms to 2000 ms after stimulus onset. They found that stimulus familiarity produced significant differences in early-window CDA but not the late-window CDA. This led them to conclude that familiarity speeds up consolidation into VWM (as reflected in the early window), while overall storage capacity is not enhanced (as reflected in the late window). The overall CDA, early-window CDA and late-window CDA data were analysed using repeated measures ANOVAs. Figures were generated using low-pass filtered data with Hamming windowed-sinc finite impulse response filter (*pop_eegfiltnew.m* from the EEGLAB toolbox) with a cutoff of 30 Hz.

4.4 Results

4.4.1 Behavioural data

Mean recall accuracy was 96.8%, 91.2% and 79.4% for the 2-item, 2-pair and 4-item conditions respectively, which corresponds to mean K estimates of 1.9, 3.6 and 3.1 (*Figure 4-3*). These estimates were significantly different across condition, $F(2,32) = 103.77, p < .001$. Follow-up pairwise comparisons revealed K in the 2 pair condition was significantly higher than in the 4 item condition, $t(17) = 2.45, p = .025$. All observers perfectly recalled the colour pairs in the recall test at the end of the experiment suggesting that observers gained explicit knowledge of the colour pairs. It appears that observers took advantage of the statistical regularity in the 2-pair condition by relying on their explicit knowledge, as previously observed by Brady *et al.* (2009) (see *Chapter 3*).

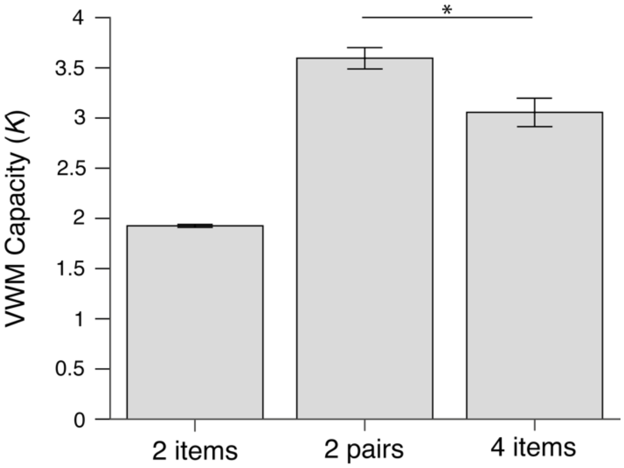


Figure 4-3. Mean VWM capacity in the 2-item, 2-pair and 4-item conditions. Error bars indicate ±1 standard error of the mean. VWM capacity was significantly higher in the 2-pair condition than in the 4-item condition.

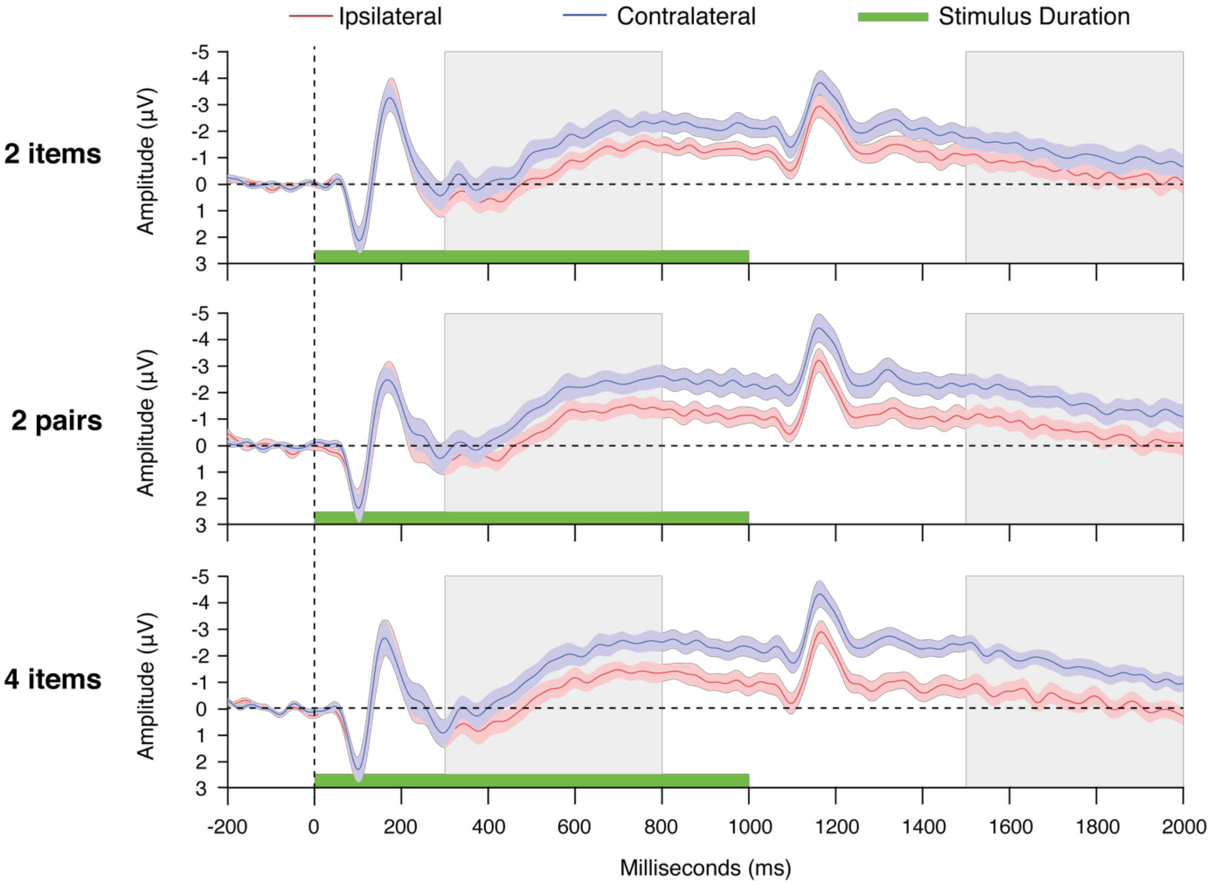


Figure 4-4. Grand average CDA waveforms for the 2-item, 2-pair and 4-item conditions. The shaded region surrounding the waveform indicates ±1 S.E.M. The green region depicts the presentation duration of the memory array. The grey areas indicate the time regions used for the early-window CDA (300 – 800 ms) and the late-window CDA (1500 – 2000 ms).

4.4.2 Electrophysiological data

4.4.2.1 Full CDA (1000 – 1900 ms)

Figure 4-4 shows the grand average CDA waveforms and *Figure 4-5* shows the average CDA for all three conditions. There were significant differences in the CDA across conditions, $F(2,34) = 10.72$, $p < .001$. Follow-up pairwise comparisons revealed that the CDA was significantly smaller in the 2-item condition ($M = -.77$) than both the 4 item condition ($M = -1.42$), $t(17) = 4.21$, $p < .001$ and the 2 pair condition ($M = -1.22$), $t(17) = 2.96$, $p = .009$. The CDA was not significantly different between the 4-item and 2-pair conditions, $t(17) = 1.64$, $p = .12$.

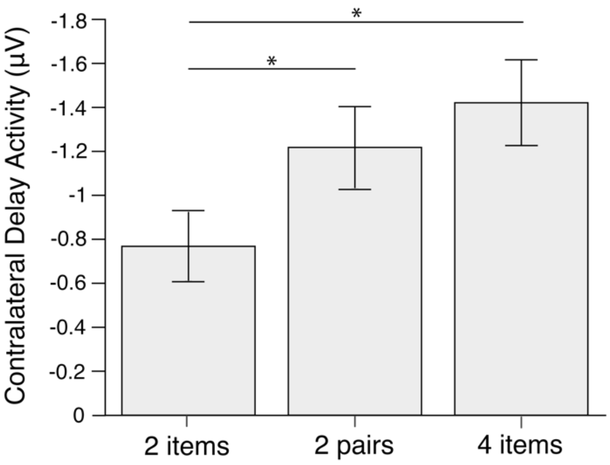


Figure 4-5. Mean CDA for the 2-item, 2-pair and 4-item conditions. Error bars indicate ±1 S.E.M. Pairwise comparisons revealed the mean CDA was significantly higher in the 2-pair condition and the 4-item condition than in the 2-item condition.

4.4.2.2 Early-window CDA (300 – 800 ms)

Figure 4-6 shows the mean CDA from an early time window (300 – 800 ms). Repeated-measures ANOVA indicated no significant differences in the early-window CDA between conditions, $F(2,34) = .63$, $p = .54$. This was confirmed in planned pairwise comparisons.

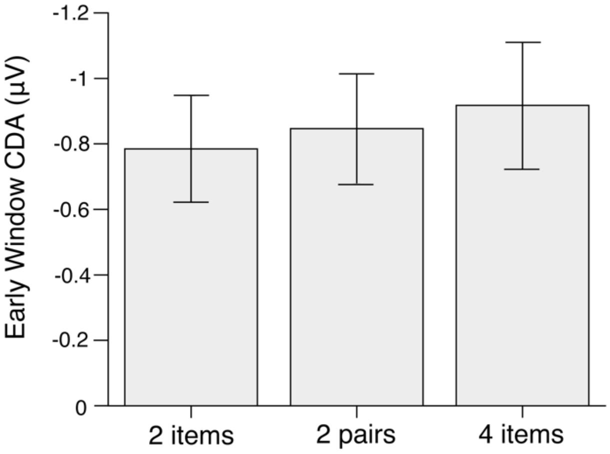


Figure 4-6. Mean early-window CDA for the 2-item, 2-pair and 4-item conditions. Error bars indicate ±1 S.E.M. There were no significant differences between the conditions on early-window CDA.

4.4.2.3 Late-window CDA (1500 – 2000ms)

The mean CDA at a late time window (1500 – 2000 ms) is shown in *Figure 4-7*. There were significant differences in the late-window CDA between conditions, $F(2,34) =$

11.49, *p* < .001. Follow-up pairwise comparisons revealed that the late-window CDA was significantly smaller in the 2-item condition than in the 4-item, *t*(17) = 3.24, *p* = . 005, and 2-pair conditions, *t*(17) = 4.43, *p* < .001. The late-window CDA did not differ significantly between the 2-pair and 4-item conditions, *t*(17) = 1.34, *p* = .20.

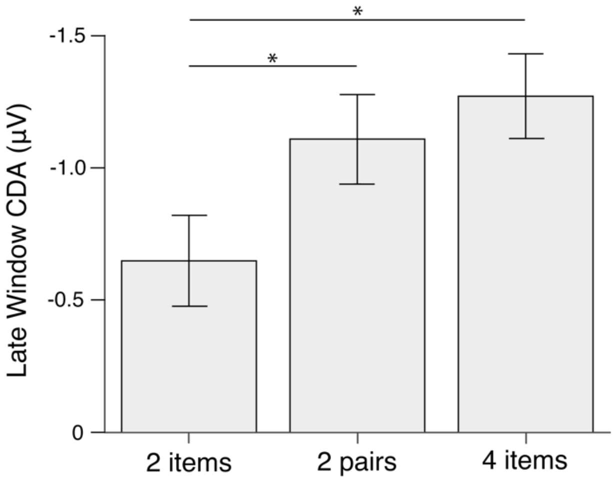


Figure 4-7. Mean late-window CDA for the 2-item, 2-pair and 4-item conditions. Error bars indicate ±1 S.E.M. Pairwise comparisons indicated the mean late-window CDA was significantly higher in the 2-pair condition and the 4-item conditions than in the 2-item condition.

4.5 General Discussion

Observers show improved recall accuracy when statistical regularities are included in memory displays. It has been argued that this improvement is produced by efficient compression of information in memory representations That is, representations in VWM have been augmented to hold more information, possibly by reducing redundancy. An embedded process perspective suggests this need not be the case, as activated LTM representations can be retrieved to aid recall. Recent work by Huang and Awh (2018) showed that the benefits of statistical regularities only manifest if observers are given long response times (~ 1 sec). We also reported in Chapter 3 that the advantage appears to be contingent on explicit knowledge of the regularities. However, behavioural responses give an incomplete picture of processes occurring during the trial. In the present study, we adapted Brady *et al.*'s (2009) paradigm to allow measurement of the CDA, a lateralised electrophysiological marker that robustly tracks the number of representations in VWM.

Consistent colour pairs in the displays, to which observers were explicitly alerted, led to significantly better recall in the 2-pair condition compared to the 4 item condition. CDA in the 2-pair and 4-item conditions was significantly higher than in the 2-item condition, replicating the previous finding that memory load is tightly associated with CDA. However, despite the 2-pair condition yielding a higher behavioural estimate of capacity than the 4-pair condition, the CDA did not significantly differ between them. It appears therefore that the recall advantage produced by explicit chunking does not involve changes to the online representations held in VWM, but rather the retrieval of learned LTM representations at a recall stage. We note that this conclusion rests on a non-significant statistical result comparing the CDA in the 2-pair and 4-item conditions. In an experiment examining four separate coloured squares combining into two colour conjunctions, but using a perceptual common-fate cue rather than explicit chunking, Luria and Vogel (2014) observed a statistically significant reduction in the CDA in a sample of 16 subjects. On this basis, the 18 subjects in the present study should provide sufficient power to observe a similar reduction in CDA in the 2-pair condition.

Separately analysing early and late-time windows of the CDA produces an interesting dissociation. Xie and Zhang (2018) split the CDA into an early time-window to index the rate of consolidation into VWM, and a late time-window to index the capacity of VWM. Given sufficient encoding time (1000 ms), change-detection performance of observers familiar with the stimuli was no better than that of observers unfamiliar with the stimuli. However, familiar observers had larger CDA amplitudes in the early time-window and not the late time-window. Xie & Zhang (2018) concluded that familiar information is consolidated into VWM at a faster rate, but the familiarity does not increase overall VWM. They propose this depends on pre-existing LTM representations, consistent with an embedded process perspective on the memory compression effects (see Chapter 3). We replicated Xie and Zhang's analysis using the same time windows and electrode pairs. Interestingly, there was no difference between the three conditions in the early-window CDA. Explicit chunking of the colour pair stimuli did not influence the consolidation into VWM, despite observers apparently maintaining LTM representations throughout the experiment. The construction of online representations does not appear to be influenced by explicit chunking, and may rely on engaging LTM processes different from those invoked by stimulus familiarity. However, in the late-window CDA, we find the same differences as in the overall CDA. Although we observe a significant memory load difference in the CDA, when comparing the 2-item and 4-item conditions, we do not observe a significant difference between the 2-pair and 4-item conditions. In conjunction with improved behavioural recall in the 2-pair condition compared to the 4 item condition, the most parsimonious account is that the CDA indexes individuated online representations within the focus of attention, and that the improved recall found with this statistical learning paradigm relies on LTM representations being retrieved when probed (Huang & Awh, 2018) with no change to how the online representations are formed.

Although observers displayed perfect memory for the colour pairs used and showed improved recall in the 2-pair condition, the CDA in that condition was not significantly different from the CDA in the 4-item condition. This is consistent with an embedded processes perspective that posits involvement of LTM at the retrieval stage. However, if observers are only required to store 2 items in the 2-pair condition, why did we not observe a significantly *lower* CDA in the 2-pair condition than in the 4-item condition? One possible reason is the number of items in the memory displays. In the present study, the effect of statistical regularities was examined at a set size of four (in a single hemifield) whereas previous behavioural studies used a set size of eight (Brady et al., 2009; Huang & Awh, 2018). As eight items far exceeds the typical average VWM capacity of three to four items, observers must chunk information efficiently to have any chance at encoding it all. With a set size of four items, chunking may not be required to encode all items and VWM may hold individual online representations of all items despite the redundancy. This likely occurs in tandem with retrieval of LTM at the retrieval stage of the task, which is why the 2-pair CDA would then not drop to the same level as in the 2-item condition. This issue is not easily addressed by increasing the set size of the displays, as the CDA typically plateaus at a memory load of 4 items and it would be difficult to discern any differences between 4 pairs and 8 items. However, given recall was significantly better in the paired condition and all observers had perfect recall of the colour pairs, we are confident observers did use explicit chunking. Thus, it appears that explicit chunking does not influence individual VWM representations in the same way Gestalt grouping factors do, as the latter reduce the CDA (Balaban & Luria, 2016; Peterson et al., 2015).

We found no increase in the early-window CDA for colour pairs, as has been found with familiarity for Pokémon (Xie & Zhang, 2018). This suggests that deliberate chunking does not speed up consolidation into VWM, even though improvements in VWM performance from both explicit chunking and stimulus familiarity are thought to engage existing LTM representations. In Chapter 2, we found that consolidation was faster for familiar stimuli, even when matched on factors such as similarity and complexity. It is thus likely that explicit chunking does not engage the same attentional processes that lead to faster consolidation with familiarity. For example, the chunking bottleneck for colours may occur at a later stage in VWM, as the identity of the two separate objects or features (colours in this case) have to be confirmed before chunking. This account matches those from an embedded process perspective where activated LTM representations retrieved at recall may be the reason for improved recall performance. Alternatively, it may be that the colour stimuli, used in the present study, are already highly familiar. The consolidation rate of colours has been reported to be quite rapid (~50 ms per item; Vogel et al., 2006). Accessing the LTM representation of a learned colour pair may then fail to produce detectable increases in the consolidation rate, and thus may be why no differences in the early-window CDA were observed. High familiarity with the base units that make up the chunk may be required for explicit chunking of the units, making it difficult to dissociate the contribution of familiarity and explicit chunking to the speed of consolidation of the contents into VWM.

Despite finding that the use of explicit chunking improved recall, the current study found no evidence of a change to the encoding or representation in VWM occurs as indexed by the CDA. The CDA—taken to be a marker of the number of individuated representations in VWM—was no different when colours were presented in consistent pairs compared to when they were presented in random pairings. This was despite behavioural evidence indicating explicit knowledge of the colour pairs led to improved recall, and increased VWM capacity estimates. We propose that the most parsimonious account of these results is that improved recall relies on activated LTM representations at the retrieval stage, and that explicit chunking does not influence object representation in VWM as indexed by the CDA.

4.6 Appendix

If an observer remembers *K* items, observers will be correct on an average of *K* in *N* trials (where *N* is the set size for that condition). On trials in which an item not remembered is probed, the observer will guess correctly on 1 in 8 trials on average in an eight-alternative forced-choice task. The following derivation is original for this study.

$$P = \frac{K}{N} + \frac{N-K}{N} \times \frac{1}{8}$$

$$P = \frac{8K + N - K}{8N}$$

$$8NP = 8K + N - K$$

$$8NP - N = 7K$$

$$K = \frac{8NP - N}{7}$$

$$K = \frac{N(8P - 1)}{7}$$

Chapter 5: Thesis Discussion

5.1 Summary of experimental findings

The goal of this thesis was to investigate how certain factors can alter the manner of encoding and storage of information in visual working memory (VWM) to overcome the typical capacity limit of three to four items. The major insight of the present work is that deeper consideration should be given to the contributions of long-term memory (LTM) to encoding and representation in VWM, and to performance on VWM associated tasks, such as change detection and probed recall.

In Experiment 1 of Chapter 2, we sought to isolate the effect of familiarity on VWM performance from its interaction with stimulus complexity and similarity. We compared change-detection performance for English letters to the Brussels Artificial Character Set (BACS), which was designed to contain the same number of strokes, junctions and terminations as English letters and had been shown to have equivalent similarity ratings among characters within the set. We also matched the two sets in perimetric complexity, an objective measure of stimulus complexity linked to the identification efficiency of letters. The familiarity from extensive experience with English letters was associated with significantly higher encoding rate and capacity, compared to the novel BACS letters.

In Experiments 2 and 3, we attempted to produce a benefit of familiarity using a recognition-training procedure that previously had been reported to provide a benefit using random polygons as stimuli. Although subjects were successfully trained to recognise a subset of BACS letters, there was no increase in encoding rate or capacity for the trained BACS letters over a novel set. These results suggest that only familiarity from extensive experience produces significant benefits in encoding rate and capacity. Having some form of learning or LTM trace available is not sufficient to produce familiarity-related improvements in VWM performance.

In Chapter 3, we examined an influential finding suggesting that statistical learning can produce an increase in the amount of information held concurrently in VWM. Across two experiments, improved recall from the inclusion of statistical regularities in displays was dependent on having explicit knowledge of the regularities, rather than occurring through implicit learning as argued by Brady *et al.* (2009). Our results indicate that this form of memory compression relies on activation of a relevant LTM trace at retrieval, rather than a change to the representations during encoding.

In the final empirical chapter (Chapter 4), the behavioural paradigm from Chapter 3 was adapted for the measurement of the contralateral delay activity (CDA). The CDA is a neural marker thought to index the number of individuated representations held in VWM, in part because it is sensitive to perceptual grouping cues. In the critical condition of our experiment, subjects were informed of the colour pairs they would see in the displays, to encourage explicit chunking of the objects in the memory array. Recall was significantly more accurate in this condition compared to when the colours were not paired. Despite this, the CDA was not significantly different between these conditions. These results suggest that the improved recall associated with pairing relies on LTM activation during retrieval rather than any change to the encoding of the representations in VWM.

Overall, there were two main results in this thesis revealing significant effects on encoding and capacity in VWM. Firstly, English letters produced a faster encoding rate and a larger capacity limit compared to novel BACS letters. This effect was apparently due to greater familiarity with the English letters, as the character sets were otherwise matched in complexity and similarity. However, benefits of familiarity were not reproduced following recognition training of a subset of BACS letters, suggesting more extensive experience is required. Secondly, the inclusion of statistical regularities in a memory display produced significantly enhanced recall, but only in those observers who had gained explicit awareness of the regularities. Observers without awareness did not show any improvement. Additionally, the CDA did not change despite improved recall produced by explicit chunking, suggesting this benefit manifests not at encoding or storage, but rather at retrieval. Improvements associated with both pairing and (extensive) familiarity appear to rely on contribution from LTM, pointing to a complex interaction between VWM and LTM that has been somewhat overlooked in classic models of VWM.

5.2 Implications for classic models of VWM

The capacity of VWM has classically been explained using *resources* or *slots* models. Resource models posit a finite amount of resources for storing items in VWM; more complex objects—those containing more features—require more resources (Alvarez & Cavanagh, 2004). Therefore, fewer complex items than simple items can be stored in VWM. Slots models suggest all features of an object are integrated into one representation such that each object is stored in a single slot (Luck & Vogel, 1997). Neither type of model inherently predicts influences from LTM, such as those related to familiarity and chunking reported in this thesis. How might these models be amended to account for such effects?

In the case of a *resources* model, the consumption of resources for storage in VWM may vary according to *perceptual fluency*, a metric that combines subjective complexity, similarity and familiarity. An individual becomes more fluent with the stimuli as the distinguishing features of the stimuli are learned, reducing their subjective complexity and similarity. For successful change detection, fluency provides a benefit in part because the individual needs to encode only the distinguishing features rather than the whole object, using less resource. Alternatively, expertise may allow the chunking of features into LTM representations of the entire objects. We favour linking the distribution of resources to perceptual fluency as it allows the resource model to explain results in which VWM capacity changes with complexity, similarity and familiarity manipulations in a cohesive manner (Awh et al., 2007; Buttle & Raymond, 2003; Jackson & Raymond, 2008), whereas the availability of entire object LTM representations does not explain the effects of complexity and similarity.

The idea of perceptual fluency also has been raised with respect to statistical learning. In a similar result to those we report in Chapter 2*,* recent work suggests that an individual's familiarity with stimuli moderates statistical learning performance far more than the complexity of those stimuli (Perfors & Kidd, 2018). Perceptual fluency might also explain the strong correlation between visual search rates and VWM capacity for stimuli of varying complexity upon which *resources* models of VWM are grounded on (Alvarez & Cavanagh, 2004; Eng et al., 2005). As the observer becomes more fluent with the stimuli, the target object may be located more quickly as the distinguishing features are known to the observer. Initial visual search rates for completely unfamiliar stimuli may reflect the complexity of the stimulus (because complexity is the primary determinant of initial fluency. After gaining expertise, visual search rates may more closely track the observer's perceptual fluency with the stimulus. If VWM capacity is also tied to perceptual fluency, the correlation between VWM capacity and initial visual-search rates may decline.

It is unclear whether a slot-based model can account for increases in both the rate of consolidation and storage capacity in VWM produced by expertise. Slot-based models make the strong prediction that objects are stored in VWM with all their features integrated. Perceptual fluency may allow the observer to store only the distinguishing features of an item, speeding up consolidation as fewer features require integration prior to storage in VWM. But it is not apparent how this would lead to increased storage capacity, which strictly requires an increased number of slots for storage. The effect of familiarity on capacity previously has been disputed. Apparent differences, such as those reported between famous faces and novel faces (Buttle & Raymond, 2003; Jackson & Raymond, 2008), may be an artefact of insufficient encoding time (Xie & Zhang, 2018). That is, capacity appears larger for familiar stimuli because after a limited time for encoding, the more slowly encoded unfamiliar stimuli have not yet saturated VWM. However, we found significant increases in capacity with familiarity when we modelled storage capacity using exposure times at which performance has clearly plateaued, suggesting such differences persist when encoding time is sufficient for saturation of VWM (Chapter 2).

Chunking may better account for familiarity-related changes in VWM capacity within a slot-based model. Under this proposal, the individual features of unfamiliar stimuli would be stored in separate slots; stimulus familiarity would then allow the features of an object to be chunked together and stored in a single slot. This proposal brings the encoding of unfamiliar stimuli closer to the initial resources model proposed by Alvarez and Cavanagh (2004) (whereby resources are distributed according to the number of features in the stimuli), with the added constraint on the maximum number of features that can be stored concurrently. A point of resolution between slot and resource models thus may come by considering the effect of stimulus familiarity. That is, the features of unfamiliar stimuli are encoded and stored in VWM according to a resource-like model, while expertise allows the storage of stimuli in an object-like manner as in a slots model. Note that this change in storage format may require extensive training that enables the recruitment of differential brain areas (Moore, Cohen and Ranganath, 2006), that is beyond the training of stimulus recognition given our findings reported in Chapter 2. Characterising the moment that storage format may shift, and whether this shift occurs in a discrete or continuous fashion, appears important to understanding the nature of capacity limits in VWM.

5.3 Embedded process model of VWM

The embedded process perspective, which characterises the complex interaction between VWM and LTM, is one framework that can help explain the limits of VWM found in the present experiments. We have relied on Cowan’s (1999) conceptualisation comprising three distinct layers of memory: a base layer that contains all LTM representations, a middle layer where a subset of LTM is activated, and lastly the limited number of online representations held in the *focus of attention*—or what we have referred to as VWM. The debate over the nature of representations epitomised by slot and resource models is centred on this focus of attention. A critical aspect of the embedded process perspective, marginalised by much of the slots and resources debate, is that activated LTM representations can fluidly shift into the focus of attention to affect behaviour on change-detection or recall tasks typically assumed to involve only VWM. This presents a noteworthy challenge to the characterisation of the VWM capacity limit especially if activated LTM representations are recruited when memory is accessed at test (Oberauer & Lin, 2017). Capacity estimates measured with behavioural responses at the end of a trial, such as with change-detection or probed recall, would then be inflated with the recruitment of activated LTM.

The embedded process perspective helps to explain the combination of behavioural results from Chapter 3 and neural measures from Chapter 4. When we included statistical regularities in memory displays by increasing the likelihood of certain colour pairs, only observers who possessed explicit knowledge of the colour pairs produced significantly improved recall on those displays. In contrast, recall performance by unaware observers was unchanged. Increased VWM capacity estimates were contingent on explicit awareness of the colour pairings, which we interpreted as reflecting the acquisition of LTM representations. Huang and Awh (2018) found that these improvements in recall only manifest if subjects are allowed a long response time, which they suggest is because this time is required for the retrieval of LTM representations. But despite improved recall when observers were relying on explicit knowledge of statistical regularities, the CDA—a neural measure of the number of individuated representations held in VWM—was no higher than it was in the absence of such regularities. These last results are consistent with the proposal that LTM representations are activated at recall, but the representations in the focus of attention are unchanged.

It is important to note that we do not claim to have found evidence supporting the embedded process theory as a model of working memory; we suggest only that its framework of interactions between VWM and LTM provides a useful account of the findings reported here and elsewhere. There exist many forms of embedded process models with various numbers of layers and different capacity limits (e.g. Ericsson & Delaney, 1999; Jonides et al., 2008; Oberauer, 2002). A significant challenge for future research is to clarify the distinction between activated LTM and VWM. Recent research on the role of VWM and LTM in the deployment of attention during visual search might inform potential approaches to this challenge. The CDA decreases after repeated presentations of the same target in a visual search, suggesting the target may be represented in LTM rather than VWM (Carlisle et al., 2011). This reduction in CDA has been found to correspond to increases in the amplitude of a different event-related potential component known as the P170, thought to index LTM activation (Reinhart & Woodman, 2014; Woodman, Carlisle, & Reinhart, 2013). The use of activated LTM representations rather than online VWM representations, predicted by embedded process models, would be substantiated if the same reduction in CDA and corresponding increase in P170 amplitude were observed during VWM tasks using familiar stimuli.

5.4 Future directions and limitations

When comparing differences in capacity estimates across stimuli, observers' familiarity with the stimuli must be taken into account. While extensive familiarity can lead to changes in VWM performance, it is unclear how this occurs. Familiarity may speed up encoding into VWM (Xie & Zhang, 2018), such that some apparent capacity differences are due to insufficient encoding times; but it may also influence sample-test similarity (Awh et al., 2007) as items become more readily distinguishable with increasing familiarity. A limitation of the present studies is the lack of a measure that captures an observer's perceptual fluency with a stimulus (Perfors & Kidd, 2018). One method to account for the effects of familiarity is to provide training using initially novel stimuli. Our recognition training, however, did not produce any improvement in change detection. This may be because the subjective similarity between trained and novel items was reduced, while the similarity among trained items was unaffected, meaning that sample-test similarity remained equivalent between conditions. A future study could directly examine the influence of recognition training on encoding and sample-test similarity by having a trained item change to a novel item, or vice versa, in a change-detection task. Significantly better performance when a trained item changes to a novel item compared to the opposite would support the notion that recognition benefits encoding in VWM because the degree of change is equivalent in both situations. This encoding benefit might also be reflected in the early-window CDA, as observed by Xie and Zhang (2018) in observers familiar with Pokémon characters. It should be noted that training might only produce improvements when it has been extensive enough to build corresponding neural pathways, as suggested by increased activation of occipitotemporal cortical areas during encoding and maintenance on a WM task specifically for trained, but not untrained, polygons (Moore et al., 2006). How familiarity and training shape working memory has important implications for real-world applications of change detection and visual search, such as in radiography and airport baggage scanning.

Behavioural indices of VWM performance, such as change detection or recall, may be insufficient to fully appreciate the nature of VWM, because LTM representations may be activated at test and affect behaviour. One approach, used in the present study, is to collect behavioural evidence in conjunction with neural measures such as the CDA to examine activity during the retention period. The CDA has been observed to reduce with perceptual grouping cues (Luria & Vogel, 2014), such that the CDA appears to index discrete item-based representations. We observed improved recall with explicit chunking of displays but it without an accompanying reduction in the CDA. This result suggests that the observed increase in VWM capacity with statistical regularity did not occur through efficient memory compression as posited by Brady *et al.* (2009). Instead, we have proposed that activated LTM representations recruited at recall produce this result. It is far from certain, however, that higher-order chunking does not influence the online representations indexed by the CDA. Extensive experience and training may be required for LTM to influence the online representations of objects in VWM, and for such changes to be reflected in the CDA. In our study, observers were not trained but informed of the colour prior to the tasks. While this was successful in producing improved recall performance, it may be insufficient to produce changes to encoding or storage in VWM itself. Further, the task demands did not necessitate explicit chunking because set sizes were within the typical VWM capacity limit of three to four items. A future study could use stimuli that require the chunking of multiple elements into a single representation, such as dice patterns. Canonical dice patterns likely have learned LTM representations that may be recruited during encoding in VWM, producing a CDA corresponding to the number of dice rather than the number of dots. Jumbled dice patterns, however, do not have such LTM representations and the CDA may reflect instead the number of dots in the dice patterns (within VWM capacity limits). If this is the case, observers could be trained to learn specific random dice patterns to examine the point at which learning influences the online representation in VWM.

One aspect of working memory not directly examined in the present thesis is the fidelity of the representations held in VWM. Fidelity in VWM is typically measured using recall on a continuous scale, such as a colour wheel (Zhang & Luck, 2008). The dispersion of responses around the true value of the presented object indexes the precision of VWM representations. Using this approach, some have presented evidence that three items are stored with a constant precision and any extra items are not represented at all (Zhang & Luck, 2008), while others suggest all items are stored but representations become noisier as more items are stored (Bays & Husain, 2008). Gaining perceptual fluency may involve the fine-tuning of representations in VWM such that there are gradual increases in precision. This would correspond with objects becoming subjectively less similar to each other. In fact, it has been shown that the precision of representations measured using a continuous scale appears to be perfectly modelled by *psychological distance*, or the subjective similarity of items (Schurgin, Wixted, & Brady, 2018). Unfortunately, it is not straightforward to adopt a continuous scale for the stimuli used in the present thesis (English letters, Brussels Artificial Characters) to explore the influence of perceptual fluency on the fidelity of the representation. It might be expected that an observer whose profession involves distinguishing colours, perhaps a painter or graphic designer, may show a higher precision for colour that leads to a higher VWM capacity for colours; it is, however, unclear exactly how this finding from expertise with colours would relate to the increased capacity we observed for English letters over novel, artificial characters.

5.5 Conclusion

The instances examined in the present thesis in which the typical capacity limit of VWM is overcome suggest a significant contribution of LTM but one that is not adequately addressed by classic slots models or resource models. The online representations in VWM do not appear to be readily influenced. Change detection was unchanged following recognition training, and the CDA did not reduce with explicit chunking. However, according to an embedded process framework, extensive experience may shape these representations in VWM—perhaps by fluidly shifting activated LTM representations into the focus of attention. The conjunction of behavioural and neural measures such as the CDA appears valuable in understanding the interplay of VWM and LTM, and the core processes involved in visual-cognition tasks.

Thesis References

Alvarez, G. A., & Cavanagh, P. (2004). The Capacity of Visual Short-Term Memory Is Set Both by Visual Information Load and by Number of Objects. *Psychological Science*, *15*, 106–111.

Atkinson, R. C., & Shiffrin, R. M. (1968). Human Memory: A Proposed System and its Control Processes (Vol. 2, pp. 89–195). Elsevier. https://doi.org/10.1016/s0079-7421(08)60422-3

Attneave, F. (1957). Physical determinants of the judged complexity of shapes. *Journal of Experimental Psychology*, *53*(4), 221–227.

Attneave, F., & Arnoult, M. D. (1956). The quantitative study of shape and pattern perception. *Psychological Bulletin*, *53*(6), 452.

Awh, E., Barton, B., & Vogel, E. K. (2007). Visual Working Memory Represents a Fixed Number of Items Regardless of Complexity. *Psychological Science*, *18*(7), 622–628. https://doi.org/10.1111/j.1467-9280.2007.01949.x

Awh, E., & Jonides, J. (2001). Overlapping mechanisms of attention and spatial working memory. *Trends in Cognitive Sciences*, *5*(3), 119–126. https://doi.org/10.1016/S1364-6613(00)01593-X

Baddeley, A. D., & Hitch, G. (1974). Working Memory. In G. H. Bower (Ed.), *Psychology of Learning and Motivation* (Vol. 8, pp. 47–89). Academic Press. https://doi.org/10.1016/S0079-7421(08)60452-1

Balaban, H., & Luria, R. (2016). Integration of Distinct Objects in Visual Working Memory Depends on Strong Objecthood Cues Even for Different-Dimension Conjunctions. *Cerebral Cortex*, *26*, 2093–2104.

Bays, P. M., & Husain, M. (2008). Dynamic shifts of limited working memory resources in human vision. *Science*, *321*(5890), 851–854.

Bays, Paul M. (2008). Dynamic Shifts of Limited Working Memory. *Physiol. Rev*, *88*, 769.

Beck, M. R., Angelone, B. L., Levin, D. T., Peterson, M. S., & Varakin, D. A. (2008). Implicit learning for probable changes in a visual change detection task. *Consciousness and Cognition*, *17*(4), 1192–1208. https://doi.org/10.1016/j.concog.2008.06.011

Besner, D., Davies, J., & Daniels, S. (1981). Reading for meaning: The effects of concurrent articulation. *The Quarterly Journal of Experimental Psychology Section A*, *33*(4), 415–437. https://doi.org/10.1080/14640748108400801

Blalock, L. D. (2015). Stimulus familiarity improves consolidation of visual working memory representations. *Attention, Perception, & Psychophysics*, *77*(4), 1143–1158.

Brady, T. F., Konkle, T., & Alvarez, G. A. (2009). Compression in Visual Working Memory: Using Statistical Regularities to Form More Efficient Memory Representations. *Journal of Experimental Psychology: General*, *138*(4), 487–502.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, *10*, 433–436.

Buttle, H., & Raymond, J. E. (2003). High familiarity enhances visual change detection for face stimuli. *Perception & Psychophysics*, *65*(8), 1296–1306. https://doi.org/10.3758/BF03194853

Carlisle, N. B., Arita, J. T., Pardo, D., & Woodman, G. F. (2011). Attentional Templates in Visual Working Memory. *Journal of Neuroscience*, *31*(25), 9315–9322. https://doi.org/10.1523/JNEUROSCI.1097-11.2011

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive Psychology*, *4*(1), 55–81. https://doi.org/10.1016/0010-0285(73)90004-2

Chen, D., Eng, H. Y., & Jiang, Y. (2006). Visual working memory for trained and novel polygons. *Visual Cognition*, *14*(1), 37–54. https://doi.org/10.1080/13506280544000282

Chen, Z., & Cowan, N. (2009). Core verbal working-memory capacity: The limit in words retained without covert articulation. *The Quarterly Journal of Experimental Psychology*, *62*(7), 1420–1429. https://doi.org/10.1080/17470210802453977

Chun, M. M., & Jiang, Y. (1999). Top-Down Attentional Guidance Based on Implicit Learning of Visual Covariation. *Psychological Science*, *10*(4), 360–365. https://doi.org/10.1111/1467-9280.00168

Conway, A. R. A., Cowan, N., Bunting, M. F., Therriault, D. J., & Minkoff, S. R. B. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence*, *30*(2), 163–183. https://doi.org/10.1016/S0160-2896(01)00096-4

Cowan, N. (1999). *An embedded-process model of working memory. In, A. Miyake, & P. Shah (Eds.), Models of working memory: Mechanisms of active maintenance and executive control (pp. 62-101)*. Cambridge: Cambridge University Press.

Cowan, Nelson. (1999). An embedded-processes model of working memory. *Models of Working Memory: Mechanisms of Active Maintenance and Executive Control*, *20*, 506.

Cowan, Nelson. (2001). Metatheory of storage capacity limits. *Behavioral and Brain Sciences; New York*, *24*(1), 154–176.

Cowan, Nelson, Chen, Z., & Rouder, J. N. (2004). Constant Capacity in an Immediate Serial-Recall Task: A Logical Sequel to Miller (1956). *Psychological Science*, *15*(9), 634–640. https://doi.org/10.1111/j.0956-7976.2004.00732.x

Cowan, Nelson, Elliott, E. M., Scott Saults, J., Morey, C. C., Mattox, S., Hismjatullina, A., & Conway, A. R. A. (2005). On the capacity of attention: Its estimation and its role in working memory and cognitive aptitudes. *Cognitive Psychology*, *51*(1), 42–100. https://doi.org/10.1016/j.cogpsych.2004.12.001

Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of Verbal Learning and Verbal Behavior*, *19*(4), 450–466. https://doi.org/10.1016/S0022-5371(80)90312-6

Dehaene, S., Cohen, L., Sigman, M., & Vinckier, F. (2005). The neural code for written words: a proposal. *Trends in Cognitive Sciences*, *9*(7), 335–341. https://doi.org/10.1016/j.tics.2005.05.004

Dehaene, S., Le Clec'H, G., Poline, J.-B., Le Bihan, D., & Cohen, L. (2002). The visual word form area: a prelexical representation of visual words in the fusiform gyrus. *NeuroReport*, *13*(3), 321.

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Drew, T., Horowitz, T. S., Wolfe, J. M., & Vogel, E. K. (2011). Neural Measures of Dynamic Changes in Attentive Tracking Load. *Journal of Cognitive Neuroscience*, *24*(2), 440–450. https://doi.org/10.1162/jocn_a_00107

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458.

Eng, H. Y., Chen, D., & Jiang, Y. (2005). Visual working memory for simple and complex visual stimuli. *Psychonomic Bulletin & Review*, *12*(6), 1127–1133. https://doi.org/10.3758/BF03206454

Ericsson, K. A., & Delaney, P. F. (1999). Long-term working memory as an alternative to capacity models of working memory in everyday skilled performance.

Fiser, J., & Aslin, R. N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological Science*, *12*(6), 499–504.

Fiser, J., & Aslin, R. N. (2002). Statistical Learning of Higher-Order Temporal Structure From Visual Shape Sequences. *Learning, Memory*, *28*(3), 458–467.

Foster, J. J., Bsales, E. M., Jaffe, R. J., & Awh, E. (2017). Alpha-band activity reveals spontaneous representations of spatial position in visual working memory. *Current Biology*, *27*(20), 3216-3223. e6.

Fukuda, K., Vogel, E., Mayr, U., & Awh, E. (2010). Quantity, not quality: the relationship between fluid intelligence and working memory capacity. *Psychonomic Bulletin & Review*, *17*(5), 673–679. https://doi.org/10.3758/17.5.673

Gobet, F., & Simon, H. A. (1996). Recall of rapidly presented random chess positions is a function of skill. *Psychonomic Bulletin & Review*, *3*(2), 159–163. https://doi.org/10.3758/BF03212414

Gold, J. M., Hahn, B., Zhang, W. W., Robinson, B. M., Kappenman, E. S., Beck, V. M., & Luck, S. J. (2010). Reduced capacity but spared precision and maintenance of working memory representations in schizophrenia. *Archives of General Psychiatry*, *67*(6), 570–577.

Hardman, K., & Cowan, N. (2015). Remembering Complex Objects in Visual Working Memory: Do Capacity Limits Restrict Objects or Features? *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *41*(2), 325–347. https://doi.org/10.1037/xlm0000031

Huang, L., & Awh, E. (2018). Chunking in working memory via content-free labels. *Scientific Reports*, *8*(1), 23. https://doi.org/10.1038/s41598-017-18157-5

Irwin, D. E., & Andrews, R. V. (1996). Integration and accumulation of information across saccadic eye movements. *Attention and Performance XVI: Information Integration in Perception and Communication*, *16*, 125–155.

Jackson, M. C., Linden, D. E. J., Roberts, M. V., Kriegeskorte, N., & Haenschel, C. (2015). Similarity, not complexity, determines visual working memory performance. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *41*(6), 1884–1892. https://doi.org/10.1037/xlm0000125

Jackson, M. C., & Raymond, J. E. (2008). Familiarity enhances visual working memory for faces. *Journal of Experimental Psychology: Human Perception and Performance*, *34*(3), 556.

Jiang, Y. V., Shim, W. M., & Makovski, T. (2008). Visual working memory for line orientations and face identities. *Perception & Psychophysics*, *70*(8), 1581–1591. https://doi.org/10.3758/PP.70.8.1581

Jiang, Y. V., Swallow, K. M., & Rosenbaum, G. M. (2013). Guidance of spatial attention by incidental learning and endogenous cuing. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(1), 285–297. https://doi.org/10.1037/a0028022

Jonides, J., Lewis, R. L., Nee, D. E., Lustig, C. A., Berman, M. G., & Moore, K. S. (2008). The mind and brain of short-term memory. *Annu. Rev. Psychol.*, *59*, 193–224.

Jungé, J. A., Scholl, B. J., & Chun, M. M. (2007). How is spatial context learning integrated over signal versus noise? A primacy effect in contextual cueing. *Visual Cognition*, *15*(1), 1–11.

Kleiner, M., Brainard, D., Pelli, D., Ingling, A., Murray, R., & Broussard, C. (2007). What's new in Psychtoolbox-3. *Perception*, *36*(14), 1.

Lee, E.-Y., Cowan, N., Vogel, E. K., Rolan, T., Valle-Inclan, F., & Hackley, S. A. (2010). Visual working memory deficits in patients with Parkinson's disease are due to both reduced storage capacity and impaired ability to filter out irrelevant information. *Brain*, *133*(9), 2677–2689.

Logie, R. H., Brockmole, J. R., & Vandenbroucke, A. R. E. (2009). Bound feature combinations in visual short-term memory are fragile but influence long-term learning. *Visual Cognition*, *17*(1–2), 160–179. https://doi.org/10.1080/13506280802228411

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10.1038/36846

Luck, S. J., & Vogel, E. K. (2013). Visual working memory capacity: from psychophysics and neurobiology to individual differences. *Trends in Cognitive Sciences*, *17*(8), 391–400. https://doi.org/10.1016/j.tics.2013.06.006

Luria, R., & Vogel, E. K. (2011). Shape and color conjunction stimuli are represented as bound objects in visual working memory. *Neuropsychologia*, *49*(6), 1632–1639. https://doi.org/10.1016/j.neuropsychologia.2010.11.031

Luria, R., & Vogel, E. K. (2014). Come Together, Right Now: Dynamic Overwriting of an Object's History through Common Fate. *Journal of Cognitive Neuroscience*, *26*(8), 1819–1828. https://doi.org/10.1162/jocn_a_00584

Makovski, T., & Jiang, Y. V. (2008). Indirect assessment of visual working memory for simple and complex objects. *Memory & Cognition*, *36*(6), 1132–1143. https://doi.org/10.3758/MC.36.6.1132

Miller, G. A. (1956). The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81–97. https://doi.org/10.1037/h0043158

Moore, C. D., Cohen, M. X., & Ranganath, C. (2006). Neural Mechanisms of Expert Skills in Visual Working Memory. *Journal of Neuroscience*, *26*(43), 11187–11196. https://doi.org/10.1523/JNEUROSCI.1873-06.2006

Nee, D. E., & D’Esposito, M. (2018). Working Memory. In *Stevens’ Handbook of Experimental Psychology and Cognitive Neuroscience* (5th Edition, pp. 1–26). American Cancer Society. https://doi.org/10.1002/9781119170174.epcn112

Ngiam, W. X. Q., Khaw, K. L. C., Holcombe, A. O., & Goodbourn, P. T. (2018). Visual working memory for letters varies with familiarity but not complexity. *Journal of Experimental Psychology. Learning, Memory, and Cognition*. https://doi.org/10.1037/xlm0000682

Oberauer, K. (2002). Access to information in working memory: Exploring the focus of attention. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*(3), 411.

Oberauer, K., & Lin, H.-Y. (2017). An Interference Model of Visual Working Memory. *Psychological Review*, *124*(1), 21–59. https://doi.org/10.1037/rev0000044

Olson, I. R., & Jiang, Y. (2004). Visual short-term memory is not improved by training. *Memory & Cognition*, *32*(8), 1326–1332. https://doi.org/10.3758/BF03206323

Olson, I. R., Jiang, Y., & Moore, K. S. (2005). Associative Learning Improves Visual Working Memory Performance. *Journal of Experimental Psychology*, *31*(5), 889–900.

Pashler, H. (1988). Familiarity and visual change detection. *Perception & Psychophysics*, *44*(4), 369–378. https://doi.org/10.3758/BF03210419

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision*, *10*(4), 437–442.

Pelli, D. G., Burns, C. W., Farell, B., & Moore-Page, D. C. (2006). Feature detection and letter identification. *Vision Research*, *46*(28), 4646–4674.

Perfors, A., & Kidd, E. (2018). What drives individual differences in statistical learning? The role of perceptual fluency and familiarity. https://doi.org/10.31234/osf.io/7jvx8

Perruchet, P., & Pacton, S. (2006). Implicit learning and statistical learning: one phenomenon, two approaches. *Trends in Cognitive Sciences*, *10*(5), 233–238. https://doi.org/10.1016/j.tics.2006.03.006

Peterson, D. J., Gözenman, F., Arciniega, H., & Berryhill, M. E. (2015). Contralateral delay activity tracks the influence of Gestalt grouping principles on active visual working memory representations. *Attention, Perception, & Psychophysics*, *77*(7), 2270–2283. https://doi.org/10.3758/s13414-015-0929-y

Rajsic, J., & Wilson, D. E. (2014). Asymmetrical access to color and location in visual working memory. *Attention, Perception, & Psychophysics*, *76*(7), 1902–1913.

Reinhart, R. M. G., & Woodman, G. F. (2014). Causal Control of Medial–Frontal Cortex Governs Electrophysiological and Behavioral Indices of Performance Monitoring and Learning. *Journal of Neuroscience*, *34*(12), 4214–4227. https://doi.org/10.1523/JNEUROSCI.5421-13.2014

Schneegans, S., & Bays, P. M. (2017). Neural architecture for feature binding in visual working memory. *Journal of Neuroscience*, 3493–16.

Schurgin, M. W., Wixted, J. T., & Brady, T. F. (2018). Psychological scaling reveals a single parameter framework for visual working memory. *BioRxiv*, *325472*.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136. https://doi.org/10.1016/0010-0285(80)90005-5

Tsal, Y., & Lavie, N. (1988). Attending to color and shape: The special role of location in selective visual processing. *Perception & Psychophysics*, *44*(1), 15–21. https://doi.org/10.3758/BF03207469

Turk-Browne, N. B., Jungé, J. A., & Scholl, B. J. (2005). The Automaticity of Visual Statistical Learning. *Journal of Experimental Psychology: General*, *134*(4), 552–564. https://doi.org/10.1037/0096-3445.134.4.552

Turk-Browne, N. B., Scholl, B. J., Chun, M. M., & Johnson, M. K. (2008). Neural Evidence of Statistical Learning: Efficient Detection of Visual Regularities Without Awareness. *Journal of Cognitive Neuroscience*, *21*(10), 1934–1945. https://doi.org/10.1162/jocn.2009.21131

Umemoto, A., Scolari, M., Vogel, E. K., & Awh, E. (2010). Statistical Learning Induces Discrete Shifts in the Allocation of Working Memory Resources. *Journal of Experimental Psychology. Human Perception and Performance*, *36*(6), 1419–1429. https://doi.org/10.1037/a0019324

Unsworth, N., Fukuda, K., Awh, E., & Vogel, E. K. (2014a). Working memory and fluid intelligence: Capacity, attention control, and secondary memory retrieval. *Cognitive Psychology*, *71*, 1–26. https://doi.org/10.1016/j.cogpsych.2014.01.003

Unsworth, N., Fukuda, K., Awh, E., & Vogel, E. K. (2014b). Working Memory Delay Activity Predicts Individual Differences in Cognitive Abilities. *Journal of Cognitive Neuroscience*, *27*(5), 853–865. https://doi.org/10.1162/jocn_a_00765

Vidal, C., Content, A., & Chetail, F. (2017). BACS: The Brussels Artificial Character Sets for studies in cognitive psychology and neuroscience. *Behavior Research Methods*. https://doi.org/10.3758/s13428-016-0844-8

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, *428*(6984), 748–751. https://doi.org/10.1038/nature02447

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*(7067), 500–503. https://doi.org/10.1038/nature04171

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions, and objects in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *27*(1), 92.

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2006). The time course of consolidation in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *32*(6), 1436.

Wagemans, J., Elder, J. H., Kubovy, M., Palmer, S. E., Peterson, M. A., Singh, M., & von der Heydt, R. (2012). A century of Gestalt psychology in visual perception: I. Perceptual grouping and figure–ground organization. *Psychological Bulletin*, *138*(6), 1172–1217. https://doi.org/10.1037/a0029333

Watson, A. B. (2011). *Perimetric Complexity of Binary Digital Images: Notes on Calculation and Relation to Visual Complexity*. Retrieved from https://ntrs.nasa.gov/search.jsp?R=20110013429

Woodman, G. F., Carlisle, N. B., & Reinhart, R. M. G. (2013). Where do we store the memory representations that guide attention? *Journal of Vision*, *13*(3), 1–1. https://doi.org/10.1167/13.3.1

Woodman, G. F., Vecera, S. P., & Luck, S. J. (2003). Perceptual organization influences visual working memory. *Psychonomic Bulletin & Review*, *10*(1), 80–87.

Woodman, G. F., & Vogel, E. K. (2008). Selective storage and maintenance of an object's features in visual working memory. *Psychonomic Bulletin & Review*, *15*(1), 223–229.

Xie, W., & Zhang, W. (2017a). Familiarity increases the number of remembered Pokémon in visual short-term memory. *Memory & Cognition*, *45*(4), 677–689. https://doi.org/10.3758/s13421-016-0679-7

Xie, W., & Zhang, W. (2017b). Familiarity Speeds Up Visual Short-term Memory Consolidation. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(6), 1207–1221. https://doi.org/10.1037/xhp0000355

Xie, W., & Zhang, W. (2018). Familiarity Speeds Up Visual Short-term Memory Consolidation: Electrophysiological Evidence from Contralateral Delay Activities. *Journal of Cognitive Neuroscience*, *30*(1), 1–13. https://doi.org/10.1162/jocn_a_01188

Xu, Z., Adam, K. C. S., Fang, X., & Vogel, E. K. (2017). The reliability and stability of visual working memory capacity. *Behavior Research Methods*, 1–13. https://doi.org/10.3758/s13428-017-0886-6

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233–235. https://doi.org/10.1038/nature06860