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The Relationship between visual working memory and visual long-term memory

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THE RELATIONSHIP BETWEEN VISUAL WORKING MEMORY AND VISUAL LONG-TERM MEMORY

by

Adam Trent Niese

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Psychology
in the Graduate College of
The University of Iowa

December 2008

Thesis Supervisors: Adjunct Professor Steven Luck
Associate Professor Andrew Hollingworth

ABSTRACT

This dissertation evaluated whether Visual Working Memory (VWM) is a distinct memory system or if it is an activated state of Visual Long Term Memory (VLTM). These two positions suggest different roles for VLTM representations in the performance of VWM. If VWM representations are an activated state of VLTM representations, it seems plausible that strong VLTM representations should facilitate VWM performance. However, if the two representations are actually distinct, it seems less likely that a facilitation interaction between VLTM and VWM representations should be observed.

Five experiments were conducted in which participants learned a set of trained stimuli over two days of training. Participant performance with the trained stimuli was compared to performance with novel stimuli on a subsequent VWM change detection task to determine the plausibility of VLTM-VWM interactions.

The first and second experiments revealed a LTM facilitation effect that could not be explained by priming, but the third experiment suggested that this facilitation effect was mediated by non-visual representations. The fourth and fifth experiments parceled out the contributions of non-visual memory representations, and failed to demonstrate any evidence of VLTM-VWM performance interactions.

These results, in conjunction with other examples from the literature, all converged on the conclusion that VLTM-VWM facilitation interactions are relatively implausible. As such, it was concluded that VWM and VLTM representations are discreet.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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To Mom, Dad, and Katie, who never took no for an answer

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ABSTRACT

This dissertation evaluated whether Visual Working Memory (VWM) is a distinct memory system or if it is an activated state of Visual Long Term Memory (VLTM). These two positions suggest different roles for VLTM representations in the performance of VWM. If VWM representations are an activated state of VLTM representations, it seems plausible that strong VLTM representations should facilitate VWM performance. However, if the two representations are actually distinct, it seems less likely that a facilitation interaction between VLTM and VWM representations should be observed.

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THE RELATIONSHIP BETWEEN VISUAL WORKING MEMORY AND VISUAL LONG-TERM MEMORY

This dissertation will evaluate whether Visual Working Memory (VWM) is a distinct memory system or if it is an activated state of Visual Long-Term Memory (VLTM). This first chapter will describe the current understanding of VWM, and how the nature of VWM representations may be related to possible distinctions between VWM and VLTM. This relies on capacity and general performance measures, so those are subsequently explored along with the role of training in the development of VLTM representations. Finally, it will describe previous attempts to train VWM performance and place them in the greater theoretical framework of the dissertation. The second chapter will be devoted to outlining the general program of research that will address the theoretical issues discussed in the first chapter. The next two chapters will be devoted to specific experiments within that general framework. The final chapter will provide a general discussion of these experiments and their implications.

Visual Working Memory

The research proposed for this dissertation revolves around the VWM system. This system briefly represents relevant visual information in the service of a variety of ongoing tasks. Although this seems straightforward on the face of things, the system plays a highly specialized role in cognition that is worth defining explicitly.

VWM is an active type of memory—a trait it shares with other working memory systems. Information maintained by VWM is flexible and can be transformed in novel ways to accommodate various tasks. This distinguishes VWM from its historical antecedent, short-term memory, which was understood to be a passive store (Miyake & Shah, 1999).

Another defining characteristic of VWM is its independent and modality-specific information representation—its use does not interfere with information maintenance in other modalities (Baddeley & Hitch, 1974). This kind of memory can be used flexibly for a variety of different tasks. In a research setting, it has been shown that VWM is critical for mental rotation (Hyun & Luck, 2007) and the visual comparison process (Hyun, 2006). More generally, it has been argued that VWM underlies the guidance of eye movements and supports the subjective impression that our observation of the world is continuous despite sudden transients like saccadic suppression (Hollingworth, Richard, & Luck, in press).

Despite this degree of specialization, VWM's contributions to cognition reach outside this visual bailiwick. Because it is part of the larger working memory system, individual differences in VWM capacity may be related to more general indices of cognitive performance, such as general intelligence (Unsworth & Engle, 2007). VWM performance is also reduced in a number of psychiatric disorders (Gold et al., 2003, Fuller et al., 2005). So, although VWM is a highly specialized and independent memory system, it plays an important role in a variety of cognitive processes ranging from the highly specific to the domain general.

Representations in Visual Working Memory

There has been relatively little theorizing about the precise nature of VWM representations. However, VWM maintains representations derived from the output of visual perceptual processes, so it seems likely that VWM representations are similar to perceptual representations. As discussed by Luck (2008), theories of the perceptual representations of objects can be divided into two main categories, and these categories can also be applied to VWM. Specifically, theories of VWM representation can be described as *Structured Primitive* theories or *Activated Visual Long-Term Memory* theories.

Structured Primitives

Structured Primitive theories assert that there is some definable set of atomic features that can be bound together into meaningful representations. While the particular set of primitives varies from theory to theory, they can be understood by analogy to perceptual representations. For example, early during cortical visual processing, there is a population of orientation-selective cells that are spatiotopically organized. If the correct oriented bar were presented in the cell's receptive field, the cell will respond rapidly, and the cell could be said to be representing the bar. If primitives like these formed the basis for representation in VWM, then the letter "x" could be represented by recruiting the primitives for two perpendicular bars and binding them into a unified object representation. While the above example is highly oversimplified, more sophisticated theories can represent complex real world objects using a small set of volumetric primitives and a smaller vocabulary of spatial relationships among them.

It's worth noting that the appellation "Structured Primitives" represents a category of theories, which spans a diversity of primitives. These primitives can range from the extremely fundamental featural primitives bound into objects by visuospatial attention (Treisman & Gelade, 1980) to the more abstract volumetric geons (Biederman, 1987) that characterize objects in less concrete precision, and no assumptions are made about whether the primitives are viewpoint dependent or viewpoint independent. However, the essential character of these accounts lies in the fact that there is some standard toolbox of fundamental primitives rather than in the properties of the primitives themselves. The remainder of this dissertation uses "Structured Primitives" in this more general sense.

Activated Visual Long-Term Memory Representations

Activated Visual Long-Term memory theories, on the other hand, handle representation quite differently. Such theories would argue that, during the course of perception, the observer develops a large number of long-term memory (LTM) representations for a wide variety of objects. Observing these objects or similar objects provides cues to activate that representation in LTM. Once activated, these representations can be selected by attention and come to the fore of consciousness (Cowan, 1999). So, observing an "x" would cue various VLTM representations of the letter (different fonts, sizes, etc), which would then be activated. Once activated, the various representations of "x" are available for selection and manipulation in the service of some task. According to these theories, the general domain of working memory includes all activated representations at a time, though an executive system selects which elements of working memory to manipulate.

At first, such a system would seem unable to represent and manipulate a novel object. After all, if an object has never been encountered before, then there is no VLTM representation to activate. However, an experienced observer has a great diversity of VLTM representations, and a novel representation might be encoded into working memory by representing it with respect to those VLTM representations. So, if an observer has never seen a "+" before, but has extensive experience with the letter "x," then the "+" could be maintained and manipulated as a rotated "x." While this explanation has been systematically examined in the context of the digit span task (Ericsson & Delaney, 1999), little research exists to explicitly apply it to VWM. However, it is possible to imagine how it would work. When presented with novel stimulation, the brain can compare the perceptual input to existing VLTM representations and compute the similarity between them (Figure 1). Once these similarities have been computed, the working memory system need only maintain an array of the similarities to maintain a representation of the novel object. This *long-term similarity vector* (Luck, 2008) can then be maintained and manipulated in the service of whatever task is at hand. The same general idea has been used to explain how viewpoint-dependent representations of objects could be used to achieve viewpoint-independent recognition (Poggio & Edelman, 1990).

As was the case for Structured Primitives theories, activated VLTM accounts represent a range of particular representational substrates. Although it is simple to talk about activated VLTM accounts in imagistic terms, nothing inherently ties these accounts to viewpoint-dependant theories of object recognition. Instead, activated VLTM accounts are characterized by the identity between VWM and VLTM representations, where the only distinction is the activation state of the VLTM representation.

Is VWM distinct from VLTM?

The primary focus of this dissertation is this issue of whether VWM is a distinct system from VLTM. It is difficult to distinguish between these two accounts, however. Both the Activated VLTM and Structured Primitives accounts are capable of representing and transforming information in a manner consistent with conventional understandings of VWM function, but the two frameworks represent fundamentally different information processing architectures with significant implications for localization of function and systemic dysfunction.

The role of VLTM representations in VWM activity may hold the answer: because the Activated VLTM account holds that VWM representations are simply Activated VLTM representations, it implies a tight link between the two systems. On the other hand, the Structured Primitives account posits no tight relationship between VLTM and VWM representations, because the atomic representations are largely unmodified by experience.

It is important to note that the Structured Primitive account does not assume that the atomic primitives are present at birth and completely immutable. There is some evidence that primitives are developmentally determined (Buisseret, Gary-Bobo, & Imbert, 1982). Moreover, stimuli such as letters of the alphabet may achieve such a strong, low-level representation that they become primitives after millions of exposures (Treisman & Gelade, 1980). However, these representations develop and change over spans of years, and the underlying changes reflect a fundamental change in the memory system rather than the more traditional VLTM representations researchers talk about with respect to Activated VLTM accounts. Traditional VLTM representations can be formed with relatively little exposure and the Structured Primitives account asserts that these relatively rapidly-forming representations do not provide the basis of VWM representations. However, before exploring the role of VLTM representations in VWM performance, it's important to understand both measures of VWM performance and how VLTM representations are developed.

Measuring VWM Performance

The flexibility of VWM representations makes VWM a powerful information processing resource. However, although information in VWM is more durable than the corresponding information in perceptual systems, information persistence seems to come at the cost of information volume. Specifically, models of VWM over the years have shared a central theme: limited capacity.

The core of capacity limitations is information load; capacity limits the number of object representations that can be simultaneously integrated. This limit plays a role in a variety of real world activities. Take a grocer’s fruit display as an example. If you want the best apple from the display, you need to simultaneously inspect new apples and compare them to apples you previously viewed. If each apple can be defined as an object, then capacity limits the number of apples you can remember. Remembering more apples and their unique characteristics gives you a larger pool of comparisons to make, and this lets you make quality judgments with a more representative apple sample.

VWM is well suited to accomplish the fruit comparison task because you select the fruits that interest you before encoding them into memory. If you could instead rapidly encode each unique fruit into LTM, all the other highly similar fruits you’ve previously seen would be competing candidates when you try to remember a particular fruit of interest—a phenomenon referred to as proactive interference. So, whatever process that selected interesting fruits for maintenance circumvents the problem of proactive interference. This example is representative of VWM's role in cognition—it selectively represents specific pieces of information in the service of some visual task.

Capacity limits represent a significant restriction to the utility of VWM—they limit the amount of information that can be simultaneously maintained and integrated in the service of tasks. So when VWM fails at a task, the underling problem is commonly capacity related: either capacity limits cannot accommodate sufficiently detailed information to succeed at the task, or already-maintained information precludes the encoding of task-relevant information. This section will examine the most prominent means of assessing VWM performance and capacity and two major theoretical positions on the nature of capacity limits.

The Change Detection Paradigm

The change detection paradigm underlies the bulk of capacity estimates in the VWM literature and is at the core of the experiments proposed later in this manuscript. The basic change detection paradigm is designed to require that the observer visually encode information, represent it in VWM over a brief delay, and then use the represented information in a visual task.

The typical formulation of a single trial this paradigm appears in Figure 2. On each trial, the participant is typically presented with two arrays of objects and then asked to make a same/different judgment about them. The first array--the *sample array*—contains a variable number of objects and is presented for a brief interval. The sample array then offsets long enough to extinguish the perceptual icon, so that participants must represent the sample information in working memory. Then a new set of items appears, called the *test array*, until the participant responds to the change detection task. Finally there is a brief intertrial interval and the process repeats. On half the trials (called *same* trials or *no change* trials), the test array is identical to the sample array. For the remaining half (*change* trials), a randomly selected element in the test array is different from the corresponding element in the sample array—in Figure 2 one of the bars has changed orientation.

To be 100% accurate, the observer must encode all of the sample items into memory. Under ideal conditions where participants were unbiased and never guessed, it would be possible to estimate VWM capacity from the error rate on change-present trials. For example, if a participant could remember 4 items and was presented with 5, then the participant would fail to encode the changing item on 20% of the trials, an observable error rate. Rearranging this, capacity would be equal to the accuracy multiplied by the number of items in the display (in this case 5 items * 80% accuracy yields a capacity of 4 items).

However, human behavior is not so simple, which means that capacity estimates must account for some element of guessing. While it is not possible to observe the degree to which participants guess correctly in the change detection task, it is possible to record their errors. Cowan et al. (2005) used false alarm rate (the percentage of same trials where participants report a change) to estimate and adjust the hit rate (percentage of change trials where participants report a change).

$k = N * (H + CR - 1)$

In this equation, k represents capacity in items, N is the number of items to be remembered, H is the hit rate, and CR is the correct rejection rate (proportion of same trials where participants reported no change).

Concrete estimates of capacity are difficult to discuss without first considering the two prevailing capacity theories in the VWM literature: the fixed-slot model and the flexible resources model.

Slots

The slot model is so named because it characterizes capacity as a set of fixed units, each of which can accommodate the representation of a single object or part. While new representations may be rapidly swapped in and out of these units, each unit can only maintain a single fixed-resolution representation. This means that, although a complex multipart object may occupy multiple units, even the simplest feature-defined object can occupy no less than one full capacity unit. It also means that, regardless of the information load represented in the unit, all representations are maintained with equal fidelity. This rigid, fill-able structure gives the slots their name.

Experiments underlying the slot model estimate that the average VWM capacity is 3-4 objects (or 3-4 parts for complex objects). It is worth noting at this point that each slot is thought to represent all of the features of the object or part. This conclusion is based on the finding that measured capacity remains constant whether the change detection task is performed with single-dimension or multiple-dimension stimuli (Luck & Vogel, 1997). Regardless of how many feature dimensions an object possesses, all those dimensions stick together and together occupy one slot per object.

Flexible Resources

These conclusions were criticized by Alvarez and Cavanagh (2004), who argued that VWM capacity is determined by the amount of information that must be stored rather than by the number of objects, with complex objects requiring more capacity than simple objects. To test this hypothesis, they used a conventional change detection paradigm with line drawings, shaded cubes, random polygons, Chinese characters, Roman letters, and colored squares. In addition to testing change detection performance, Alvarez and Cavanagh used the same six types of stimuli in a visual search task. Participants searched for the presence or absence of a unique target in displays of 4, 8, or 12 objects. Alvarez and Cavanagh took the search slope (the average number of milliseconds required to search each item) as an indicator of the difficulty of searching items of a particular type with more difficult items, of course, being slower to search per item. They argued that this difficulty is a good measure of information per item.

Participants showed a reduced capacity for some items relative to others, with shaded cubes leading to the lowest capacity (1.6 items) and colored squares leading to the highest (4.4 items). Search slopes for different types of items also varied. Critically, there was a very tight correlation between search slopes and VWM capacity, with higher search slopes corresponding to lower capacity. Alvarez and Cavanagh used this relationship to argue that capacity is actually determined by the complexity of information being maintained rather than just the raw number of items. It is important to note that this model does not actually discredit the bound object representation as the unit of capacity in VWM because, although more complex objects seem to require more capacity, it does not describe a systematic featural demand on capacity limits. Instead, the flexible resources model conceives of a continuous resource pool (as opposed to a set of fixed-resolution slots). Some objects must recruit more of this pool to maintain representation than others, which means that fewer of these objects can be represented overall.

Although these two models are in direct competition, distinguishing between them exceeds the scope of this dissertation. The critical information to be gleaned here is what the two frameworks have in common: that capacity is best understood in terms of bound objects and that stimuli used in the change detection task should all have equivalent complexity to avoid confounding complexity with capacity.

How VLTM Representations Can Help Distinguish Activated VLTM Accounts From Structured Primitive Accounts

With some understanding of VWM performance measures and what they mean, we can briefly revisit the issue of representation. Although both Structured Primitive and Activated VLTM accounts are capable of explaining the performance of VWM, each should interact differently with VLTM representations. The interactions between LTM and VWM are discussed below.

Activated Visual Long-Term Memory Representations

If VWM representations are Activated VLTM representations, then a better VLTM representation of a to-be-remembered object should result in a better VWM representation of that same object. A veridical VLTM representation would improve the quality of representation relative to a similarity vector by virtue of directly containing the relevant information. Such a representation could also reduce capacity demands because only one representation would need to be recruited to keep a stimulus active in VWM (instead of recruiting several approximate representational proxies).

To imagine how this would work, consider a change detection task with a set size of 6 items performed by a participant with a capacity of 3 items. With a randomly generated array to remember on every trial, the participant could represent 3 randomly selected items from the array and would successfully catch about half of the changes. However, if the same array were repeated on every trial, the observer could form a VLTM representation of the array and use this representation to notice all the changes. That is, the entire array could be linked to a single representation in LTM, and only this one representation would need to be activated in VWM to retain the array. That is, because a strong VLTM representation existed for the entire array of 6 objects, this array could be represented as a single item in VWM. This example is oversimplified, but it captures the essential properties of using VLTM representations to perform the change detection task—activating a single VLTM representation to store a complex pattern in VWM rather than activating a separate representation for each part of the pattern.

The role of VLTM representations in this case does not usurp the role of VWM. If VWM representation are actually activated VLTM representations, as many researchers have argued (see Miyake & Shah, 1999 for an overview), the use of a single chunked display does not represent a significant departure from business as usual in the working memory system—it just represents particularly extensive experience with a single representation. However, the use of VLTM is not compatible with a Structured Primitive representational system. Structured Primitives represent information through dynamic bindings between atomic representational components—meaning that the substrate is largely inflexible, but the momentary representation is flexible. VLTM representations, by contrast, can be encoded with a great deal of flexibility, but once information is encoded, the VLTM representation is extremely stable and lacks the dynamism that characterizes Structured Primitives (though a degree of dynamism could be achieved through the inclusion of other VLTM representations into a similarity vector).

VWM and Supporting LTM Systems

If VWM representations consist of Structured Primitives, VLTM representations would not be connected so directly to VWM performance. Since primitives are only very gradually modified by post-developmental experience, they represent a basic toolbox that can represent any novel stimulation. However, memory systems do not operate in isolation during everyday functioning; they share information and represent information about the same stimuli in parallel. As a rule, memory research attempts to isolate these systems, but this reductionist approach can easily neglect the interconnectedness that makes the brain such an effective interpreter of stimulation.

For example, information repetition confers an advantage in various visual tasks, even when participants are not informed that information repeats (Olson, Jiang, & Sledge, 2005; Chen, Eng, & Jiang, 2006). This suggests that stable and useful VLTM representations formed in parallel with VWM representations while people perform tasks that are designed to tap into VWM. Although experimenters normally try to rule out contributions from this sort of parallel coding, accumulation of alternate representations is a plausible strategy to perform memory tasks successfully.

Part of the reason the change detection task is so commonly used is because it is generally understood that participants must rely on VWM to succeed with the task. However, humans have a tremendous pool of experience with which to interpret different kinds of information, and these different interpretations may not be strictly visual. If information is represented outside VWM, the change detection task can be undermined and may not be a valid measure of visual performance. To take an extreme example, imagine that an observer is shown a complex array of line segments that happens to form the observer's name. The ability of the observer to store this array of line segments as a nonvisual, conceptual representation would presumably lead to enhanced change detection performance, but not because of the nature of VWM.

Although it is not known whether participants can rapidly represent information using VLTM representations as mentioned above, there is no shortage of other memory representations that might complement the role of VWM. *Conceptual short-term memory* is a memory system that could play this role.

The conceptual short-term memory system is a postperceptual, pre-working memory representation that codes information in an abstract, amodal, and conceptual manner (Loftus & Ginn, 1984; Potter, 1976; Potter, 1993). For example, viewing a photograph of a clock may activate the amodal concept "clock" in addition to activating the visual properties of the specific clock. It is this relatively abstract character that positions conceptual representations to play a role in other memory tasks. Indeed, conceptual memory has been shown to influence performance on visual tasks. Potter, Staub, & O'Connor (2004) showed participants rapid streams of color photos and then asked them to perform a new/old recognition posttest with the viewed images, new images, and one foil image selected to be conceptually similar to one of the old images. Although participants were most likely to report the images from the rapid stream as old, they were more likely to report the conceptual foils as old than the new images. This suggests that conceptual information can play a role in visual memory tasks.

Consider Figure 3a. Although it is possible to represent the figure as 3 distinct visual objects in VWM, it could also be interpreted with the conceptual label, "Mickey Mouse." If this array of objects were to appear in a size change detection task as a sample array, the observer would not need to use a visual representation to successfully notice the change in Figure 3b—a decision may be made from the fact that one display contains Mickey Mouse and one does not. Thus, extensive experience with a given stimulus might lead to improved change detection performance because of the recruitment of amodal, conceptual representations rather than because the training has impacted the VWM representations themselves.

So, when conceptual short-term memory (STM) representations are active, they recruit related conceptual information in LTM. Simultaneously active conceptual information from both conceptual short-term memory and LTM tend to associate, and this association increases the likelihood of successful long-term retention (Potter, 1993). So, experience with visual stimuli, even in the context of a visual task, should give this conceptual system multiple opportunities to form links between currently active conceptual information and LTM representations.

These principles can be applied analogously to nearly any other proposed memory system. It is worth evaluating whether and to what degree the demonstrated training effects hinge on contributions from VWM.

VLTM Interactions Summarized

The Activated VLTM and Structured Primitives accounts explain interactions between LTM and VWM representations in subtly different ways. The Activated VLTM account is relatively straightforward in that VLTM representations should facilitate VWM performance by disambiguating representation and reducing information load. The Structured Primitives account can accommodate facilitation of VWM performance by LTM representations as well, but facilitation stems from other LTM representations, like conceptual LTM. The general approach of this dissertation will be to use training to create LTM representations and then assess how this influences change detection performance, both when conceptual representations could or could not be helpful in task performance. However, before concretizing the use of LTM representations in an experimental context, it is important to consider how to create this LTM representation.

Alternative Possible Roles of Training in Capacity Tasks

To evaluate the interactions between LTM representations and VWM, it will be necessary to first develop a controlled way to create a LTM representation of a stimulus. Fortunately, issues of training and VWM performance have been explored before, albeit largely in the context of improving capacity.

Training can have many different effects on VWM tasks, and it is easy to confuse one type of effect for another. For example, an accidentally trained improvement in the efficiency of perceptual encoding might lead to an increase in *measured* VWM capacity performance without actually developing a LTM representation of any kind, so it is important to determine exactly what is changed by training. Consequently, the following sections will explore the specific ways in which training might improve VWM performance, including expertise, plasticity, and prioritization.

Circumventing Capacity Limits Through Expertise

An apparent violation of working memory capacity limits comes from expert memory. For example, the famous memorist Rajan has committed over 30,000 digits of the mathematical constant pi to memory and can, given a brief exposure to large matrices and series of letters or numbers, remember them with perfect accuracy (Ericsson, Delaney, Weaver, & Mahadevan, 2004). While not visual in nature, it is possible that expert encoding strategies might improve performance in capacity estimation tasks for VWM.

Expertise, however, develops over a period of many years and is not infallible. In an experiment that has found its way into nearly every cognitive psychology textbook, Chase and Simon (1973) showed that chess players who have extraordinary memory for the locations of chess pieces in meaningful arrangements are reduced to normal capacity for randomly arranged pieces. The narrow limits of expert skills make them quite easy to identify and eliminate using transfer tasks that extend outside the expert's bailiwick.

Not all formulations of working memory treat expertise as an exception to normal memory, however. The *long-term working memory* model of Ericsson and Delaney (1999), an example of an Activated VLTM Model, is one such formulation. In this model, retrieval skills are domain specific—an expert runner who repeatedly commits running times to memory might be highly skilled with retrieval of 3-digit number strings. Such an expert would be able to inflate performance on a digit span task by recoding the digits into groups of 3 and recoding them as running times—a chunking strategy that might be employed by experts in the visual domain. However, expert retrieval strategy still requires the better part of a decade of practice to develop and is susceptible to the same difficulties with transfer discussed above.

Prioritization

It is possible to ignore redundant and irrelevant information in favor of diagnostic information. The strategic selection of only particularly relevant information limits the burden on memory and can lead to improvement in VWM tasks. Wagar and Dixon (2005) explicitly tested this phenomenon by examining the effect of diagnosticity on memory. They taught participants to categorize artificially created figures called greebles into families based on conjunctions of manipulable greeble features. Participants were trained by exposure to greebles labeled with correct family names and by verifying random greeble names as correct or incorrect. Participants were tested with a greeble change detection task with a simultaneous secondary task that occupied either verbal or visual working memory capacity. Unknown to the participants, for change trials, the greeble differed either on a feature of the trained conjunction set or by family-irrelevant feature (a diagnostic or a non-diagnostic feature). Greeble change detection was better for changes in diagnostic features than non-diagnostic features, suggesting that participants were strategically focusing on the trained characteristics.

The simplest way to reduce the contributions of prioritization to a change detection task is to minimize the number of features that distinguish stimuli from one another and to manipulate only one of those. Simple objects of this type are encoded into VWM as bound units (Luck & Vogel, 1997). Even if it is possible to selectively encode information about these objects after extensive training, manipulation of just one featural dimension of the stimuli will ensure that there is no strategic benefit to be had by reducing the memory load. Designing stimuli in this way also resolves the issue of complexity in a flexible resource pool (Alvarez & Cavinagh, 2004).

Plasticity

Most models describe VWM capacity in terms not particularly amenable to plasticity, such as activation limits, intrinsic information decay, and limited processing speed (Miyake & Shah, 1999). Though most models do not deny the possibility outright, there are no mechanisms proposed to modify capacity in VWM. This is not unreasonable, given the dearth of evidence for genuine plasticity of VWM capacity in the literature (Olson, Jiang & Sledge, 2005; Chen, Eng, & Jiang, 2006).

Working from the slot model, improved capacity would directly correspond to adding new slots. While untested, it has been proposed that cell assemblies—pools of neurons capable of representing any object by synchronously representing its component features—underlie the slot construct (Raffone & Wolters, 2001). If this is the case, then genuine plasticity in VWM capacity would be expressed as an increase in the number of cell assemblies that can be maintained concurrently (which depends on factors such as the strength of mutual inhibition between the cell assemblies).

The flexible resources model would use an analogous mechanism to increase capacity. However, unlike added slots, improvement in a flexible resource pool can proceed fractionally—that is to say, flexible resource capacity can be said to increase without the addition of enough representational substrate to accommodate an entire new object.

Capacity change can be distinguished from other types of improved VWM performance through transfer. As discussed earlier, the distinguishing property of a working memory system is its flexibility of representation in the service of diverse tasks. So, if training produces a *bona fide* improvement in capacity, the improvements observed should generalize to all visual tasks for which performance is limited by the capacity of this memory system. In other words, benefits from training with one task should generalize to other tasks without additional training.

Very little research has shown such results. In a monumental study, Olesen, Westerberg, & Klingberg (2004) trained participants daily on three VWM tasks (Grid, Grid Rotation, and 3D Grid) for 5 weeks. At weekly intervals during training, participants were asked to complete a probe task where they would reproduce, in order, a serial presentation of five or seven dot onsets on a 4x4 grid of placeholders. Participants became more and more accurate over the course of training, culminating in an overall 20% improvement on this relatively untrained task—suggesting that perhaps the extensive training regimen had produced generalizable improvements. However, participants reported on post-experimental questionnaires that they used chunking as a primary strategy for the task, so it is not clear that they had augmented the capacity of memory *per se*, or if the training had yielded strategies to make more efficient use of the set capacity limit.

These questionable improvements in memory capacity with more than a month of constant training suggest that improvements with lighter training regimens likely stem from some other source. However, a suitable test to identify capacity change would be to test transfer of the improvement in performance to other visual memory tasks.

Recap of Possible Training Effects

To summarize, training could impact VWM performance in one of four ways. First, enough training could produce expertise, where VWM capacity limitations can be circumvented through extensive knowledge, skilled retrieval, and recoding information in the domain of expertise. Second, it could encourage information prioritization strategies, limiting the amount of information encoded into VWM and therefore using the limited capacity more efficiently without actually increasing capacity. Third, it could hypothetically drive underlying capacity change, literally increasing the amount of information that can be maintained across a delay. Finally, training (or extensive naturalistic experience) can form representations in other memory systems, which could either be used to supplement VWM, or could be the core representations underlying VWM.

To minimize contributions from expertise, prioritization, and capacity change and thereby ensure that the primary benefit of training can be attributed to the formation of

VLTM representations that contain task relevant information, two simple restrictions to the training method can be employed. To eliminate prioritization as an alternative explanation requires only that the trained stimuli contain the smallest number of task-relevant feature dimensions possible. If there is no irrelevant information to discard, prioritization will offer no benefit. Expertise and capacity change, on the other hand, can be easily minimized by limiting the training regimen so that neither develops. In the case of expertise, however, the accumulation of skill is probably a continuous process whose culmination is simply named expertise, and VWM frameworks like the long-term working memory model might argue that any training represents the development of expertise. That said, limiting training to a handful of hours across as many days should minimize participant expertise while still allowing the development of a strong VLTM representation. That is, the training regimen will be sufficient to create strong VLTM representations without creating the rich set of strategies and representations that would constitute expertise.

Additional methodological insights may also be gleaned by examining previous attempts to train performance improvements in VWM. The following section will review the relevant literature.

Prior Research on Training and Familiarity

There have been a handful of previous attempts to use training to improve performance on VWM tasks, but all have yielded little or no effect on VWM performance. This section will briefly survey this research with an eye to why training efforts did or did not have an effect.

Limited Repetition Does Not Aid Recall

Olson, Jiang, and Sledge (2005) investigated the effect of repeated exposure to a stimulus array in a change detection paradigm where the sample array contained N randomly placed objects and the test array contained N-1 objects. The subjects' task was to indicate the location of the missing item; thus, this was a spatial VWM task. Participants were given 384 trials across 32 blocks at set sizes 6, 9, and 12. Among the many randomly generated arrays, one display repeated in each block, though the absent item was randomly selected on each presentation the display. No difference in performance was observed between the repeated (trained) displays and novel (untrained) displays. Participants also completed a recognition posttest where they saw arrays of dots and indicated whether that pattern had appeared in the experiment. The rate of reporting that an array was familiar was found to be higher for the repeated arrays (80-90% across experiments) than for the novel displays (30-50% across experiments), and so it was concluded that participants had successfully acquired a LTM trace of the repeated array.

Although it is reasonable to conclude that participants had some VLTM representation of the repeated array, this makes no guarantees about the strength or quality of that representation. Even in the face of a large number of interfering stimuli, it is believable that 32 repetitions of an array are adequate to allow participants to identify the array when it is provided to them (Brady et al., 2008). The change detection task where participants localize the missing item in the test display, however, requires generation of the missing item's location—a much more demanding task requiring a spatially precise representation of every dot in the array. It is possible, then, that 32 exposures to a stimulus array that is highly similar to the remaining 352 arrays in the experiment is not adequate to drive accurate and precise localization performance.

Training Enhances Strategic Prioritization

In another study, (Chen, Eng, & Jiang, 2006), participants were trained on a shape memory task in which they saw a sample array of four items and then a test array of two items, one of which was identical to one of the original four items and one of which was not present in the sample array. Participants indicated which of these two test items had been in the sample array. The sample and test items were drawn from a pool of 8 polygons with which participants became familiar over a one-hour session of 320 training trials. Performance improved by 5-10% throughout training, but this may have reflected a general improvement due to task familiarity rather than an improvement in memory for the sample arrays. At the end of training, participants were tested on the same task, but the stimuli were drawn from a pool of all familiar items, all novel items, or a mix of both. Participants retained the trained level of performance under all conditions except with familiar stimuli in the mixed condition, which suffered a 5 percent *decrement* in performance. Chen, Eng, & Jiang reasoned that the polygons were complex and might require additional encoding time, so they also performed an experiment that was identical with the exception of participant-regulated viewing time of the sample display. Under these conditions, test performance reached the training levels across all conditions. In a final experiment, the training regimen was tested to see if it would provide transfer benefits to the traditional "same or different" change detection paradigm. The improvement failed to generalize, and it was concluded that the performance benefits were not linked to capacity change.

Although it is reasonable to rule out capacity change, training did drive a modest improvement in VWM performance. What is odd about this experiment, however, is the unlimited viewing time that was necessary to show a benefit with trained stimuli. Sample viewing times in change detection tasks are usually brief to limit participant opportunities for eye movements and the adoption of strategies such as verbal recoding. Under these conditions, it seems plausible that the boost to performance can be traced to a prioritization strategy. When participants were confronted with both novel and familiar stimuli, they may have preferentially encoded visual information about the novel stimuli and relied on the conceptual familiarity of the trained items to support change detection performance on some trials. However, since familiar items could only change to other familiar items, the neglect manifested in a small overall performance decrement. This possibility is especially plausible in light of the fact that eight stimuli were trained across only 320 trials, which might not be enough to develop a suitable VLTM representation that can facilitate performance. However, when participants had unlimited sample duration, they could spend time explicitly encoding both kinds of stimuli.

Extensive and Uncontrolled Familiarity

Other experiments have used stimuli with which participants were thoroughly familiar rather than attempting to train them with new stimuli. For example, Pashler (1988) presented participants with a change detection task using letters from the English alphabet. The letters were inverted in half the blocks and presented upright in the remaining blocks. Pashler reasoned that, if familiarity contributed to memory performance, then the less familiar inverted letters should make the change detection task more difficult. Participant behavior was equivalent in the two conditions, and Pashler concluded that familiarity had no effect on the change detection task.

Should we take from this that familiarity has no effect on VWM performance? Native English speakers begin training with letters at a very young age and exercise their reading skills regularly throughout life. As such, the undergraduates who participated in the experiment would have had between 15 and 20 years of experience using letters in a variety of contexts and for diverse tasks. It is possible that the participants had acquired a degree of expertise with the letters (and indeed, perhaps inverted letters as well as their more typical orientation) so that mere inversion is inadequate to make them unfamiliar.

Deep Encoding in Multiple Memory Systems

Even the least commonly occurring letters in the alphabet are likely very familiar, so letters may not be the best stimuli to test familiarity. In contrast, faces can range from highly familiar to completely unfamiliar, and Buttle & Raymond (2003) leveraged this fact to provide a stronger test of naturalistic familiarity effects. Participants performed a two-alternative forced choice change detection task—a variant of the basic paradigm where one of the items changes on every trial and participants are asked to pick which of two test stimuli is the changed item. The target face was systematically selected from a pool of famous and non-famous faces at both sample and test. So, for example, a famous target could change to a novel famous face or to a non-famous face.

Participants localized the change more successfully when the changed face was famous than when it was novel. This was true whether the famous face appeared in the sample display, the test display, or both—the target benefited from being a famous face at any point during the trial.

Because famous faces are more familiar than novel faces, it is tempting to conclude that familiarity yielded better VWM representations for the famous faces (Jackson & Raymond, in press). However, semantic knowledge about the famous faces or verbal recoding might have been responsible for the improved performance when the famous face changed, with no difference in the representation of the visual features of the faces. To control for these issues, a new pool of participants were familiarized with the pool of "novel" faces for an average of 8 minutes and tested until they could accurately name and report a fact from a brief biographical sketch about each face. They then completed the same change detection task as described in the previous experiment. Despite the familiarization period, the famous-face advantage persisted, and Buttle & Raymond concluded that there was no semantic contribution to the familiarity effect.

While these experiments provide better support for a familiarity benefit in VWM performance than the evidence presented in Pashler (1988), the support is still limited. The control experiment effectively dismisses verbal recoding as an alternative explanation; participants could name all the faces, and so whatever advantage would have been offered by recoding was available to both categories. However, it really doesn't account for contributions from semantic or conceptual memory. Famous faces, being highly familiar and integrated with our environments, enjoy fairly extensive semantic connections with a variety of information. Furthermore, there is a discrepancy in the overall amount of exposure between the amount of familiarity between the trained faces and the famous faces. By sole virtue of extensive experience, semantic information may have sprung to mind effortlessly for famous faces, whereas participants may not have been inclined to expend the effort to retrieve the same information for the less familiar trained faces. The combination depth of encoding with strength of representation confers a significant retrieval advantage from supporting memory systems, and may not actually operate through VWM at all.

The major shortcoming in the last two experiments can be traced to control. In the Pashler study, participants may have had such extensive experience with letters that ceiling effects masked any discrepancy between normal and inverted stimuli. In the Buttle & Raymond study, participants could have relied on conceptual and semantic encoding instead of VWM representations to do the task. Strong evidence that familiarity with a particular exemplar can improve VWM performance is most easily obtained under controlled conditions. While it is impossible to entirely prevent elaborative processing, it may be possible to minimize its impact through controlled familiarization.

Evidence From the Verbal Domain

Although evidence regarding the role of familiarity in visual tasks is fairly equivocal, there has been some research with verbal WM suggesting that phonemic frequency and vocabulary size contribute to verbal WM performance. Building upon previous work showing a positive relationship between vocabulary size and nonword production accuracy (Edwards, Beckman, & Munson, 2004; Gathercole & Baddley, 1989, Metsala, 1999) Munson, Edwards, & Beckman (2005) asked young participants to produce nonwords that systematically varied in terms of phonotactic frequency. Participants produced nonwords containing the high frequency diphones better than the low frequency diphones, regardless of the real-word frequency of the diphones. Regression analysis suggested a relationship between vocabulary size and the frequency effect that could not be explained by differences in speech perception or phoneme production.

Unfortunately, it is difficult to map these results directly onto the visual domain. Representational persistence in verbal WM is constrained by rapid decay. The necessarily serial nature of phoneme production could lead to completely different functional connectivity between verbal WM and verbal LTM representations than exists in the more parallel visual system.

Furthermore, the study was conducted with participants aged 3 through 6 years. At such a young age, participants' relative dearth of experience with phonemes places them at a developmental juncture where the line between a Structured Primitives account and an activated LTM account of WM representation may not be as clear-cut as it is in fully-developed adults. That is, even if the fully-developed character of the WM system is best described by Structured Primitives, participants' relatively lesser experience with uncommon diphones (regardless of diphone frequency in natural language) may correspond to developmental differences among the primitives used to construct the WM representations.

The next chapter will survey the general approach that this dissertation research will take.

CHAPTER 2

OVERVIEW OF THE PRESENT APPROACH

Hypotheses of Interest

The issue of representation in VWM raises two competing hypotheses. In one case, VWM *is composed* of activated VLTM representations, as with Activated VLTM theories. A change detection array of six oriented bars, for example, could be represented as a vector of similarities to various VLTM representations. However, the vector of similarities between a sample pattern of six randomly oriented bars and a set of VLTM representations will be very similar to the vector of similarities for a test pattern that is identical to the sample pattern except for the orientation of one bar. Thus, change detection performance will not ordinarily be very accurate for large arrays that are not very similar to distinctive VLTM representations. However, if the sample array is identical to an existing VLTM representation and the test array is not, then the vectors for the two arrays should be easy to distinguish. For example, if six bars were arranged to form the pattern FIT as the sample array, and one bar was changed to form the pattern FIL for the test array, it would be easy to perform the change detection task. This hypothesis will be referred to as the *Unitary Storage Hypothesis* to emphasize the idea that VWM representations consist of Activated VLTM representations rather than being stored in a different system.

In the second case, VWM *exists independently* from VLTM representations, as with Structured Primitive theories. That is, although both systems may contribute to change detection performance, VWM representations are stored in a system that is not directly tied to LTM. In this case, performance in a given task could potentially be improved by storing information both in VWM and in LTM. For example, even if the pattern FIT were coded as a set of oriented bars in VWM, a verbal or conceptual code for the word "fit" might be used in addition to the VWM representation. This hypothesis will be referred to as the *Parallel Storage Hypothesis* to emphasize the proposed separation between the VWM and LTM systems.

The purpose of the experiments in this dissertation is to distinguish between the Unitary Storage Hypothesis and the Parallel Storage Hypothesis, which are specific components of the competing Activated VLTM and Structured Primitive theories, respectively. The present chapter will be devoted to explaining the general experimental approach, identifying the specific empirical questions that must be addressed, and demonstrating how these individual points come together to select between the two hypotheses.

Core Paradigms and Logic

The following task is used to help distinguish between the Parallel Storage and Unitary Storage Hypotheses. Participants train on an orientation discrimination task with a particular pattern of eight oriented bars for two days. After demonstrating improved performance on the discrimination task and conserved improvement between days, participants perform an orientation change detection task on a third day to test their ability to remember the trained array and untrained arrays. Half the trials in this change detection task will contain the trained array (as either the sample or test array) and half will contain a randomly generated array. By comparing participant performance on the trials containing the trained array to the trials containing random arrays, it becomes possible to see what benefit the LTM representation of the trained array can grant to performance of the change detection task.

The demonstration of a VWM benefit with trained arrays in the change detection test is especially important in light of the previous research that has shown no such effect (Olson, Jiang, and Sledge, 2005; Chen, Eng, & Jiang, 2006). However, extensive training with a single trained array should make for more optimal learning conditions.

That is, hundreds of trials of training with a single pattern should certainly yield a very robust VLTM representation.

The Unitary Storage hypothesis obviously predicts that VLTM representations should facilitate VWM performance, but the Parallel Storage hypothesis could also accommodate this finding for the reasons described in Chapter 1 (i.e., because a conceptual representation of the sample array could be used to help solve the change detection task). So, once an effect of LTM training on VWM performance has been demonstrated, follow-up experiments are necessary to determine whether the improvement in performance can be explained by the Unitary Storage Hypothesis versus the Parallel Storage Hypothesis. The way that VLTM representations interact with VWM performance in these subsequent experiments will be used to distinguish between Unitary and Parallel Storage.

Testing VWM Performance

Why was the change detection task selected to evaluate performance? As can be seen from the literature, the bulk of research with familiarity and training effects in VWM consists of behavioral work using the change detection paradigm (or minor variations of this paradigm). The change detection task consists of a sample→blank→test sequence (see Figure 1 in Chapter 1) that encourages the use of VWM during the blank interval and is well suited to assessing VWM performance under a variety of conditions. As such, the change detection paradigm will be at the heart of these experiments and will be used to test the trained LTM representation.

Developing the Trained VLTM Representation

Though the change detection paradigm is appropriate to test performance with the trained LTM representation, a different task should be used to produce the LTM representation. As noted in the discussion of Olson, Jiang, & Sledge (2005), practice with a VWM task may drive improvement either through development of a LTM representation of the specific stimuli or through the acquisition of a more general skill with the task. To ensure that change detection benefits are truly derived from the development of LTM representations of the specific stimuli, a separate task must be used for training. A reasonable candidate is discrimination training, in which participants learn to determine whether a given pattern is or is not a specific target pattern. That is, observers are shown a target pattern at the beginning of the experiment for several seconds, and then they must classify whether subsequently presented patterns are or are not the target pattern. As the number of exposures increases, discrimination accuracy increases and reaction time decreases, presumably because the LTM representation of the target is becoming stronger (Medin & Schaffer, 1978; Logan, 2002).

The training regimen relies on the assumption that discrimination training is adequate to form a long-term representation of the array of oriented bars. However, this need not be merely an assumption. By stretching training across multiple days and demonstrating that improvements of discrimination performance are conserved from day to day, it may be safely concluded that benefits derived from the training are long-term in nature.

Is discrimination training adequately different from the change detection task to ensure that any transfer between the training and test tasks is due solely to the developed LTM representation? Both tasks require participants to maintain a memory representation of a sample stimulus, retain it over some interval, and then eventually compare that memory representation with a newly presented stimulus to discern any differences between the two.

The tasks are not identical, however. In the discrimination task, participants are given a considerable length of time to inspect the sample array and then are expected to maintain it over a period of several minutes. In the change detection task, participants are only briefly presented with the sample array and then are typically expected to maintain it very briefly (around one second).

It is worth reiterating at this point that even training with a two-alternative forced choice change detection paradigm does not seem to provide generalizable facilitation to the standard change detection paradigm (Chen, Eng, & Jiang, 2006). Unfortunately, there is no standardized metric for "how different" two tasks must be to limit the transfer of expert skills. Nevertheless, due to the considerable overlap between the training and test tasks, the present study will not be able to demonstrate broad generalization of learning.

Specific Issues

The Unitary Storage and Parallel Storage Hypotheses differ on whether VWM representations are composed of VLTM representations. So, the core issue addressed by this dissertation is whether or not a strong VLTM representation can improve participants' ability to store the representation in VWM. However, the joint use of VWM and VLTM could cause improved performance for trained patterns. The following sections describe my approach to distinguishing whether the training effects involve the parallel operation of VWM and VLTM or the enhanced operation of a single, unified system.

Foundational Behavioral Experiments

The first step was to demonstrate that training could, under appropriate conditions, lead to improved change detection performance for the trained stimuli. This was achieved in Experiment 1, which proceeded as described above. Each participant learned an array through discrimination training and then performed a change detection task involving the trained array or novel arrays. Both the Unitary Storage and Parallel Storage Hypotheses predict that change detection should benefit from the use of a trained array. Although such an experiment does not directly move toward distinguishing the hypotheses in question, it establishes a manipulable paradigm and an observable effect for use in the following experiments.

Because the most efficient way to identify the impact of training in Experiment 1 is to compare performance with a trained stimulus to performance with a random stimulus there is a necessary inequality of exposure during the experiment. That is, participants will see the trained array more often than any given randomly generated array during the change-detection task. This inequality could result in simple priming of the repeated array, which could facilitate performance with the trained array in a way indistinguishable from contributions from LTM representations. Experiment 2 addresses the possible role of priming in the effects observed in the change detection task from Experiment 1.

Event-Related Potential Experiment

Experiment 3 will use the event-related potential (ERP) technique as a source of converging evidence to augment the behavioral results, so a brief overview of the ERP technique will be provided here. During the course of neural activity, cells produce small electrical potentials. The brain is a massively parallel computational machine, however, and all the individual electrical signals sum together as they propagate through the brain, skull, and scalp. By recording and amplifying the microvolt-level signals that reach the scalp, it is possible to measure the summed activity as a series of voltage peaks and troughs. In the case of the change detection task, stimuli are presented at known intervals and it is possible to take snapshots of the waveform when, for example, the test array onsets (Figure 4a). Each of these snapshots contains the electrical activity related to processing the test array as well as whatever other random activity happened to coincide with that moment (autonomic processes, unrelated thoughts, etc). By averaging enough of these snapshots together, the random activity averages to zero, leaving only the consistent stimulus-dependent activity (Figure 4b). The net result is a consistent series of positive and negative voltage excursions known as peaks or components.

Prior research has revealed several consistently identifiable components of these averaged waveforms, and these components are named for their polarity and position in the waveform (e.g., *N2* for the second major negative component). Each is thought to be associated with certain cognitive processes and can provide highly precise timing information about those underlying processes. Consequently, ERPs can provide a useful source of information about on-line cognitive processing.

Of particular interest to this research is the N2pc (N2 posterior contralateral) component. The N2pc is generally thought to reflect the spatial locus of visual attention, because it is elicited by a shift of visuospatial attention to either the right or left visual hemifield (Woodman & Luck, 1999). This quality makes the N2pc component useful for identifying the role of pre-VWM selective mechanisms that may influence change detection performance.

It has been demonstrated elsewhere that visuospatial attention shifts to the spatial locus of a change in the test array in change detection tasks—a process that can be observed with the N2pc component. There seems to be a specialized mechanism that rapidly compares perceptual inputs to VWM representations, leading to a rapid shift of attention to the changed item (Hyun, 2006). Examination of the N2pc in response to trained and novel arrays will be used to determine whether the enhanced change detection performance for trained arrays can be attributed to the strategic use of attention based on nonvisual, conceptual representations rather than to an improvement in the quality of the VWM representations. An in-depth discussion of the predictions will be provided in Chapter 4.

Verifying the Visual Character of the LTM Representation

The preceding three experiments can demonstrate whether a LTM representation is capable of driving a change in performance in the visual domain, but they cannot conclusively determine the nature of the pivotal LTM representation. That is, it is plausible that participants are developing a VLTM trace that guides the comparison process in the change detection task, but Experiments 1-3 do not rule out contributions from supporting memory systems like conceptual memory or verbal memory.

Experiment 4 will isolate the contributions of VLTM representations using a one-to-many mapping scheme. Participants will be trained with a group of visually similar but discriminable arrays to identify them as a single conceptual category. During the change detection task, both the sample and test arrays will be members of this family even on change trials. Because the sample and test arrays belong to the same conceptual category, but differ visually, participants will be able to perform the task only by means of nonconceptual, visual representations. Thus, improved performance for trained stimulus arrays could not be explained by the use of conceptual representations and would provide unambiguous support for the Unitary Storage hypothesis. However, if training does not improve performance, then this will support the Parallel Storage hypothesis.

Experiment 5 will converge on the results of Experiment 4 by testing to see if visual information in a trained stimulus can be used to cue an untrained visual property of that same stimulus. Participants will be trained extensively with the color properties of a stimulus that contains task-irrelevant texture information. During the change detection test, they will be asked to detect texture changes under conditions where the trained stimulus is used and where an untrained stimulus is used. If the Unitary Storage hypothesis is true, then the binding of the color and texture features in VWM should allow participants to use their strong VLTM representation of the color information to cue their weaker representation of texture information. However, if participants cannot use the color information to improve texture performance, the outcome will support the Parallel Storage hypothesis.

Summary

The empirical issues described in this chapter serve to distinguish between the Unitary Storage and Parallel Storage Hypotheses, which are subcomponents of the Activated VLTM and Structured Primitives theories. To accomplish this goal, these five experiments will indicate whether a trained representation can improve VWM performance, and whether the representation is visual. A VLTM representation facilitating VWM performance would be consistent with the Unitary Storage hypothesis, whereas a failure to demonstrate the same facilitation in the absence of contributions from conceptual memory supports the Parallel Storage hypothesis.

CHAPTER 3

TRAINING DISCRIMINATION AND TESTING CHANGE DETECTION

Experiment 1: Demonstration that Training Can Influence Change Detection Performance

The studies discussed earlier have found that training has little or no effect on change detection performance, but these studies may have failed because they tried to train too many different patterns with too few trials, resulting in insufficiently strong VLTM representations of the trained patterns. Experiment 1 was designed to demonstrate that substantial training with a single pattern can lead to improved performance when that pattern appears in a change detection task. This experiment is not sufficient to demonstrate that the improved performance is a result of changes in the quality of the VWM representations of the pattern, but it is important to provide an initial demonstration that training can improve change detection performance.

Experiment 1 is the template from which all the experiments in this dissertation are derived. It consisted of two phases: training and test. The training task was an orientation discrimination task and consisted of a familiarization segment and a task segment (Figure 5). It proceeded in a series of blocks, each containing both segments. During the familiarization segment, participants spent 30 seconds passively viewing an array composed of 8 randomly oriented bars called the *trained array*. After the familiarization segment concluded, the task segment began. Participants were presented with a series of arrays of 8 oriented bars. Half of these arrays were identical to the trained array, and the other half were identical except that one randomly selected bar was rotated 45° from the orientation of the corresponding bar in the trained array. These latter arrays were collectively known as *trained-1* (trained minus one) *arrays*. The task was to indicate whether a given array was the trained array. After participants responded, a feedback tone was played: high-pitched if the response was correct, and low-pitched if the response was incorrect. Discrimination training proceeded for two consecutive days, with a total of 1600 training trials.

Development of a suitable training task emphasized obtaining sufficient training. The issue of sufficiency arises because it has been shown that an hour of training with a set of 8 different polygons does not produce generalizable learning (Chen, Eng, & Zhang, 2006). So, to be certain that participants had developed a strong LTM representation of the trained array, they received 1600 trials of training to discriminate a single pattern from highly similar foils over a period of two consecutive days, and their performance was tracked to demonstrate both gradual improvement within each day and retention from day to day. This quantity of training represents a sledgehammer approach to ensure a strong LTM representation.

The relatively small change magnitude between the trained array and the trained-1 arrays was designed to encourage the acquisition of a complete and precise representation of the trained array. To successfully perform the training task, participants needed to represent the orientations of all eight elements in the trained array.

On the third day, the test phase began. The test phase consisted of an orientation change detection task (Figure 6) with arrays of 8 oriented bars. On 50% of the trials (change trials), the test display contained a 45° orientation change in one of the items relative to the corresponding item in the sample display. The remaining trials were no-change trials.

There were two main trial types: trained and random. Half the trials were trained trials and contained the trained array in either the sample display or the test display. The remaining trials were random trials and contained randomly generated orientations. Because only one item in the test array changed orientations on change trials, the trained array and random array each had unique complementary arrays: trained-1 (trained minus one) and random-1 (random minus one), respectively. That is, if the sample display was a trained array on a change trial, the test display could only be one of the eight trained-1 arrays, and vice versa. If the sample was a random array, it could change to one of eight different random-1 arrays. However, this is just a notational convention: The specific arrays used for both random and random-1 were completely random from trial to trial, except that they were identical to each other with the exception of one bar. It was arbitrary which array was called random and which was called random-1.

Methods

Participants

Ten volunteers recruited from the University of California at Davis participated in this experiment for course credit. They reported normal color vision and normal or corrected-to-normal acuity.

Stimuli and Procedure

Participants were trained on an orientation discrimination task for one hour on each of two consecutive days. On the following and final day, they briefly practiced the discrimination task before being tested with the change detection task.

Stimuli during training and test all consisted of an array of oriented bars arranged in two rows with each row of bars centered relative to fixation (Figure 5). Each bar was positioned 1.23 degrees away from its neighbor. The presentation of the bars was anti-aliased (4x), and each subtended a region of 1.15 by 0.33 degrees. All displays contained a fixation cross subtending 0.82 degrees.

Across training and test conditions, there were 4 types of displays: trained, trained-1, random, and random-1. Each participant was assigned a different randomly generated trained array, which was an array of 8 oriented bars whose orientation remained constant through both training and test. The trained-1 arrays were a class of arrays identical to the trained array except that one randomly-selected bar from the trained array was rotated by ±45° from its trained orientation; any of the 8 bars could be rotated, so the participants could not know in advance which bar might change between the trained array and a trained-1 array. Random arrays consisted of orientations selected randomly at the beginning of each trial in which they appeared, and random-1 arrays contained one bar whose orientation had increased or decreased by 45° from its original orientation. Because the random-1 arrays were generated with respect to randomly generated arrays, the labeling of one arrays as a random array and the other array as a random-1 array was purely arbitrary.

Training

After consent was obtained, instructions were provided. After brief practice with the task, participants completed 2 blocks of training on the first day and 3 blocks on the second day. Each block began with the familiarization segment, in which participants passively viewed the trained array for 30 seconds. After this familiarization period, the discrimination task began. Discrimination trials were presented in a series of blocks of 320 trials. During each trial, participants were presented with either a trained or trained-1 array that remained on screen until the participant responded, followed by a 500-ms blank intertrial interval. Responses were made on a Logitek Precision game pad. Participants responded with the index finger of the left hand if the presented array was the trained array, and the index finger of the right hand if the presented array was a trained-1 array. After the response, participants heard a high pitched tone (1.6 kHz) if the response was correct or a low pitched tone (0.5 kHz) if incorrect. Participants were instructed to respond as quickly and as accurately as possible, but with an emphasis on accuracy.

Test

Before the test task was undertaken, participants underwent 90 trials of the discrimination training task. This task proceeded in the same way as it did for the previous two days, except for the number of trials.

The test task was a standard change detection task. The sample array was presented for 100 ms, followed by a blank 900 ms inter-stimulus interval, and then the trial concluded with the presentation of the test array until the participant responded. There was a blank interval of 1000 ms between trials. There was one block of 896 trials. Participants were given a brief break every 2-3 minutes.

Half of the trials were change trials where one random bar changed orientation by ±45 degrees between sample and test; the remaining half were no-change trials where the sample and test displays were identical.

In half the trials, the sample array was either trained or trained-1, and in the other half, the sample array could be random or random-1. On change trials, the trained sample array could change to a trained-1 test array, and a trained-1 sample array could change to a trained test array. Random sample arrays could only change to random-1 test arrays, and random-1 sample arrays could only change to random test arrays.

Participants were asked to compare the sample array to the test display and report the presence or absence of a change between the two. Responses were made on a Logitek Precision game pad. Participants responded with the index finger of the left hand to report no change, and the index finger of the right hand to report a change. Participants were instructed to respond as quickly and as accurately as possible, but with an emphasis on accuracy.

Results

Data Processing

Trials with RTs of less than 200 ms were eliminated because they presumably indicate fast guesses rather than actual discriminations. Trials with RTs of greater than 2000 ms were eliminated because they may involve the use of unusual strategies that do not reflect typical performance. These criteria resulted in the rejection of 15% of training trials across all participants (range = 1-45%) and 6% of the test trials (range = 0-13%). Of these participants, only two required exclusion of more than 10% of their total trials. Analyses conducted excluding these participants (not included here for brevity) did not substantially alter the significance outcomes of the following data.

Training

Training data were analyzed using a single factor ANOVA with five levels: one for each block of training. Participant accuracy data were converted to d' and are shown in Figure 7. Participant performance rose gradually (block 1 d' = 2.18→block 5 d' = 3.34) across the 5 blocks of discrimination training and was conserved between blocks 2 and 3; that is, improvement was conserved across days. The increase in d' over blocks was statistically significant, $F(4, 36) = 9.40$, $p < .01$.

Reaction times appear in Figure 8. Reaction times improved monotonically across training blocks (block 1 RT = 1216 ms → 909ms). The monotonic improvement was conserved between blocks 2 and 3, again indicating that the improvement was conserved across days. The reduction in RT over blocks was statistically significant, $F(4, 36) = 19.45$, $p < .01$.

Test

Test data were analyzed using a single factor ANOVA with two levels: trained and untrained. Change detection accuracy was converted into d' and appears in Figure 9. Participants performed significantly better on the change detection task with the trained and trained-1 arrays (d' = 1.36) than with the random and random-1 arrays (d' = 0.96), $F(1, 9) = 19.51$, $p < .01$. Mean participant reaction times were statistically indistinguishable (Figure 10) between the trained arrays (750 ms)) and the random arrays (771 ms), $F(1, 9) = 1.83$, $p = .21$.

Discussion

Performance with the discrimination task gradually improved with increasing training, and the improvement was conserved between days of training. This suggests that the performance benefit that participants developed using this core paradigm during training was long-term in nature. When participants performed the change detection task, they performed better overall on trials that included the trained array as either the sample or the test than on trials containing the random array. Taken together, these results suggest that a strong LTM representation developed in one task can substantially facilitate subsequent performance in another task.

The outcome of this experiment is not consistent with previous research (Olson, Jiang, & Sledge, 2005; Chen, Eng, & Jiang, 2006) that has shown little or no effect of LTM representations on VWM performance. Although the present experiment shares a number of similarities with the paradigms used in earlier research, the addition of a more extensive training regimen in the present study may explain the presence of a facilitation effect. The remaining experiments in this thesis will focus on characterizing the nature of the facilitation, its origins, and how it may be used to distinguish between the Unitary Storage and Parallel Storage hypotheses.

Experiment 2: Is Training Necessary?

Although the results of Experiment 1 were consistent with an effect of training on change detection performance, there is an alternative explanation based on priming that must be ruled out. When a representation is activated, subsequent activations of the same representation are briefly facilitated. For example, imagine two groups of participants, one that reads a brief paragraph about various types of light bulbs and their environmental impact, and another group that does not. If subsequently presented with the letter string, "_ight" and asked to fill in the blank, participants from the light bulb group would be more likely to fill in "light" than their counterparts. This phenomenon is known as priming.

During the change detection task used to test working memory performance in Experiment 1, participants were exposed to the trained array or a highly similar trained-1 array a total of 896 times (including both sample and test arrays). Consequently, priming of the trained array through repeated exposure during the change detection task may account for the observed performance improvements for the trained array.

Priming is an effortless and automatic event in human cognition, so eliminating its contribution would be extremely difficult. However, by eliminating the training task from the paradigm used in Experiment 1, we can determine if priming alone is sufficient to produce the greater performance observed for the trained array in Experiment 1.

The purpose of Experiment 2 was therefore to rule out priming as an alternative explanation for the results of Experiment 1. In this experiment, a pool of new participants participated in the change detection task under the same conditions as Experiment 1, but without the preceding training. Unfortunately, this precludes the use of the *trained/random* nomenclature, so instead the array conditions will be referred to as *repeated/novel*, respectively.

If the development of a LTM representation of the trained array in Experiment 1 solely underlies the facilitation effect, then participants should show no difference in performance between the repeated and novel arrays in the present experiment. If instead, priming underlies the facilitation effect, participants should perform better for the repeated arrays than for the novel array.

It's worth noting that the contribution of priming may not account for the entire facilitation effect demonstrated in Experiment 1. If that is the case, then there may be some performance disparity between the repeated and novel arrays, but not with the same magnitude as exists between the trained and random arrays in Experiment 1. Furthermore, participants may be able to rapidly accumulate a LTM representation of the trained array during the change detection task. This is reasonably plausible; each trial in the trained blocks contains a completely intact or mostly intact trained array, so any LTM representation forming during the task will not be subjected to much interference. Indeed, this is how Olson, Jiang, and Sledge (2005) attempted to train a LTM representation of a set of arrays.

Methods

Participants

Twelve volunteers recruited from the University of California at Davis served as participants in this experiment. They reported normal color vision and normal or corrected-to-normal acuity.

Stimuli and Procedures

The methods for this experiment were identical to those of Experiment 1 except that the training phase was eliminated. That is, participants experienced only the test phase.

Results

Data Processing

Trials where the reaction time was greater than 2000 ms or less than 200 ms were omitted from the analysis. This resulted in the rejection of 9% of the test trials across all participants (range = 0-42%). Of these participants, only two required exclusion of more than 10% of their total trials. Analyses conducted excluding these participants (not included here for brevity) did not substantially alter the significance outcomes of the following data.

Test

Test data were analyzed using a single factor ANOVA with two levels: repeated and novel. Change detection accuracy was converted into d' and appears in Figure 11. There was no significant difference in performance between the novel condition (d' = 0.90) and the repeated condition (d' = 1.02), $F(1, 11) = 1.42$, $p = .26$. The same was true of reaction time (Figure 12) in the random (817 ms) and trained (794 ms) conditions, $F(1, 11) = 2.33$, $p = .16$.

To verify that there was a significantly smaller effect in Experiment 2 than in Experiment 1, the difference in performance between the trained and untrained arrays in Experiment 1 was compared with the difference in performance between repeated and novel arrays in Experiment 2. These difference scores represented a measure of the facilitation effect in both experiments and were compared in a two-tailed t-test. There was a significant difference ($p = .048$) between the Experiment 1 effect (d' difference = 0.41) and the Experiment 2 effect (d' difference = 0.12).

Discussion

The comparable performance of participants with novel and repeated arrays suggests that the relative consistency in the appearance of repeated arrays during the change detection task does not contribute to a priming-derived facilitation of participant performance. Thus, the training procedure used in Experiment 1 plausibly led to the formation of an LTM representation of the trained array, and this LTM representation must have been responsible for the observed enhancement of change detection performance for the trained array.

This conclusion is bolstered by the earlier research that showed little or no effect of training (Olson, Jiang, & Sledge, 2005; Chen, Eng, & Jiang, 2006). These experiments also used change detection tasks with repeating arrays to look for training contributions to VWM performance and found no evidence supporting it. Because the primary difference between the paradigm used in Experiment 1 and this earlier research is the extensive discrimination training, it seems clear that the training regimen underlies the VWM facilitation effect found in Experiment 1.

Experiment 3: Does Change Detection Elicit a Shift of Attention?

The Unitary Storage Hypothesis readily accommodates the combined results of Experiments 1 and 2. It stands to reason that, if VWM representations are activated VLTM representations, VWM performance derived from a strong VLTM trace should be better than VWM performance without such a trace. However, the brain is a massively parallel computational machine, and it is entirely plausible that a nonvisual LTM representation may contribute to the facilitation effect observed in Experiment 1.

Consider as an example how conceptual memory might help on change detection trials where the sample array is a trained-1 array and the test array is a trained array. In this case, participants might simply store the orientation of the trained-1 item in VWM, using conceptual memory (or some other nonvisual abstract representation) to remember that the rest of the array was simply the trained array. This would greatly reduce the amount of information that observers would need to store in VWM, improving performance without any direct link between VWM and VLTM. Alternatively, they might simply use conceptual memory to store the fact that there was a trained-1 item in the sample array *at all*, without needing to maintain a *visual trace* of the trained-1 item's visual properties. When the test array is presented, the participant would only need to recognize it as the trained array to realize that there was a change. So although visual representations contribute to the facilitation effect, they do not necessarily mediate it. In either case, participants would shift visuospatial attention to the -1 item in the sample array because it is behaviorally relevant.

Covert shifts of attention like these can be tracked using the N2pc component. When visuospatial attention is shifted to the left or right visual hemifield, the N2pc component can be observed over the contralateral hemisphere of the brain (Luck et al., 1997). So, if conceptual or other abstract memory representations mediate the facilitation effect observed in Experiment 1, it should be possible to observe the N2pc contralateral to the side of the trained-1 sample array that mismatches the trained array.

Such an outcome is not obviously predicted by the Unitary Storage hypothesis, because it rests on the assumption that the facilitation effect in Experiment 1 is driven exclusively by visual representations. That is, if VWM representations are activated VLTM representations, then there is relatively little to be gained by comparing the perceptual representation of the trained-1 array to the VLTM representation of the trained array. This is because the eventual VWM representation of the trained-1 sample is stored as a similarity vector with respect to the VLTM representation of the trained array, and no special linkage to the VLTM representation could be gained by comparing it to the perceptual representation of the sample.

This is not to say that the Unitary Storage Hypothesis precludes the possibility of an N2pc in response to a trained-1 sample array. It is possible that participants, especially after extensive discrimination training, automatically compare presented arrays to their VLTM representation of the trained array. However, if this is the case, the automatic process should not distinguish between presentation of the trained-1 array at sample or at test. So in this case, the Unitary Storage hypothesis predicts an N2pc in response both to trained-1 sample arrays and trained-1 test arrays, even on no-change trials.

The Parallel Storage hypothesis, by contrast, does predict the strategic intervention of abstract representations to reduce the load on VWM. Under this account, VWM capacity is limited, and segregation between VWM and VLTM representations would mean that improving VLTM representations should have no impact on participant ability to store sample arrays with large set sizes. So, to lighten the load on VWM and improve performance, participants shift their attention to the trained-1 element in the sample array, consolidate it into VWM, and simply code the remainder of the array as being trained. Alternatively, they execute the comparison and simply code the whole array abstractly as trained-1.

However, in neither of these two Parallel Storage cases, do participants have a reason to execute a comparison in response to a trained-1 test array on no-change trials. In this context, whatever LTM representations participants have are orthogonal to the task at hand, and participants should respond as they did in Hyun (2006) and not generate the N2pc component in response to a test array on no-change trials.

Collectively, the Unitary Storage hypothesis predicts a sort of all-or-nothing N2pc effect. The simplest version of the Unitary Storage hypothesis predicts that the general pattern of processing will be identical for trained and untrained arrays, and an N2pc will be observed only for changed items in the test array (as in the Hyun study). However, it is possible that attention will automatically be allocated to the -1 item in trained-1 arrays because of the mismatch between this item and the strong representation of the trained array in LTM. If this is automatic rather than strategic, however, then it should occur whether the trained-1 array is a sample array, a test array on a change trial, or a test array on a no-change trial. In contrast, the Parallel Storage hypothesis predicts that attention will be used strategically to encode the -1 item in trained-1 sample arrays but that there is no reason why attention should also be allocated to the -1 item when the trained-1 array appears as the test array on no-change trials. These predictions appear in Figure 13.

Finally, it is worth noting that the Unitary and Parallel Storage hypotheses share several predictions about the generation of the N2pc under typical change detection conditions. Both predict a shift of attention in response to any test array on a change trial (Figure 13a) for the same reason: the VWM representation of the sample array does not match the perceptual input of the test array, and the comparison process drives a shift of attention to the location of the change. Furthermore, they share identical predictions for the trained array on a no-change trial (Figure 13c): there should be no N2pc because both the sample and test arrays match the LTM and VWM representation of the trained array and there is no change to drive an attention shift.

Methods

Participants

Seventeen paid participants recruited from the University of California at Davis served as participants in this experiment. They reported normal color vision and normal or corrected-to-normal acuity. They also reported no history of epilepsy or other neurological disorders.

Stimuli and Procedures

The stimuli and procedures were identical to those used in Experiment 1 except where the ERP method required minor changes as noted below.

Because the N2pc is elicited by changes only when the change is detected (Hyun, 2006), it is necessary to exclude trials on which the change is not detected. Low levels of participant performance may therefore cause too many trials to be excluded, yielding an inadequate signal to noise ratio. To reduce the difficulty of the task and thereby increase the number of correctly detected changes, the set size was reduced to 6 items.

Also, because the N2pc is lateralized across visual hemifields, the six-bar array was presented as two columns of three rows centered around fixation. Stimulus size and spacing were unchanged (an example of the change detection test appears in Figure 14). It is also worth noting that these minor changes did not have any impact on the design property that trained-1 arrays could only change to trained arrays and vice versa (and indeed that these two changes are essentially identical, just presented in reverse order). The same was true of random and random-1 arrays.

Recording and Data Analyses

Raw EEG data were recorded using a BioSemi ActiveTwo system using Ag/AgCl electrodes. The electrodes were arranged in a 32-channel cap according to the International 10/20 system, though the research presented here focuses on a subset of those electrodes (P1/2, P3/4, P5/6, P7/8, P9/10, PO3/4, PO7/8, O1/2). In addition to the cap electrodes, there were four electrooculogram (EOG) electrodes that were used to monitor eye movements and two mastoid electrodes that were used for referencing. Two of the EOG electrodes were used to record horizontal EOG, and each was located immediately adjacent to the lateral canthus of one of the eyes. The remaining EOG electrodes were used for vertical EOG, with one placed above the left eye and one placed below it. The mastoid electrodes were positioned behind the ears, one on the left and right mastoid processes. The signals from each were recorded in a single-ended mode and referenced offline to the average of the left and right mastoid signals. The data from all the electrodes was recorded with a sampling rate of 1024 Hz. Consistent with our laboratory's standard practice, participants were eliminated from all analysis if 25% or more trials were rejected due to artifacts were rejected from the analysis. Only correct trials were included in the analysis. On incorrect trials, participants presumably did not localize the change and therefore would not generate the N2pc component.

The N2pc component was isolated by subtracting the electrophysiological response ipsilateral to an item of interest from the response contralateral to the item of interest on correct change trials. The item of interest could be the -1 item when the trained-1 array was presented as the sample or test array, or it could be the changed item for any other type of array presented as the test array. The subtraction removes activity unrelated to the target shift information. N2pc amplitude was characterized by the mean voltage from 150-250 ms after stimulus onset (which was the interval used in the Hyun study). All p values related to this amplitude measure were corrected with the Greenhouse-Geisser epsilon correction for non-sphericity.

Results

Data Processing

As in the preceding experiments, trials where the reaction time was greater than 2000 ms or less than 200 ms were omitted from the analysis. This criterion resulted in the rejection of 1% of training trials across all participants (range = 0-3%) and 1% of the test trials (range = 0-3%).

Behavioral Results

Training Phase

Training data were analyzed using a single factor ANOVA with five levels: one for each block of training.

Mean accuracy data were converted to d' for each of the five blocks of training and are shown in Figure 15. Participant performance rose gradually across the 5 blocks of discrimination training (block 1 d' = 2.29→block 5 d' = 3.16, $F(4, 64) = 13.10$, $p < .001$) and was conserved between blocks 2 and 3; that is, improvement was conserved across days.

Reaction times appear in Figure 16. Reaction times improved monotonically across training blocks (block 1 RT = 913 ms→ block 5 RT = 623 ms, $F(4, 64) = 47.44$, $p < .01$). The monotonic improvement was conserved between blocks 2 and 3, again indicating that the improvement was conserved across days.

Test Phase

Test data were analyzed using a single factor ANOVA with two levels: trained and untrained. Change detection accuracy was converted into d' and appears in Figure 17. Participants performed better ($F(1, 16) = 55.54$, $p <= .01$) on the change detection task with the trained array (d' = 1.76) than with the random array (d' = 1.31). Mean participant reaction times (Figure 18) were statistically indistinguishable ($F(1, 16) = 3.13$, $p = .10$) between the trained arrays (622 ms) and the random arrays (632 ms).

Because the parallel storage hypothesis predicts strategic encoding as the mechanism driving the facilitation effect observed in the first experiment, it seems plausible that participants should perform better with trained-1 sample arrays on change trials than trained sample arrays. To evaluate this possibility, we performed a one-way ANOVA to compare participant performance under these conditions. No significant difference was observed for d' between trials with a trained-1 sample (1.78) and trials with a trained sample (1.75, $F(1, 16) < 1$, $p = .69$). The same was true of reaction time for trials with trained-1 (632 ms) and trained (647 ms) sample arrays ($p = .72$).

Electrophysiological Results

A significant negative amplitude deflection during the 150-250 ms time window was used as an index of the N2pc component. Analyses were performed using measurements taken from the contralateral-minus-ipsilateral difference waves in a single-factor ANOVA with eight levels corresponding to collapsed electrode site pairings: P1/2, P3/4, P5/6, P7/8, P9/10, PO3/4, PO7/8, O1/2.

Figures 19 and 20 show the ERP waveforms from lateral occipital scalp sites contralateral and ipsilateral to the changed item in the test display, along with the contralateral-minus-ipsilateral difference wave. The presence of a significant N2pc component was determined by comparing the voltage from 150–250 ms in the difference waves to zero.

As can be seen in Figure 19, the N2pc was significantly different from zero when the test display contained a changed item, whether it was a random array ($-0.57\mu V$, $F(1, 16) = 24.57$, $p < .01$), a trained array ($-0.68\ \mu V$, $F(1, 16) = 22.86$, $p < .01$), or a trained-1 array ($-1.04\ \mu V$, $F(1, 16) = 35.74$, $p < .01$). These results verify that participants are shifting visuospatial attention to the changed item in the test array on change trials. This outcome is consistent with the results shown by Hyun (2006) and suggests that participants are performing a visual comparison between the sample and test array representations and successfully detecting the differences between the two.

Figure 19 also shows that the mean amplitude of the N2pc is noticeably greater for the trained-1 test arrays than the trained and random arrays. This was confirmed with a 2-way ANOVA (display type vs. electrode) that compared the amplitude of the N2pc elicited by the trained-1 array to each of the trained and random arrays. The comparison yielded a significant difference between the trained-1 and random arrays ($F(1, 16) = 5.14$, $p = .038$), and between the trained-1 and trained arrays ($F(1, 16) = 4.30$, $p = .05$)

The N2pc elicited when participants viewed a trained-1 sample array ($-0.33\ \mu V$, see Figure 20) was significantly greater than zero ($F(1, 16) = 14.84$, $p < .01$), indicating that participants' knowledge of the trained array can drive a visuospatial shift of attention to the trained-1 element. This could mean that participants are strategically encoding the -1 item into VWM because they know that this is the most informative item in the array. Alternatively, it could mean that attention is automatically attracted to items that mismatch LTM.

These two possibilities were distinguished by examining the N2pc elicited by the trained-1 array when it appeared as a test display on no change trials. Under these conditions, the single factor ANOVA described above revealed no significant negative deflection from zero ($-0.17\ \mu V$, $F(1, 16) = 2.11$, $p = .14$). Moreover, an ANOVA comparing the N2pc to the trained-1 array when it was the sample versus the test indicated that the N2pc was significantly larger when the trained-1 array was the sample item rather than the test item ($F(1, 16) = 20.50$, $p < .001$). This pattern of results demonstrates that attention is not automatically attracted to the -1 item because it mismatches the LTM representation of the sample array. Instead, these results indicate that participants are strategically focusing attention onto the -1 item in the trained-1 sample arrays so that they can focus their VWM resources on this item rather than encoding the entire array.

Discussion

Unsurprisingly, behavioral performance was consistent with previous experiments. The growth and conservation of improved task performance in both d' and RT measures suggests that the training regimen was successful in promoting a long-term benefit. The reduced set size for the experiment naturally also elevated d' relative to Experiments 1 and 2.

More interesting are the electrophysiological results. An N2pc was generated under all the conditions that would ordinarily be expected in a change detection task (the comparison process elicited a shift of attention to a changed item in the test array, regardless of whether the array was trained or untrained). This confirms the methodology is adequate to observe the shifts of visuospatial attention and corresponding N2pc components described by Hyun (2006).

Of particular interest to the hypotheses at hand is the fact that an N2pc was generated in response to the trained-1 array when it was presented in the sample display, but not in the test display on no-change trials. So, even before participants were expected to generate a response, they were making systematic shifts of attention to informative parts of the sample display. This outcome is consistent with the Parallel Storage hypothesis. That is, observers may enhance their performance by using conceptual memory to store the fact that the sample array is identical to the trained array except for one item and then storing this one item in VWM or by simply remembering the conceptual identity of the array and using that representation to execute the change detection task. In fact, this latter explanation seems most likely in light of the fact that participants do no better on change trials where the sample display is a trained-1 display than on trials where it contained a trained display. If participants were using the conceptual representation to guide strategic VWM encoding, then the -1 item in the sample display (which is the only item that could have changed) could have guided participants to correctly encode the candidate changed item on trials where it was perceived in the sample array.

In contrast, the Unitary Storage hypothesis provides no direct explanation of this finding. It might be possible to explain it by positing that attention is automatically directed toward parts of displays that mismatch LTM representations, but if this were true we should have observed an N2pc for the test array when both the sample and test items were identical trained-1 arrays. That is, even though the test array did not contain a change in this case, it contained a single item that mismatched a strong LTM representation. Because the trained-1 array did not elicit a significant N2pc component under these conditions, we can reject the possibility of an automatic deployment of attention to mismatching items. Thus, the Parallel Storage hypothesis can easily explain the presence of an N2pc component for the sample array when it was the trained-1 array, but the Unitary Storage hypothesis provides no explanation for this finding. This does not disprove the Unitary Storage hypothesis, but it certainly demonstrates the plausibility of the Parallel Storage hypothesis.

Although the present experiment clearly demonstrates that there is a VLTM representation underlying the strategic shift of visuospatial attention within the sample array, it also suggests that the facilitation effect observed in Experiment 1 is mediated at least partially by conceptual memory or other abstract memory representations. The remaining experiments in this dissertation will be dedicated to parceling out possible contributions from abstract memory representations.

CHAPTER 4

TEASING APART CONTRIBUTIONS FROM MULTIPLE MEMORY SYSTEMS

As mentioned earlier, memory systems do not work alone. Although this makes it possible for VLTM representations to contribute to VWM tasks, there are many other memory systems that may also contribute to participant performance during and after training. Unfortunately, the preceding experiments conflate the contributions from these memory systems. Take, as an example, conceptual memory representations.

Conceptual memory representations are relatively abstract and amodal representations of information that do not represent the specific sensory details of an input but can nonetheless contribute to performance of visual tasks. If, over the course of training, participants can develop a long-term conceptual code for the trained stimulus, they may use this nonvisual conceptual code to facilitate change detection performance. In Experiment 1, for example, seeing the trained array (or a very similar array like a trained-1 array) may cue retrieval of a conceptual representation of the trained array. That is, subjects may simply note that the current array is the trained array without retaining this information in a format that is tied in any direct way to the visual system. This code could be verbal (e.g., subjects might verbally rehearse "trained, trained, trained, …") or it could be nonverbal (e.g., a simple representation of the fact the current array is the trained array). If this is the case, then it is possible that the benefits derived from using the trained array may not be traced to VLTM at all.

The final two experiments in this dissertation will refine the approach used in the previous experiments so that contributions from nonvisual memory representations on participant performance are minimized.

Experiment 4: Mapping Many Representations in One Memory System to One Representation in Another

How might parallel memories of a visual stimulus array be isolated? Different memory representations have different properties that, in many cases, give them complementary functionality. Thus, it is possible to design tasks that rely heavily on one type of representation but cannot be solved with other types of representations.

In the case of visual and conceptual memory, the former system maintains highly concrete representations, while the other is more abstract. To clarify, consider Prince Charles in two photographs: one taken in the summer (Figure 21a) and one in the winter (Figure 21b). The name "Prince Charles" may be ascribed to both (along with activation of the nonverbal concept of *Prince Charles*), regardless of lighting conditions, context, or even skin color, which may be influenced by vascular dilation at different temperatures. Both are Prince Charles, and although the extrinsic context of each photo does much to distinguish them visually, it does little to distinguish them conceptually. Put another way, two visual representations (the visual features of the two images) map onto one conceptual representation (Prince Charles).

Recontextualizing this idea in the present experimental paradigm, if these two images were used in a change detection task, conceptual representations would be inadequate to distinguish the sample display from the test display (Prince Charles→Prince Charles). Visual memory, however, would readily detect the multiple large magnitude changes in the visual content of the images (red pallor → pink pallor). Of course, an observer might use conceptual representations of other aspects of the photos, forming a temporary representation of *Prince Charles in Winter* or *Prince Charles in Summer*. However, this would presumably begin to stress the capacity of the conceptual working memory system, and this sort of possibility could be minimized with an appropriate experimental design.

The potential role of nonvisual conceptual representations is clear in the study of Buttle & Raymond (2003), in which participants were trained on novel faces and then performed a change detection task where famous faces could change to different famous faces or to the recently trained faces. Memory performance was higher when the sample stimulus was a famous face than when it was a recently trained face, and this facilitation may have been a consequence of the relatively stronger conceptual representations participants developed for famous faces than for briefly trained faces. That is, participants may have noted conceptually that the sample array contained Prince Charles, and a change to Ronald Reagan in the test array could have been accurately reported even if the participants did not remember any of the visual properties of the photograph of Prince Charles.

In principle, the problem of removing conceptual contributions to visual memory performance could be accomplished by modifications to the paradigm of Buttle & Raymond (2003). Specifically, instead of changes from the face of one famous individual (e.g., Prince Charles) as the sample stimulus to the face of another famous or non-famous individual (e.g., Ronald Reagan) as the test stimulus, which could easily be detected by means of nonvisual conceptual representations, one could use changes between two instances of the same famous person (e.g., Prince Charles with two different facial expressions). Unfortunately, it would be difficult to obtain two photos of each famous face and each nonfamous face that were equated for the magnitude of changes in visual features.

Furthermore, the stimuli and training paradigm would represent a larger departure from the present paradigm than is strictly necessary. The idea of mapping multiple visual instances to one concept translates readily into the oriented bar stimuli used in this dissertation.

To implement this approach within the present experimental paradigm, participants were trained with a family of visually similar arrays instead of a single trained array (analogous to different photos of Prince Charles). This was intended to create, during the training phase, a single nonvisual conceptual representation of a class of visual stimuli (just as we develop a single conceptual representation of Prince Charles by exposure to a variety of different images of him). Then, during the change detection task, changes were created by going from one member of this family to a different member (like a change between Prince Charles with two different facial expressions). This task cannot be helped by a nonvisual representation of the array, because the conceptual category remains the same whether or not there is a change from one family member to another. Thus, if subjects are more accurate for detecting changes of this sort of change than for a change between two members of an untrained family, this will indicate that training can influence performance via purely visual representations. However, if there is no advantage for the trained family, this will support the Parallel Storage hypothesis, which claims that VWM representations are not influenced by training.

These trained families were generated by taking an array of three oriented bars and calling it a *reference array*. This array was never seen by the participants and was analogous to the prototype patterns used in the classic categorization studies of Posner and Keele (1968). For each bar in the reference array, two different orientations were created, one rotated 10° clockwise and the other rotated 10° counterclockwise. These were called *family bars*, because they were used to create the members of the family of arrays that participants actually saw. Each of the two family bars in each of the three array positions was used to create a family of eight different arrays (i.e., the eight possible combinations of the two different rotations of each of the three bars). This pool of *family arrays* were all visually similar to each other, making them easy to combine into a visual category (much like different pictures of Prince Charles). Because the family bars were always 20° rotations of each other, it was simple to control the change magnitude when the family arrays were used in a change detection task.

In this way, no single family array contained all the information necessary to completely characterize the family as a whole. That is, the conceptual property of being a family representation was distributed across several visually discriminable representations.

Because participants were being trained to recognize a family of bars rather than a single stimulus array, the passive familiarization phase was replaced with a relatively simple training task where participants used feedback to learn to classify family arrays. In this familiarization task, participants were shown arrays of oriented bars and asked to judge whether the bars all belonged to the family or not.

This means that participants were completely blind to what constituted a family array at the outset of the familiarization task and had to learn the trained family through trial and error. To facilitate the rapid acquisition of a VLTM representation of the trained family, two major modifications were made to the training paradigm: feedback was enhanced and the set size of each array was reduced relative to previous experiments.

The trial feedback was enhanced by presenting a color-coded answer key on every trial after participants responded. Any family bars present in the discrimination display changed from black to green, and any non-family bars changed from black to red. This answer key was provided in addition to the usual audible feedback. So if the participant was presented with a family array and responded that it was a non-family array, the onscreen bars would turn green and the participant would hear a low tone.

The set size was also reduced from 8 items to 3 items to facilitate overall performance by minimizing the to-be-learned information load. A reference array with a set size of three bars therefore produced 6 family bars: one positive rotation and one negative rotation for each of three reference bars. The various combinations of family bars could be integrated resulted in a set of eight possible family arrays.

After completing the familiarization task, participants were administered two training tasks across two days: the easy and difficult training tasks. These tasks were designed to enhance the precision of the visual representations participants had developed of the family arrays, but were otherwise similar to the familiarization task.

Both tasks accomplished this by changing the non-family arrays to be more similar to the family arrays. In the easy task, non-family arrays consisted of three *near-family* bars. These bars were generated by rotating family bars a further 20° from the original orientation of the reference array. In this way, the near-family bars were rotated as far from the family bars as the family bars were from each other (Figure 22). The non-family arrays in the difficult task were even more similar to the family arrays in that non-family arrays were constructed from two family bars and one near-family bar. These arrays were analogous to the trained-1 arrays from Experiments 1-3.

When participants performed the change detection task on the third day, half the trials were trained family trials and half were untrained family trials. On trained family trials, both the sample and test arrays contained a family array. On no-change trials, sample and test contained the same family array. However, on change trials, one of the bars in the test display changed to a family bar that had not been present in the sample array. Untrained family trials were similar to trained family trials, but participants had never seen the family used to construct the stimuli used for those trials.

This two-family change detection paradigm was also useful in eliminating priming differences between the trained and untrained conditions, because participants were exposed to equally many trained family arrays and untrained family arrays. This means that, during the course of the change detection task, representations of the trained and untrained families occurred equally frequently, and so neither condition should have an advantage based on mere exposure over the other. It also equated the change magnitude for the trained and untrained families: In both cases, change trials consisted of a 20° rotation of one of the bars, changing the array from one member of the family to a different member of the same family.

Conceptual memory representations of the trained family should not be helpful in performing this task, because the sample and test arrays always belong to the same conceptual group on both change and no-change trials. Because the role of conceptual memory has been minimized, the Parallel Storage hypothesis now makes the unambiguous prediction that training will not lead to improved change detection performance for the trained family. That is, this theory posits that VWM representations are based on a relatively fixed alphabet of features that cannot be influenced by a few days of training, so training should not improve performance in change detection tasks (unless conceptual representations can be used).

The Unitary Storage hypothesis, in contrast, posits that VWM representations are simply activated VLTM representations, and the VLTM representations that should be created over training for the trained family should lead to enhanced VWM representations of a given member of the family. That is, if VWM representations are activated VLTM representations, then a strong VLTM trace should facilitate participant performance with the trained family arrays because the activated representation is stronger and more precise than the more approximate representation of the untrained family arrays. Thus, the Unitary Storage hypothesis predicts enhanced change detection performance for the trained family.

Given that participants are trained to group the different family members together, it may seem implausible that developing a VLTM representation of the trained family could lead to an improved ability to discriminate between different members of the same family in the change detection task (even if VWM representations are simply activated VLTM representations). However, this prediction is actually quite plausible. Most contemporary theories of category learning propose that categorization is based, at least in part, on LTM representations of the individual exemplars of a category (Vanpaemel & Storms, 2008), and there is substantial evidence for memory of the exemplars (Nosofsky, 1987). Thus, the category training task used here should lead to VLTM representations of the eight possible combinations of family bars as well as the general category of the family. In addition, many studies have shown that training leads to an increase in the pool of neurons that represent the trained stimuli (Sigala & Logothetis, 2002). This could potentially increase the ability to retain the details of the individual family members. Thus, it is entirely plausible that training the family would lead to improved VWM for individual family members.

Methods

Participants

Eighteen volunteers recruited from the University of California at Davis served as participants in this experiment. They reported normal color vision and normal or corrected-to-normal acuity.

Stimuli

Stimuli were arrays of three oriented bars with the same dimensions as in Experiment 1. The three bars were placed evenly around an imaginary circle (2.50° visual angle in radius) that was centered around fixation (Figure 23).

Each participant was assigned a unique reference array of randomly generated orientations. This array was never seen, but was used to generate the presented arrays, which were divided into three types: family, near-family, and random. Family bars were characterized by an orientation that deviated 10° from the corresponding bar in the reference array, clockwise or counterclockwise. This means there were two possible family orientations at each of three stimulus positions, for a total of eight possible arrays that consisted entirely of family bars. Near-family bars deviated 30° from the prototype array. These relationships are depicted in Figure 22.

Procedure

Training

The two days of training were divided among three tasks: familiarization, easy, and difficult. On the first day, participants performed one block each of the familiarization, easy, and difficult tasks. The second day was occupied by two blocks of the difficult task interleaved with two microblocks of the easy task.

All three training tasks were discrimination tasks as with the previous experiments. Participants were shown a stimulus array and asked to judge if the presented array was a family array or not. Arrays were only counted as family arrays if they contained three family bars in the correct positions in the array (that is, corresponding to the unseen reference array). The array persisted until the participants responded, at which time it was replaced by a feedback array, in which any family bars present in the display changed color to green, and any near-family or random bars changed color to red for 500 ms. The display was then blanked during the intertrial interval (500 ms) and participants heard a feedback tone that was high frequency if they had responded correctly and low frequency otherwise (Figure 24).

Because participants never saw the reference array, there was no sample viewing period. Instead, participants performed an unrecorded familiarization task for 60 trials. In the task, 50% of the test displays consisted of family bars, and the remaining displays consisted of random bars. Participants were instructed to initially guess which displays were family displays and infer from the feedback what made a display a member of the family. If participants did not achieve a minimum performance of 50% correct, they performed the familiarization task a second time.

After completing the familiarization task, participants performed 120 trials of the easy discrimination task and 228 trials of the difficult discrimination task. These tasks were identical to the easy task except for the non-family arrays. In the easy task, non-family arrays consisted of three near-family bars. In the difficult task, non-family arrays consisted of two family bars and one near-family bar. The second day of training consisted of two blocks of 168 trials of the difficult task. Every block of the difficult task (on both days of training for a total of three blocks) was followed by a micro-block (24 trials) of the easy task. These micro-blocks made it possible to determine whether training on the difficult task led to continued improvement in performance of the easy task.

Test

On the third day, participants performed a change detection task. This task proceeded similarly to the test phase of the preceding experiments with the following exceptions. Sample arrays could consist of three bars from the trained family, or three bars from another randomly generated family with which the participant had not been trained. The same untrained family was used throughout the change detection task for a given observer. On change trials, test arrays were identical to the sample arrays, except for one bar that changed from its original orientation to the other orientation for that bar that was still part of the same family. As a result, the conceptual category of the array did not change between sample and test. Participants performed a total of 756 trials during the course of the change detection task.

Results

Data Processing

Trials where the reaction time was greater than 2000 ms or less than 200 ms were omitted from the analysis. These criteria resulted in the rejection of 16% of training trials across all participants (range = 2-42%) and 5% of the test trials (range = 0-12%). Of these participants, five required exclusion of more than 10% of their total trials on any task.

Analyses conducted excluding these participants (not included here for brevity) did not substantially alter the significance outcomes of the following data.

Training

The easy and difficult task each served separate purposes in the experiment, so they are analyzed separately here. Participant performance in the easy task and difficult task were converted to d' and are plotted in Figure 25.

The block on the first day of training was subdivided into five subsidiary micro-blocks. These, combined with the three micro-blocks presented after each block of the difficult task of training make eight total microblocks. Performance in the easy task was evaluated with a single-factor ANOVA with eight levels, one for each serial microblock. Participant d' improved overall (microblock 1 d' = 1.64 → microblock 8 d' = 2.59) during the course of training ($F(7, 119) = 2.58$, $p = .02$). Reaction times (Figure 26), however, did not show a significant reduction (microblock 1 RT = 1009 ms→ microblock 8 RT = 915 ms) over the course of training ($F(7, 119) = 1.34$, $p = .24$).

The subset of the final three microblocks, in which participants received minimal training with the easy task and extensive training with the difficult task, did not show significant improvement in d' ($F(2, 34) = 1.77$, $p = .19$) or reaction time ($F(2, 34) = .07$, $p = .93$). However, performance remained stable and did not decline during training with the difficult task. In fact there was a trend toward d' improvement between microblocks 5 and 6 ($p = .08$), which represents the break between day 1 and day 2.

The difficult task was evaluated in a single-factor ANOVA with one level for each block. Participant performance improved steadily (block 1 d' = 1.33 → block 3 d' = 2.19) over training ($F(2, 34) = 14.09$, $p < .001$). Reaction times, however, showed no significant decline (block 1 RT = 1054 ms →block 3 RT = 1022 ms, $F(2, 34) = 2.16$, $p = .13$).

Test

Change detection performance was also converted to d' and appears in Figure 27. Data were analyzed using a single factor ANOVA with two levels: trained family and untrained family. Performance for the trained family condition (d' = 1.03) was not significantly different than in the untrained family condition (d' = 1.04, $F(1,17) < 1$, $p = .85$). Because it is not possible to prove the null hypothesis that there would be no difference between these conditions in an infinite sample, we conducted a confidence interval analysis to provide a statistical boundary on the size of any difference that might be present in the population. The 95% confidence interval for the difference in performance between the trained and untrained arrays was 0.13, meaning that we can be 95% confident that any benefit of training was less than 0.12 (the observed 0.01 advantage of the novel condition less the 95% confidence interval of the difference of 0.1 d'). Reaction time data (Figure 28) also showed no significant difference between the trained family (763 ms) and untrained family (759 ms) conditions ($F(1,17) = 0.19$, $p = .67$). A confidence interval analysis indicated that any training advantage was less than 14 ms (the observed 4 ms advantage of the untrained condition less the 95% confidence interval of the difference of 18 ms).

Discussion

Because the training regimen was changed for this experiment, it would be prudent to examine it carefully to ensure that it still fosters LTM improvements. Fortunately, despite the division of training into two tasks, participant performance on the easy task improved steadily and proceeded without decrement between days, even though the task was split across multiple days and interleaved between blocks of the difficult task. Performance on the difficult task was also conserved across days and increased significantly, making it plausible that this new type of divided training paradigm produces comparable learning (a d' improvement over blocks of 0.95 and 0.86 on the easy and difficult tasks, respectively) to that demonstrated in experiments 1-3 (a d' improvement of 1.16). Moreover, given that the families were based on a randomly determined set of orientations, it is safe to assume that d' was at zero prior to the beginning of training. Thus, the final d' values of 2.59 for the easy task and 2.19 for the difficult task relative to an assumed d' of zero prior to training really indicate that training increased the d' level by 2.59 and 2.19 for these tasks, respectively.

The lack of a significant reduction in participant reaction times may seem surprising given the relatively large improvement in the d' level. This outcome can be understood in terms of a floor effect driven by task difficulty. The relatively small change magnitudes between family and non-family members and the relative complexity of the stimulus set suggest that the both the training tasks were relatively difficult, and overall slow participant reaction times contributed substantially to the trial exclusion rate of 16% across participants. Given these data, it seems plausible that participants adopted a stringent decision criterion while performing the training tasks. This strict criterion drove longer RTs as participants engaged in deliberative task decisions.

It may be tempting to dismiss this experiment as being too different from Experiment 1 to truly be comparable. However, the overall d' improvement for the Easy task (0.95) and the difficult task (0.86) was quite similar to the improvement observed in Experiment 1 (1.16) and Experiment 3 (0.87). Participants clearly developed a robust VLTM representation of the trained family, because they exhibited the ability to distinguish between arrays that were members of the family and arrays that were not in the family but differed from the family by an amount that was the same as the differences between individual family members. Indeed, any two family members could differ in the orientation of 1–3 of the individual bars, whereas the difficult training task required participants to distinguish between family arrays and arrays that differed from the family in terms of a single bar that was very close to the orientation of the corresponding family bars. This is an extremely challenging task (see the examples in Figure 23).

The high task difficulty also explains the absence of improving reaction times during training. The combination of task difficulty and the relatively high trial exclusion rate (16%) suggest that participants adopted a stringent decision criterion while performing the task. The resulting slow deliberative behavior resulted in a floor effect for reaction times that precluded observable improvement.

Returning to d', training led to a d' of 2.19 for this task, meaning that the participants were able to treat subtly different classes of arrays as being more than two standard deviations apart in their internal representational space. Thus, the training led to an impressive degree of learning. Despite this impressive VLTM learning, however, change detection performance was nearly identical for the trained family and for an untrained family. Thus, extensive training of VLTM provided no benefit for VWM performance. This pattern of results supports the Parallel Storage hypothesis and is inconsistent with the Unitary Storage hypothesis.

The final experiment in this dissertation was designed to replicate this finding and provide converging evidence that these results are not the outcome of an extrinsic property of the specific stimuli and conceptual framework.

Experiment 5:

Experiment 4 used memory for different members of a single conceptual family to test the effects of training on VWM while ruling out contributions from nonvisual, conceptual representations, and Experiment 5 uses a different approach to achieve the same general goal. Specifically, Experiment 5 asks whether having a strong representation of a visual pattern in VLTM facilitates the ability to bind other features to this pattern in VWM under conditions that rule out contributions from nonvisual conceptual representation.

To demonstrate how a VLTM representation might help with VWM binding, imagine that you were performing a change detection task in which you were shown the image of Prince Charles in Figure 21a. In this image, Prince Charles is wearing a beret, which is a visual detail that is unrelated to your conceptual representation of Prince Charles. However, if VWM representations are simply activated VLTM representations, it might be relatively easy for you to form a VWM representation that includes the beret because you already have a robust VLTM representation of Prince Charles's face. If you did not have a representation of Prince Charles's face in VLTM, then the details of his face might consume storage capacity that could otherwise be used to store the beret. Moreover, if you were asked to remember the location of the hat within the image, having a robust VLTM representation of Prince Charles's face could make it easier to link elements of the face with the beret.

Thus, if VWM representations are activated VLTM representations, then it should be easier to bind specific features to a trained pattern than to an untrained pattern. If VWM representations are not tied to VLTM representations, however, then training should not influence performance. Thus, the predictions of the two theories are the same in this experiment as in Experiment 4.

Though the predictions are the same, the present approach differs from the approach of Experiment 4. That experiment tested the defining properties of the stimulus; it tested whether a strong VLTM representation of Prince Charles's face would help you remember whether his eyes were open or closed in a particular photograph. The present experiment is about the relationship between intrinsic and extrinsic properties; it asks if that representation of the Prince's face can help you remember if his eyes were covered by reading glasses or sunglasses. It is a second distinct case where the Unitary Storage hypothesis predicts VLTM-based facilitation of VWM performance, and broadens the conditions under which the hypotheses may be evaluated.

To test this idea, participants were trained in an easy and difficult discrimination task with colored, textured, multipart objects called *propellers* (Figure 27). These objects consisted of four colored blades, each of which was covered by an identical checkerboard texture. The four blades were attached to a white center square and surrounded by a black border to reinforce that the array of parts constituted a single object. The propeller could be presented at four rotations around the center square to reinforce its coherence as a single object and to reflect our normal experience with objects; that the retinal image cast by real world objects changes based on the object's extrinsic position and the location of the viewer.

Each participant was assigned a single trained propeller that contained a consistent selection of four colors and a consistent spatial relationship among the colored blades throughout the experiment. As with Experiments 1-3, participants spent several seconds passively viewing the trained propeller before beginning the discrimination task.

In the easy discrimination task, participants were presented with a propeller and asked if it was the trained propeller or not, irrespective of the propeller's extrinsic rotation. On the 50% of trials when the presented stimulus was not the trained propeller, one of the blades changed color to a novel color not presented in the trained propeller.

Participants were asked the same question in the difficult task, but the difference between the trained propeller and the foils was subtler. The foils consisted of the same selection of colors as were presented in the trained propeller, but two of the blades had swapped positions. In this case, successful performance of the task required knowledge of the spatial relationships among the trained propeller's visual features as well as their identity.

The change detection task that participants ultimately performed was designed to test the binding between a task-relevant and task-irrelevant feature, in this case color and texture, respectively. In the sample array, participants were presented with a propeller consisting of four colors and four textures at one of the four possible rotations. However when the test array was presented, participants saw only one textured blade at fixation. They were asked to judge if the texture on the presented blade matched the texture on the same blade when it was presented in the sample display. Because the blade was dissociated from its context in the larger object and even its extrinsic position in the sample array, participants could perform the task only by binding the color and texture information together in memory.

On 50% of trials, the sample array contained a trained propeller, and on the remaining trials the sample array contained a novel propeller consisting of novel colors. A different randomly generated set of colors was used for each novel propeller. Under these conditions, the Unitary Storage hypothesis predicts that participants should be able to bind the VLTM color representation of the trained propeller to the untrained VWM texture information on each blade. So despite the fact that participants were not trained with the trained propeller's texture information, the necessary binding between that feature and the trained feature should produce facilitation with the trained propeller relative to the novel propeller. The Parallel Storage hypothesis, in contrast, predicts no such tight relationship between the two memory systems. Consequently, it predicts no performance disparity between the trained and novel propellers.

It is worth noting that the present design is analogous to the design in Experiment 1, and the fact that participants see the trained propeller more often than the untrained propellers in the change detection task means that priming may contribute to the experimental outcome. However, by the same token, the results of Experiment 2 suggest that it is unlikely that this method will produce any significant contribution of priming. Moreover, if the present experiment converges on the results of Experiment 4, then there should be no difference between the trained and untrained conditions. So, if anything, possible contributions from priming should work against the predictions of the Parallel Storage hypothesis.That is, priming is a problem only if we find that performance is improved for the trained propeller relative to untrained propellers.

Methods

Participants

Ten volunteers recruited from the University of California at Davis served as participants in this experiment. They reported normal color vision and normal or corrected-to-normal acuity.

Stimuli

Stimuli consisted of textured propellers (Figure 27). Each propeller was constructed of five colored squares (2.96° x 2.96°): 4 exterior and one central. The central square was centered at fixation with each exterior square abutting one of its sides. The central square was a placeholder that was always colored white (63.24 cd/m^2), whereas the exterior squares (the blades) were assigned a particular set of four colors that varied randomly between participants, but were consistent for a particular participant. The set and arrangement of a participant's trained colors were collectively known as the trained propeller.

The colors were drawn randomly and without replacement for each participant from a pool of brown (x = .443, y = .331, 3.378 cd/m^2), orange (x = .572, y = .360, 30.31 cd/m^2), red (x = .635, y = .308, 21.85 cd/m^2), green (x = .311, y = .559, 78.05 cd/m^2), blue (x = .156, y = .061, 11.88 cd/m^2), purple (x = .284, y = .124, 27.00 cd/m^2), yellow (x = .424,y = .475, 78.98 cd/m^2), and cyan (x = .220, y = .267, 73.79 cd/m^2). Each participant's unique array of colors was collectively referred to as the trained propeller. Each blade of the propeller had a checkerboard texture that was the same color as the background. The checks could be one of five possible sizes: larger (0.99°), large (0.74°), medium (0.49°), small (0.33°), and smaller (0.16°). To make the propeller appear more like a single, coherent, multipart object, a black border (0.41° thick) surrounded the entire object.

Each propeller could be presented at one of four rotations. That is, although the relative spatial relationships among the colors remained consistent for a given participant throughout the experiment, the entire propeller could be rotated by 0, 90, 180, or 270 degrees.

Procedure

The experiment proceeded across three days, with the first two days allocated to training and the last to testing.

Training

Training was broken into two blocks on each day: both blocks consisted of an easy task on the first day and a difficult task on the second. Both tasks followed a similar procedure. Participants were initially presented with a familiarization display containing the trained propeller for 20 seconds. Thereafter, participants were presented with 480 discrimination trials, each containing a single propeller centered at fixation that persisted until the participant generated a response. Fifty percent of the trials contained the trained propeller in one of the four rotations, and the remaining trials contained a propeller that was different in some way. Participants were asked to press a button with the left index finger for the trained propeller or a button with the right index finger for an untrained propeller. They then heard a high feedback tone if they responded correctly or a low feedback tone if they responded incorrectly.

The easy and difficult training tasks were distinguished by the discrimination displays that did not qualify as trained propellers. For the easy task, one blade of the trained propeller was recolored. The new color was selected at random with replacement on each trial from the pool of four colors not present in the trained propeller. In the difficult task, all the colors were unchanged from the trained propeller, but the relative locations of the blade colors were changed. Specifically, any two blades could exchange locations (for a total of six possible swaps), creating a visually similar, but not identical copy of the trained propeller. To perform the easy task correctly, participants needed only remember which four colors were present in the trained propeller. To perform the difficult task correctly, participants needed to remember the relative locations of the four colors. The blades of all propellers displayed during the training tasks had a texture of medium checks.

Test

On the third day, participants completed 416 change detection trials for the test task. Each trial consisted of a 100-ms sample display, followed by a 900-ms blank delay, and finally by a test display that persisted until the participant responded.

On 50% of the trials, the sample display contained the trained propeller in one of the four rotations; the remaining trials contained a propeller constructed from the other four colors used in the experiment. Notably, instead of a uniform texture of medium checks, each of the blades in the sample propeller was randomly assigned a texture drawn without replacement from the pool of very small, small, large, and very large checks. In this way, each blade was assigned a different texture.

The test display consisted of a single propeller blade presented at fixation (see Figure 28). It was always drawn in the color of one of the propeller blades from the sample propeller. On 50% of trials (no change trials), this blade possessed the same texture as had the blade of the same color in the sample display. On the remaining trials, the texture changed to a randomly selected texture from the pool of the remaining three textures presented in the sample display (excluding the medium texture used during training, which was never used during the change detection task). Participants were asked to judge whether the blade's texture was the same as it was in the sample display, or if it had changed. The test display persisted until the participant responded, and was followed by a 500-ms blank intertrial interval.

Posttest

After the conclusion of the test task on the third day, participants performed a brief posttest to ensure that they still retained an accurate representation of the trained propeller. Participants were not informed during the test instructions that there would be a posttest at the conclusion of the test block. The posttest task was identical to the easy training task with the following exceptions: there was no sample display, there were no feedback tones, and the task consisted of only 64 trials. Participants were instructed to respond whether the discrimination displays contained the trained propeller or if they did not, using the same button scheme as in the easy training task.

Results

Data Processing

Trials where the reaction time was greater than 2000 ms or less than 200 ms were omitted from the analysis. These criteria resulted in the rejection of 7% of training trials across all participants (range = 4-12%) and 7% of the test trials (range = 3-14%). Of these participants, only two required exclusion of more than 10% of their total trials for a given task. Analyses conducted excluding these participants (not included here for brevity) did not substantially alter the significance outcomes of the following data.

Training

The easy and difficult tasks were analyzed independently, each using a single factor ANOVA with two levels: one for each block of training. Participant accuracy was converted into d' and appears in Figure 29.

D' in the easy task showed significant improvement between blocks (block 1 d' = 3.95 → block 2 d' = 4.44, $F(1, 8) = 14.18$, $p = .01$), though no such difference was found in the difficult task (block 1 d' = 3.15 → block 2 d' = 3.26, $F(1, 8) < 1$, $p = .50$), presumably because task performance was already very good during the first block.

Reaction times (Figure 30) significantly decreased during both the easy task (block 1 RT = 841 ms → block 2 RT = 664 ms, $F(1, 8) = 46.14$, $p < .001$) and the difficult task (block 1 RT = 1188 ms → block 2 RT = 1049 ms, $F(1, 8) = 12.21$, $p = .01$). Training presumably affected RT rather than d' because accuracy was already near ceiling in the first block of training. It is the converse of the pattern observed in Exp 4, and this helps to establish the generality of any effects (or lack thereof) of training on change detection performance. That is, if the effects of training on change detection performance are the same across these experiments, that means that they can occur regardless of whether training influences d' or RT.

Test

Change detection accuracy was also converted into d' and appears in Figure 31. D' and reaction times were each analyzed using a single factor ANOVA with two levels: trained and untrained. Participants did not exhibit a benefit in d' for the trained array (d' = 1.13) over the untrained array (d' = 1.21); indeed, d' was somewhat greater for the untrained array, although this did not reach significance ($F(1, 8) = 3.55$, $p = .10$). A 95% confidence interval analysis indicted that any advantage in the population for the trained array was no larger than 0.02 d' (the observed 0.08 advantage of the novel condition less the 95% confidence interval of the difference of 0.1 d'). RT (Figure 32) for the trained array (920 ms) was approximately equivalent to RT for the untrained array (910 ms, $F(1, 8) = 1.41$, $p = .27$). Confidence intervals indicated that any differences in the population were less than 9 ms (the observed 10 ms advantage of the novel condition less the 95% confidence interval of the difference of 19 ms).

Posttest

Posttest performance was converted into d' and appears in Figure 31. To see if participants had retained the high level of performance they had achieved while training with the easy task, a simple F-test was performed to compare mean performance from the first 64 trials of the easy task (d' = 3.73) and performance at posttest, which also consisted of 64 trials (d' = 3.75). There was a trend suggesting that d' was lower at posttest ($F(1, 8) < 1$, $p = .96$). Unfortunately this outcome does not adequately characterize the relatively high hit rate (94%) and low false alarm rate (3%) shown by participants. Instead, this trend is likely an artifact of the already high performance participants demonstrate at the very beginning of the training task.

It is also reasonable to expect that, given the significant RT effect observed in both training tasks, that performance facilitation between training and posttest might manifest in the RT domain. To verify this, participant RTs for the first 64 trials of the easy training task were compared to performance on the posttest (which also consisted of 64 trials) in a 1-way ANOVA. There was a trend ($F(1, 8) = 3.35$, $p = .10$) that participants were faster at posttest (827 ms) than the first block of easy trials (977 ms).

Another way to determine if participants could distinguish the untrained propellers from the trained propellers would be to perform a two-tailed t test against the null hypothesis that participant d' was equal to zero. Participants scored well above zero (d' = 3.76, $p < 0.01$), and the d' value indicates that their representation of trained and untrained arrays differed by almost four standard deviations in representational space. Thus, they retained significant information about the trained propeller in long-term memory through the test period.

Discussion

This experiment converges on the result demonstrated in Experiment 4: VLTM does not seem to play a role in this change detection task. However, although the training regimen was fairly similar to the one in Experiment 4, the failure to demonstrate improving d' on the difficult training task as well as the dramatic change in stimuli merits evaluating whether the task was sufficient to create a VLTM representation.

It may seem surprising that the training task showed no d' improvement in the difficult task on day 2, but the overall means may explain this outcome. Comparing this experiment's overall training performance (d' = 3-4) with the overall performance properties of previous experiments (d' = 1-2), it is clear that the reduced set size and large change magnitudes among colors and their positions in this experiment's training task made it substantially easier than previous tasks. It is possible that, between the challenge of the difficult training task and the initially high performance during the first block, participants may have rapidly reached ceiling performance. The presence of improving reaction times between blocks of the difficult training task is consistent with this possibility, since there was still some manifestation of a training benefit. Further strengthening the plausibility that participants have formed a VLTM representation of the trained propeller is the fact that they consistently (and easily) recognized it as such in the posttest.

This d' and RT effect asymmetry is complementary to the one observed in Experiment 4. That is, between the two experiments, there is a difficult category learning task in which accuracy but not RT improved over training (detecting small orientation discrepancies in Experiment 3) and an easy category learning task in which RT but not accuracy improved over training (detecting large color changes in Experiment 4). In the former case, the high decision criterion required to discriminate the small orientation deviations may have required substantial time and effort, which kept reaction times high even as accuracy improved. In the latter case, performance with the large color change magnitudes started high and rapidly reached ceiling, so the only way that learning could manifest performance improvement was through decreasing RT. The relatively higher trial rejection rates for excessively long RTs in Experiment 4 (16%) than in Experiment 5 (7%) are consistent with this idea.

This experiment also contributes to the generality of the observed LTM/VWM interactions. Experiments 1-4, regardless of any observed training effect, universally exploited orientation as the task-relevant feature dimension. The extension of the training to color information demonstrates generality of learning across different kinds of visual information.

As with the previous experiment, it seems very likely that participants acquired a VLTM representation. Although there was no significant d' improvement in the difficult training task, the relatively high d' (3.26) at the end of training suggests that participants were quite skilled with the VLTM discrimination task at the end of the second day of training. This conclusion is augmented by participant performance in the posttest, where they proved quite adept at recognizing the trained propeller (d' = 3.73), even without feedback.

However, even with a strong enough VLTM representation of the trained propeller to drive performance in an unexpected posttest, participant performance with the trained propeller was no better than their performance with an unfamiliar propeller. When participants are denied the use of conceptual memory representations, VLTM representations do not facilitate VWM performance.

This outcome is not merely inconsistent with the predictions of the Unitary Storage hypothesis. In combination with Experiment 4, this experiment demonstrates a second context in which participants cannot facilitate their VWM performance through the use of strong VLTM representations. Given that this null effect can generalize between two types of tasks, it seems plausible that it will manifest elsewhere as well.

This failure to demonstrate facilitation is not a consequence of inadequate training. During training, participants develop a non-conceptual representation that shows continuously improving performance over the course of training that can manifest in the accuracy or RT domain, does not diminish between days of training, and that persists even after 24 hours without direct use. The same training time scale can produce significant facilitation of change detection when conceptual representations can be used.

Overall, the Unitary Storage hypothesis would be hard-pressed to accommodate these results. The Parallel Storage hypothesis, on the other hand, predicts clearer divisions between the VWM and VLTM systems. Under this view, it is entirely plausible that VLTM representations are distinct from VWM representations in a way that precludes using representations in VLTM to improve VWM representations, except insofar as VLTM representations can be used conceptually to avoid the need to use VWM representations.

CHAPTER 5

CONCLUSION

Summary

The purpose of this dissertation was to help disambiguate between two major theoretical frameworks for the nature of representation in VWM. One, the Structured Primitives theory, suggests that VWM representations consist of atomic representational components and their relationships with one another. The other, the Activated VLTM theory, conceives of VWM representations as activated VLTM representations.

The differences between the theories can be understood in terms of sculpting. Structured Primitive theories build VWM representations analogously to building with Legos. You have a toolbox of blocks (primitives), and whenever you need to sustain information in VWM, you select the best blocks for the job, snap them together, and break them down when you're done so the blocks can be reused later.

Activated VLTM is more like sculpting with clay. Whenever you see anything, you select a lump of clay and work on shaping it to reflect what you see. The more often you see it, the more chances you have to work on the clay to make it look exactly right. This is like developing a LTM representation. Whenever something you see needs to be represented in VWM, you select a handful of the best-matching sculptures and use them as a sort of placeholder. However, if you happen to have a perfect match already, you only really need that one, and your representation is higher quality and easy to maintain.

The essential difference between these two positions is whether the time you spend working on the clay sculpture pays off when you need it. Put another way, it is whether strong VLTM representations can facilitate VWM performance. If VWM representations are actually activated VLTM representations (the Unitary Storage hypothesis), then strong VLTM representations should be able to facilitate VWM performance and it would be consistent with the Activated VLTM theory. However, if VLTM representations are not beneficial, this implies that there is a division between the

VLTM and VWM systems that precludes interaction between them (the Parallel Storage hypothesis). Such an outcome would be consistent with the Structured Primitives theory.

The first experiment showed the plausibility of a facilitation interaction between LTM representations and VWM performance. Participants underwent two days of training, and showed continuous improvement in both the d' and reaction time domains that was conserved between days of training. When participants performed the change detection test on the third day, they demonstrated a d' advantage for VWM performance for the arrays with which they had trained. Although there was an exposure asymmetry between trained and novel arrays in the change detection task, Experiment 2 ruled out possible contributions of priming. This experiment demonstrated that two days of training with a single complex pattern can lead to robust improvements in change detection performance. This was important for being able to interpret that absence of improvements in the subsequent experiments.

Experiment 3 was intended to scrutinize the results of the first experiment to test if the observed facilitation effect was visually mediated or if it was driven by some abstract nonvisual representation. To that end, we measured ERPs to observe the N2pc component that is associated focused attention (Hyun, 2006). Participants showed a significant N2pc in response to trained-1 sample arrays, suggesting that they were strategically using their knowledge of the trained array to focus attention on the one item within the trained-1 array that would distinguish between a change trial and a no-change trial. The strategic nature of this effect was supported by the finding that trained-1 test arrays did not elicit an N2pc component on no-change trials, showing that it was not an automatic response that occurs whenever an element of an array mismatches a changed array. This pattern of results establishes the plausibility of the hypothesis that the improved performance observed for trained and trained-1 arrays reflects the use of strategies to minimize the use of VWM rather than an improved VWM representation for the trained array. This is important, because this hypothesis is necessary for the Parallel

Storage hypothesis to “explain away” the finding of improved performance for the trained array in Experiments 1-2. By providing independent evidence for this explanation, Experiment 3 demonstrates that this is not just an ad hoc, unsupported move designed solely to avoid falsification of the Parallel Storage hypothesis.

Experiments 4 and 5 were designed to test whether VLTM training would improve change detection performance under conditions that could not involve “tricks” such as encoding a single item from the array or using nonvisual, conceptual representations of the arrays. Experiment 4 accomplished this by mapping multiple visual representations (arrays) to one abstract representation (family) during training. That way, when the change detection task was administered, changes could occur between two visually dissimilar arrays that fell into the same category. When abstract representations like conceptual and verbal memory were parceled out in this way, the effect of training on change detection performance vanished.

Experiment 5 converged on this outcome while returning to the core training procedures established in Experiment 1 and extending the stimulus generality. Where Experiment 4 was designed to test performance based on the intrinsic properties of the trained stimuli, Experiment 5 tested performance based on the extrinsic properties instead. When participants were tested on their ability to bind extrinsic VWM information to intrinsic VLTM information, a strong VLTM representation did not facilitate their performance at all.

Taken together, these results indicate that, although participants can use LTM representations to improve their performance in putatively visual tasks, the effects do not appear to be mediated visually. Assuming that the developed representations included a VLTM representation, this suggests a division between VLTM and VWM representations that is more consistent with the Parallel Storage hypothesis than the Unitary Storage hypothesis.

Can Activated VLTM Be Disconfirmed?

Proving the Null

The conclusion that the present experimental results favor the Parallel Storage hypothesis hinges on the outcomes of Experiments 4 and 5, which show that our training regimen does not result in preferential facilitation for VWM performance with trained stimuli once the use of conceptual representations has been eliminated. Although we have interpreted these results as being consistent with the Parallel Storage hypothesis, it is worth considering possible criticisms from the Unitary Storage perspective.

As a simple example, consider the possibility that VWM representations *are* activated VLTM representations, but the representations can only interact in the sorts of contexts where we cannot rule out contributions from nonvisual, conceptual memory representations. If this were true, the fact that we observe no facilitation when we parcel out abstract contributions in Experiments 4 and 5 does not prove that there was no direct facilitation between VWM and VLTM in Experiment 1. Perhaps visual and conceptual representations work in tandem during normal cognition, and separating them inadvertently stifles both.

Whether this particular example seems plausible is orthogonal to the underlying issue: demonstrating that an effect is absent under a particular set of experimental conditions cannot eliminate every possible alternative explanation of the vanishing effect. Addressing this problem is a matter of scale. Although it is infeasible to dismiss every possible alternative supporting the Unitary Storage hypothesis, the hypothesis becomes less tenable as the hypothesis fails to be confirmed in an ever-broader context.

Experiments 4 and 5 serve this purpose by demonstrating that VLTM representations do not facilitate VWM performance across two kinds of familiarization (passive exposure vs. feedback), stimulus types (complex multicolor objects vs.

orientation arrays), and information embedding (intrinsic vs. extrinsic stimulus properties).

Although these results may not be sufficient to disconfirm the Unitary Storage hypothesis alone, the literature reviewed in Chapter 1 is consistent with the present conclusion. Olson, Jiang, and Sledge (2005) demonstrated, after training participants with unannounced repeating stimulus arrays, that even though participants could identify the repeating arrays as familiar, the familiarity did not facilitate VWM performance. Chen, Eng, & Jiang (2006), showed that two-alternative forced choice "old vs. new" training with a set of repeated stimuli did not transfer to a subsequent visual change detection task. Pashler (1988) showed that letters, extremely familiar stimuli with presumably very strong VLTM representations, did not particularly facilitate change detection performance in their canonical orientation relative to an inverted presentation.

There is one case where the Unitary Storage hypothesis is borne out, however: famous faces (Buttle & Raymond, 2003). Even after training participants for 8 minutes with a background story to attach a meaningful conceptual representation to novel faces, participants performed better on a two-alternative forced choice change detection paradigm with famous faces than with non-famous familiar faces. Although the results of that experiment do follow the predictions of the Unitary Storage hypothesis, the 8 minutes spent learning about each novel face is not really comparable to naturalistic experience with famous faces. The substantial imbalance of exposure and richness of representation between trained novel and famous faces raises serious questions about the underlying assumption that the groups are comparable. This is especially problematic in light of Experiments 3 and 4, because the availability of abstract memory representations obviously relates to VWM facilitation effects. The difference in strength between the conceptual representations for famous faces and trained novel faces may well explain the observed facilitation.

So the Unitary Storage prediction of VLTM facilitation of VWM performance is not borne out under passive statistical learning conditions, simple transfer conditions, or even with highly overlearned stimuli. Even in the one example where the results are borne out, they are confounded with strength of conceptual representation. It may not be feasible to rule out all the possible conditions where VLTM representations can facilitate VWM performance, but the repeated failure to confirm the Unitary Storage hypothesis during the past two decades makes the Parallel Storage hypothesis both more parsimonious and more plausible.

Sufficiently Developed VLTM Representation

Another possible criticism of the present results is that it is possible that no VLTM representation was developed in any of the five experiments. If that were the case, then the present results don't speak to possible VLTM-VWM interactions at all. Indeed, in Experiments 4 and 5, where the results are unlikely to be contaminated by abstract memory representations, not only is there no facilitation effect observed at test, but the training results are asymmetrical between d' and RT. That is, Experiment 4 shows gradual improvement in d' without corresponding RT improvement, while Experiment 5 resulted in RT improvement without d' effects.

Closer examination of these results reveals that they are not readily dismissed, however. In the case of Experiment 4, the discrepancy between family bars and near-family bars was only 20°, a relatively small change magnitude. This, combined with the emphasis on accuracy in the instructions and the fact that a set size of 3 is right at the edge of human VWM capacity, makes it plausible that participants adopted a stringent decision criterion. In other words, participant RTs reached floor early in the training process, and task difficulty precluded any RT improvement. The relatively higher number of rejected trials in Experiment 4 for excessively long RTs is consistent with this explanation.

Experiment 5 was easier. Stimuli in this task were composed of highly discriminable colors, and so discrepancies the gestalt of the trained propeller were readily detected. The relative ease of this task compared to the one in Experiment 4 resulted in a lower RT floor than in Experiment 4, but participants rapidly reached ceiling performance for d'. The initially and consistently high participant performance observed on d' measurements is consistent with this idea.

Even without plausible ceiling and floor explanations of the performance asymmetry, any assertion that there was no VLTM representation developed would need to account for the significant results present in both experiments. Furthermore, in Experiment 4, the last 3 microblocks of the easy task, although they did not show a transfer of training improvement from the difficult task, maintained the improved level of performance established during training on the first day. In Experiment 5, participants not only showed gradual improvement of RT, but also demonstrated that they could discriminate the trained propeller from novel propellers, even though they were not instructed to prepare for a posttest.

Perhaps even more important than the strength of the results themselves, however, is the utility of VLTM. Even if multiple results inconsistent with VLTM-VWM interactions are not sufficient to disconfirm the phenomenon's *possibility*, they raise serious questions about its *utility*.

Take the position that VLTM and expertise are one and the same as an illustrative caricature. In this case, the only way in which VLTM representations could facilitate VWM performance is after a decade of intensive experience—the sort of extensive experience that could have an impact on representation at a fundamental level (i.e. modifying the selective properties of the representational substrate).

The acquisition and development of expertise lie well beyond the scope of this dissertation. The sense in which most research describes interactions between VLTM and VWM performance refers to a useful cognitive resource that plays a role in daily life.

We don't need a lifetime of experience to easily recognize Prince Charles, just a few hundred exposures. Even if you had never seen him before, two hours across two days seems like ample time to obtain a durable representation of his appearance.

The conditions under which expertise accumulates may be enough time perhaps to change even the building blocks in a Structured Primitives account of VWM. If these are the only conditions under which VLTM can facilitate VWM performance, VLTM representations may only play a meaningful role in VWM performance for chess grandmasters and chicken sexers.

Conclusion

In this dissertation, it has been demonstrated that, despite repeated failures to show LTM facilitation of VWM performance in prior studies, the effect is possible when a single pattern is trained for hundreds of trials. However, it is likely the case that the facilitation stems primarily from conceptual or other nonvisual memory representations. When the contributions of nonvisual memory are experimentally eliminated, any evidence of facilitation disappears. These experiments, along with other attempts to address this issue that have been conducted since 1988, all converge on the Parallel Storage hypothesis and therefore on a Structured Primitives account of VWM representation.

APPENDIX: FIGURES

Figure 1. Similarity vector: An example similarity vector that could be used to code for a novel array. Image reproduced with permission from Steven Luck.

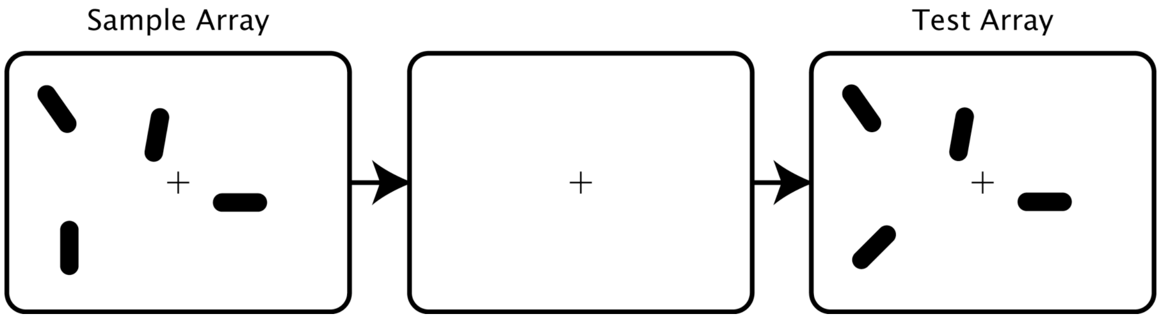

Figure 2. Change Detection: A schematic change detection task. The bar in the bottom left hand corner changes orientation between the sample array and the test array.

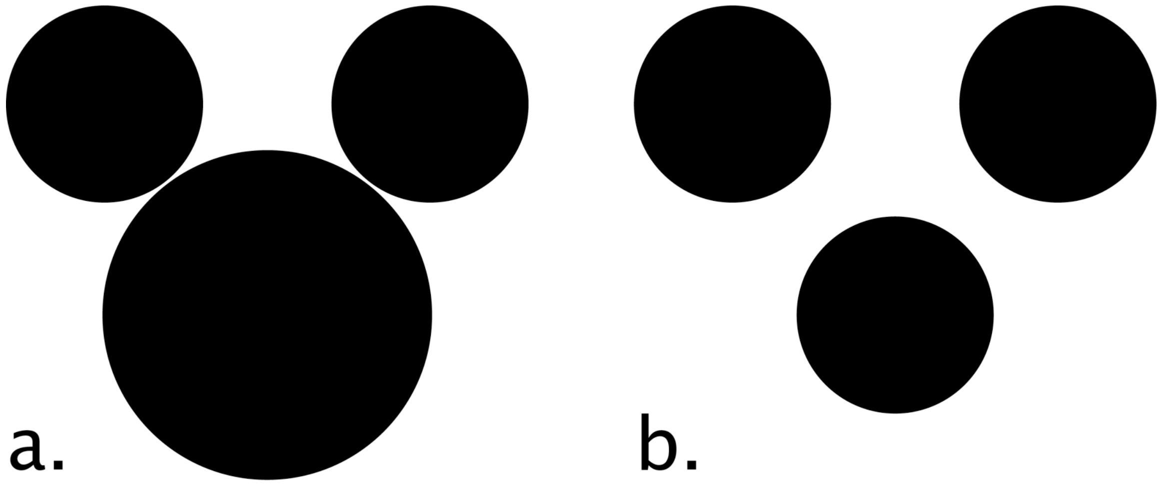

Figure 3. Conceptual Representations: a) A size change detection sample display that can be recoded in conceptual short-term memory as "Mickey Mouse." b) A corresponding array that is not so easily conceptually recoded.

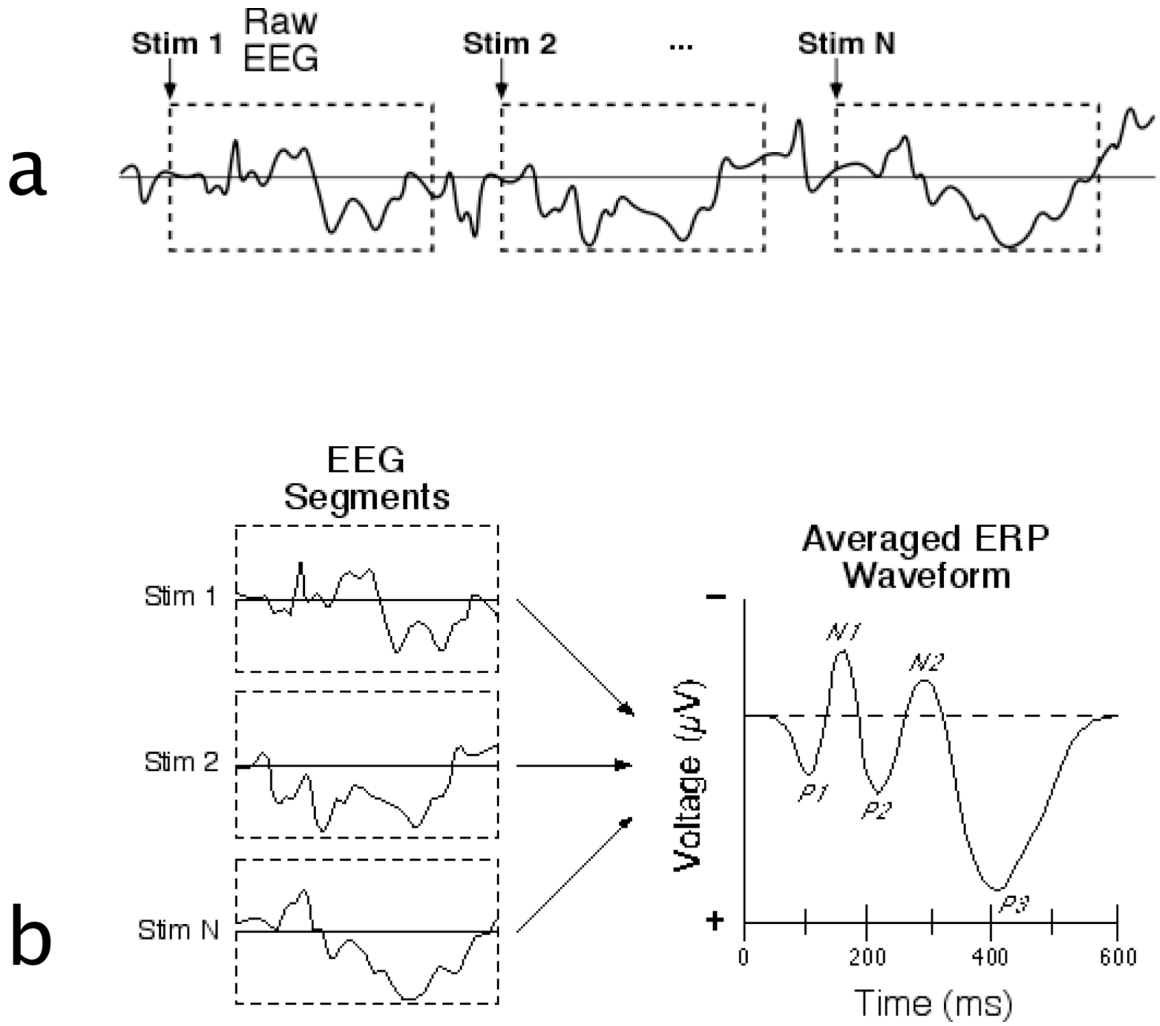

Figure 4. ERP Derivation: a) "Snapshots" from a raw electroencephalogram waveform. b) These snapshots are merged through the averaging process into a waveform that more accurately reflects the electrophysiological signature driven by the linked stimulus event.

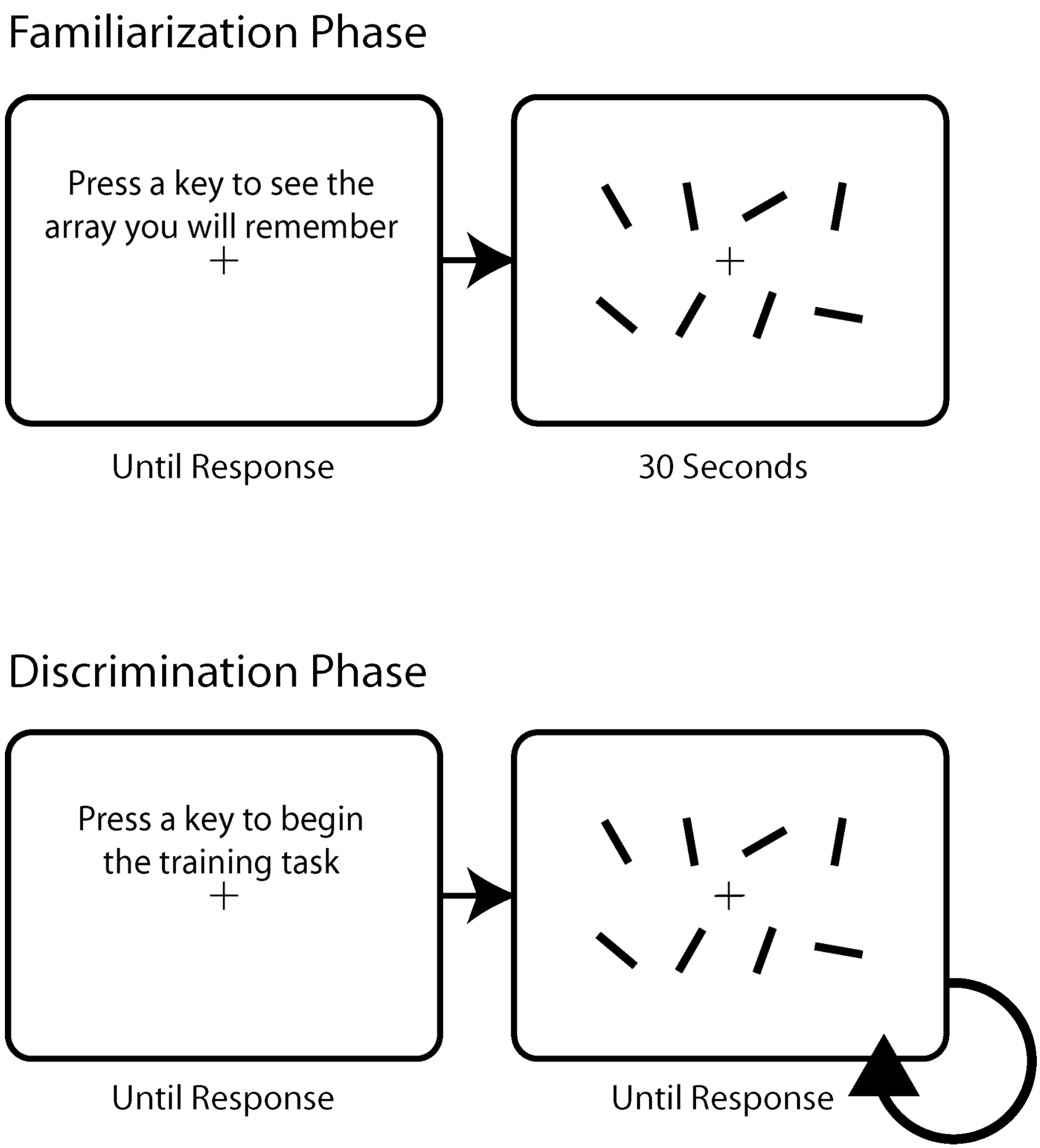

Figure 5. Familiarization and Discrimination: The two phases of the orientation discrimination training task. The familiarization phase was a passive viewing period for the trained array. Trained and trained-1 arrays were randomly presented in the discrimination phase. Participants were asked to identify if the presented array was the trained array or not.

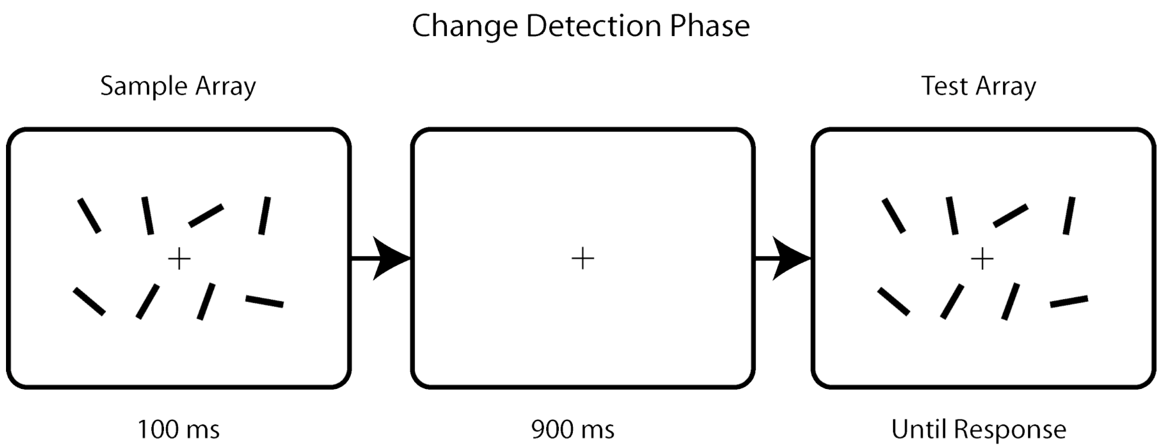

Figure 6. Test Task: The change detection test task performed in Experiment 1. Participants were asked to determine if the sample array was identical to the test array or not. 50% of trials contained a trained array that could change to a trained-1 array or a trained-1 array that could change to a trained array. The remaining 50% contained a random array that could change to a random -1 array.

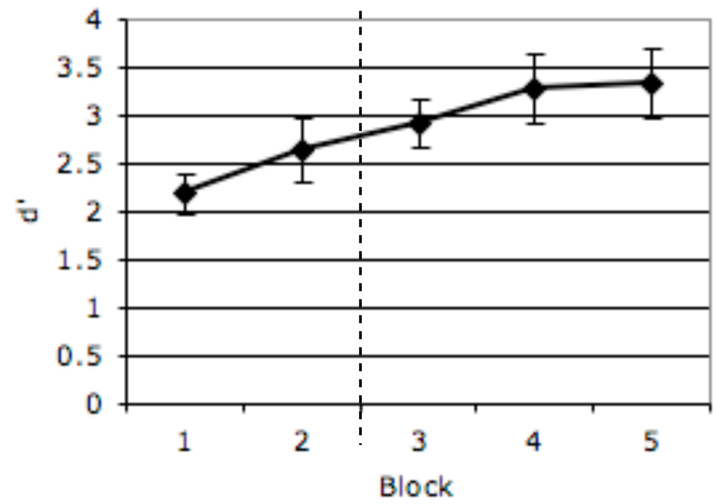

Figure 7. Experiment 1 Training d' (n=10): Participant d' across the 5 blocks of training. Blocks 1-2 took place on the first day of training, and blocks 3-5 took place on the second day. The broken line indicates a break between days of training. Note the monotonically increasing performance, even between days.

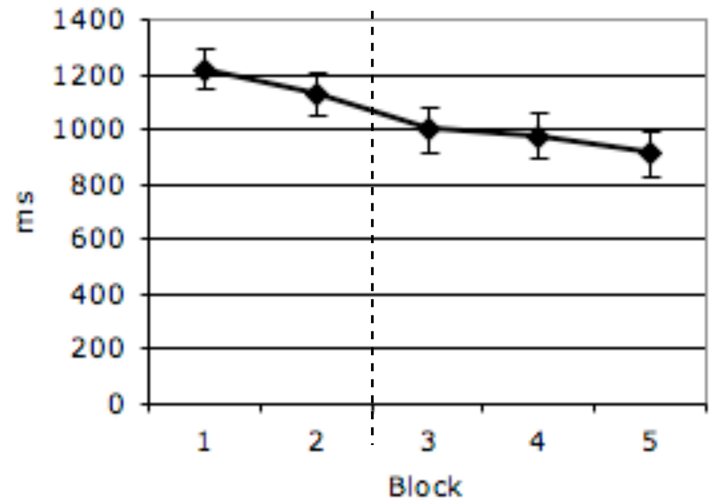

Figure 8. Experiment 1 Training RT (n=10): Participant RT across the 5 blocks of training. Blocks 1-2 took place on the first day of training, and blocks 3-5 took place on the second day. The broken line indicates a break between days of training. Note the monotonically improving performance, even between days.

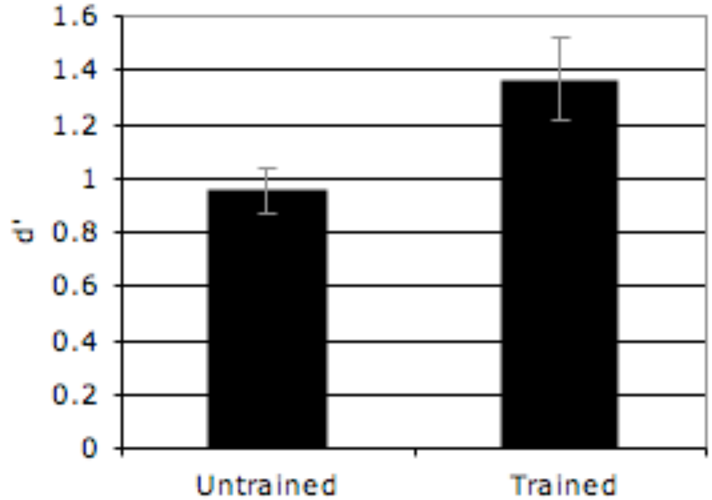

Figure 9. Experiment 1 Test d' (n=10): Change detection d’ data: Participants performed significantly better on the change detection test with trained stimuli than with untrained stimuli.

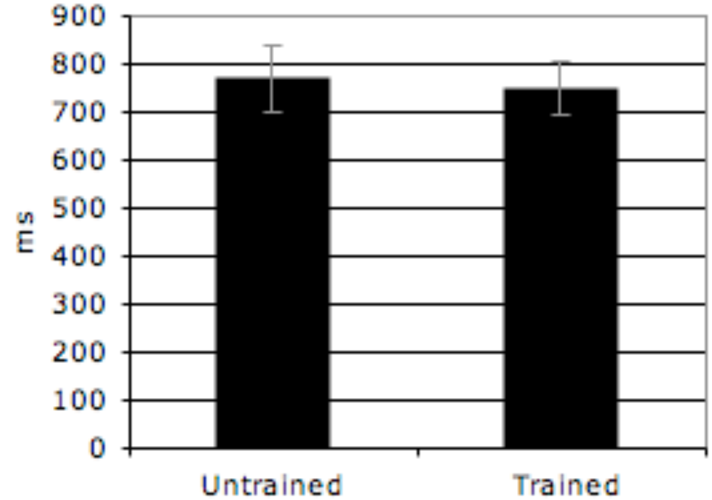

Figure 10. Experiment 1 Test RT (n=10): Change detection RT data: There was no significant difference in RT performance with trained or untrained stimuli.

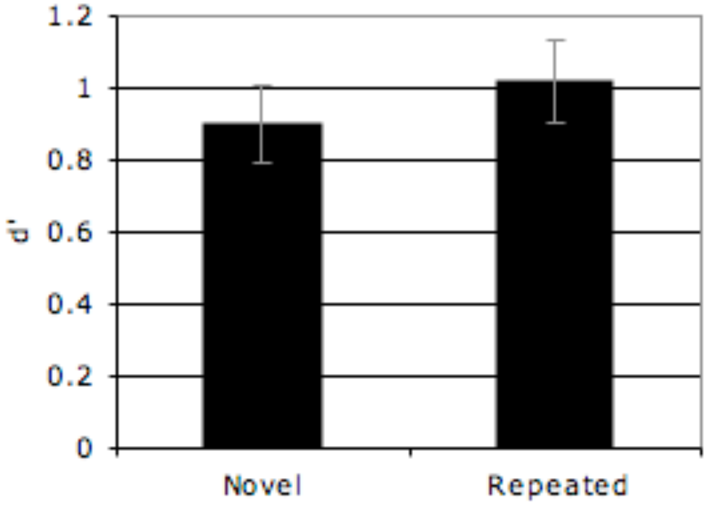

Figure 11. Experiment 2 Test d' (n=12): Change detection d' data: There was no significant benefit for repeated stimuli over the novel stimuli.

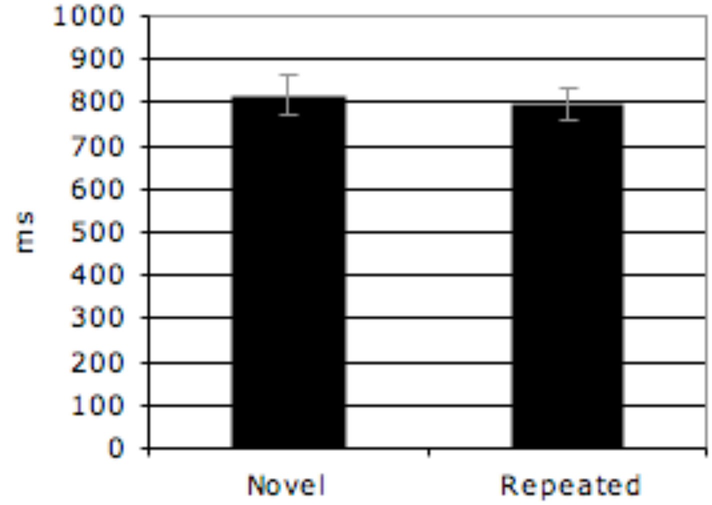

Figure 12. Experiment 2 Test RT (n=12): Change detection RT data: There was no significant benefit for repeated stimuli over the novel stimuli.

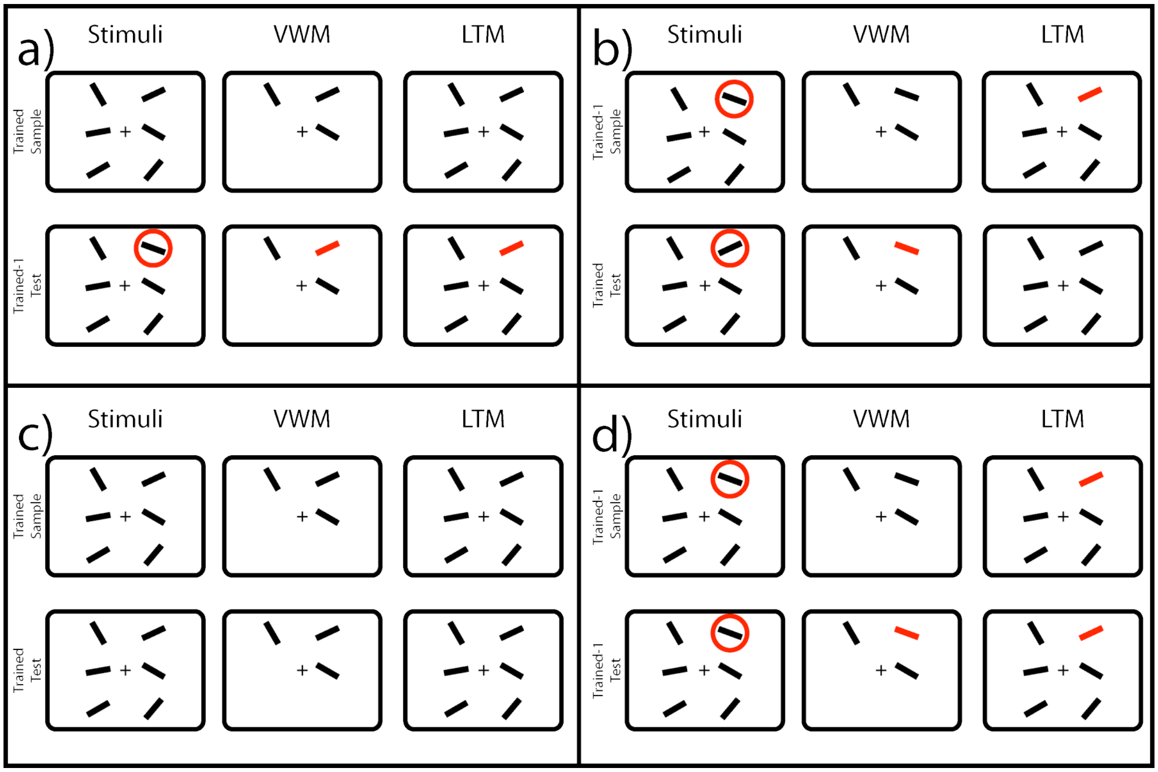

Figure 13. Experiment 3 Predictions: Predicted locus of attention and underlying representations for the Parallel Storage Hypothesis. a) and b) are change trials, c) and d) are no-change trials. In a) and c), the trained array is the sample, and in b) and d), it is the trained-1 array. The top row in each cell represents the sample array and the second row represents the test array. The VWM and LTM columns contain the represented information at each time point. Red bars are candidate representations to drive attention shifts. The red circle represents the spatial locus of attention in the stimulus array.

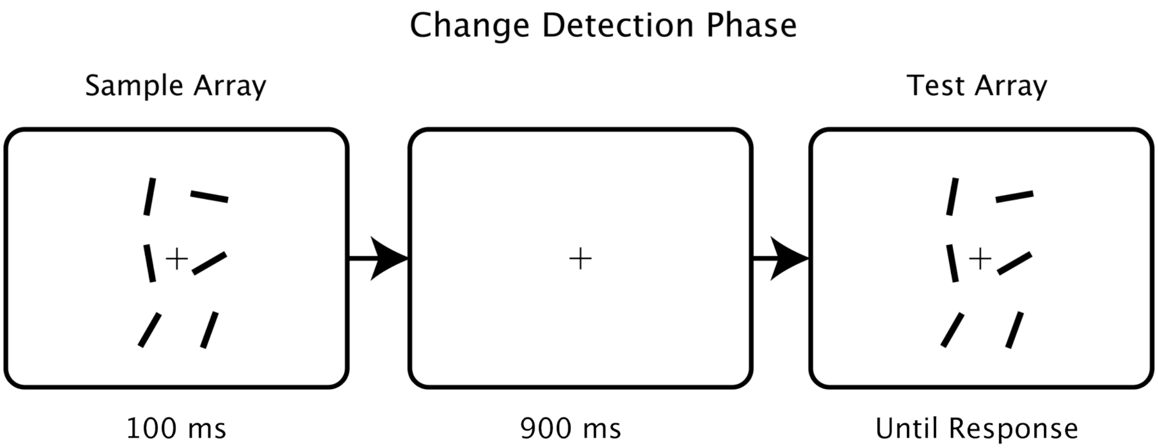

Figure 14. ERP Test Task: The change detection test task performed in Experiment 3. Set size was reduced to 6 and stimuli were oriented vertically. The task was otherwise identical to the test task presented in Experiment 1.

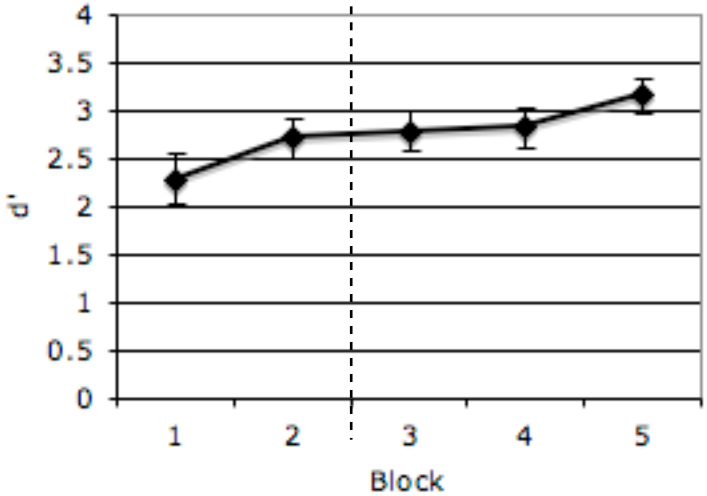

Figure 15. Experiment 3 Training d' (n=17): Participant d' across the 5 blocks of training. Blocks 1-2 took place on the first day of training, and blocks 3-5 took place on the second day. Performance improvement was again monotonic. The broken line indicates a break between days of training.

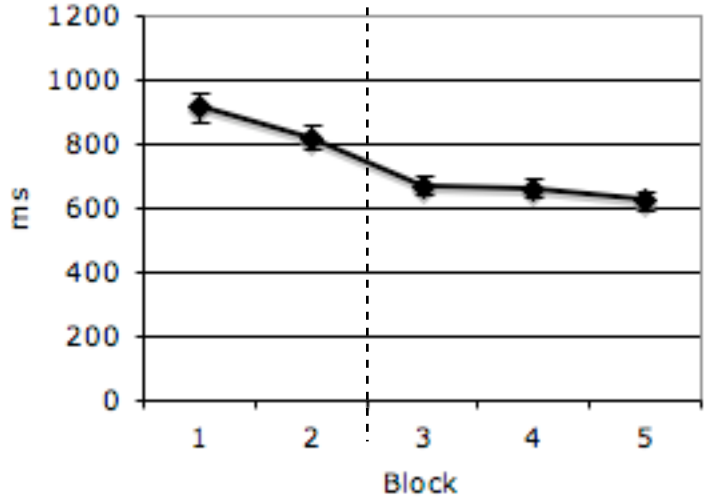

Figure 16. Experiment 3 Training RT (n=17): Participant RT across the 5 blocks of training. Blocks 1-2 took place on the first day of training, and blocks 3-5 took place on the second day. Performance improvement was again monotonic. The broken line indicates a break between days of training.

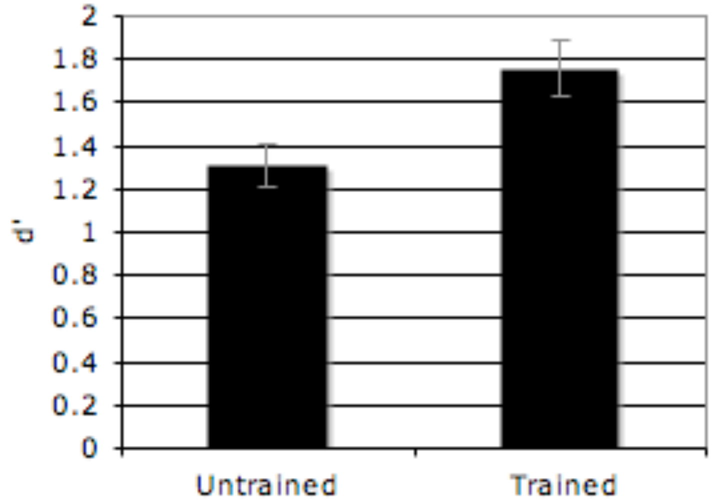

Figure 17. Experiment 3 Test d' (n=17): Behavioral change detection d’ data: The advantage conferred by trained stimuli mirrors the outcome of Experiment 1.

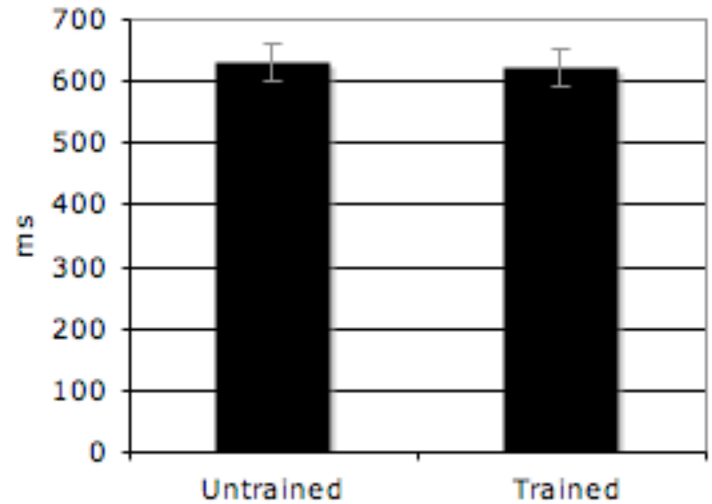

Figure 18. Experiment 3 Test RT (n=17): Behavioral change detection RT data: The null difference in RT performance again mirrors Experiment 1.

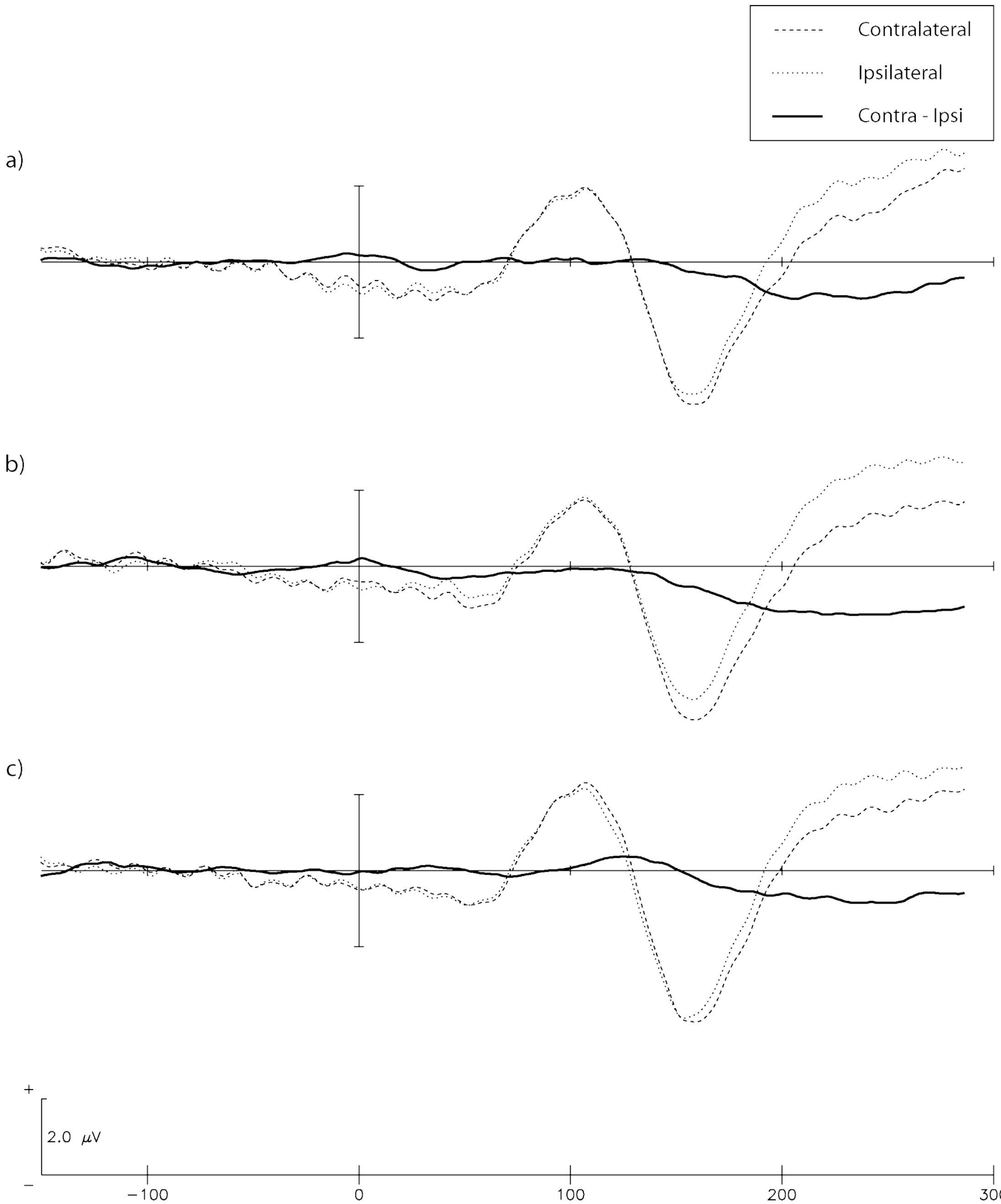

Figure 19. Experiment 3 N2pc (n=17) data: ERP waveforms derived by plotting the average of two groups of eight posterior electrode sites. Averages were time-locked to the onset of the change detection test display. a) Response to trained test arrays. b) Response to trained-1 test arrays. c) Response to random and random-1 test arrays.

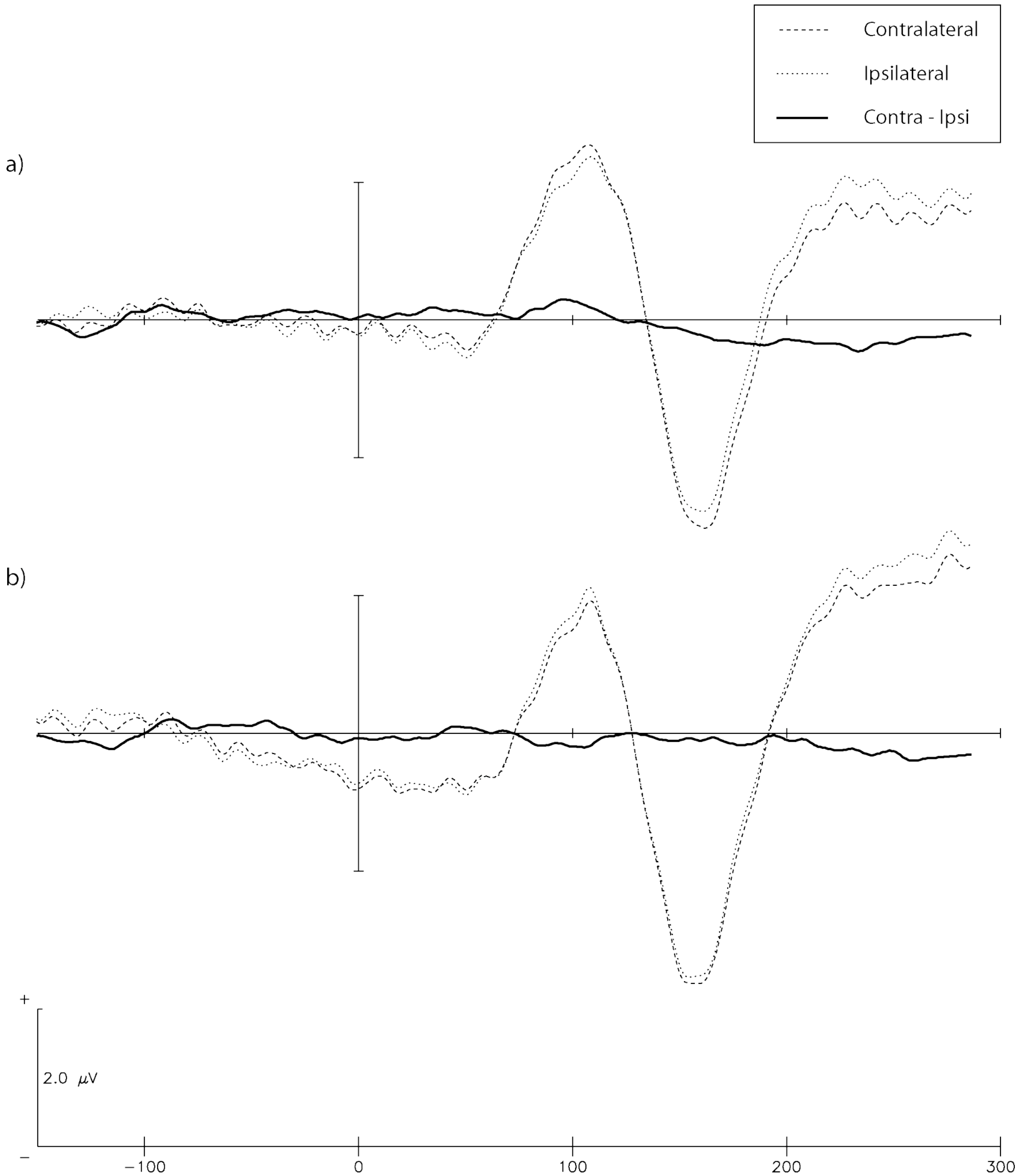

Figure 20. No automatic N2pc (n=17): ERP waveforms derived by plotting the average of two groups of eight posterior electrode sites. Averages were time-locked to the onset of a) trained-1 sample arrays on change and no-change trials and b) trained-1 test arrays on no-change trials. Note the presence of a negative deflection in the contra-ipsi wave between 150-250 ms in a) that is absent in b). This suggests a volitional shift of visuospatial attention in response to trained-1 sample arrays that does not appear in response to trained-1 test arrays on no-change trials.

a) b)

Figure 21. Prince Charles: a) Prince Charles Visiting British Troops. b) Prince Charles visiting the 2006 Ashden Awards. Latter image © Andrew Aitchison and used with permission.

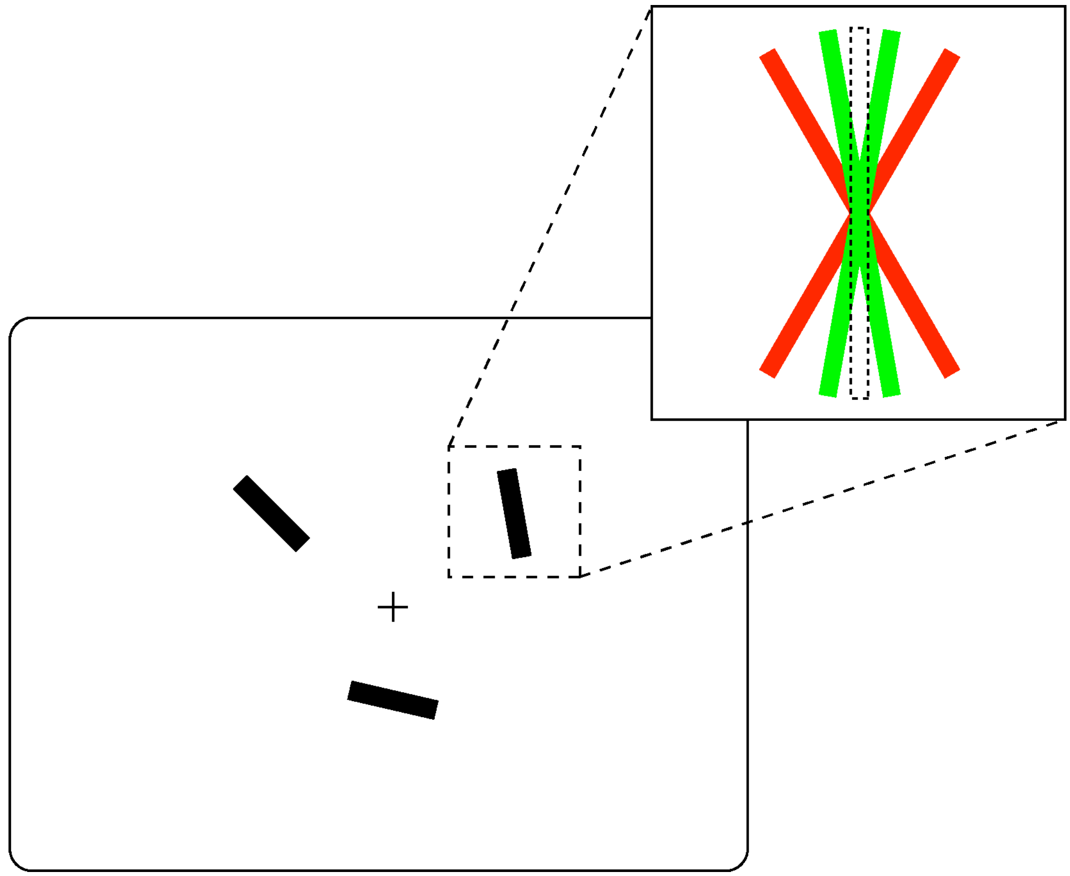

Figure 22. Family and Near-Family Bars: Family bars (green) were generated by rotating a reference bar 10° clockwise or counterclockwise. Near-family bars were rotated a further 20° from the family bars.

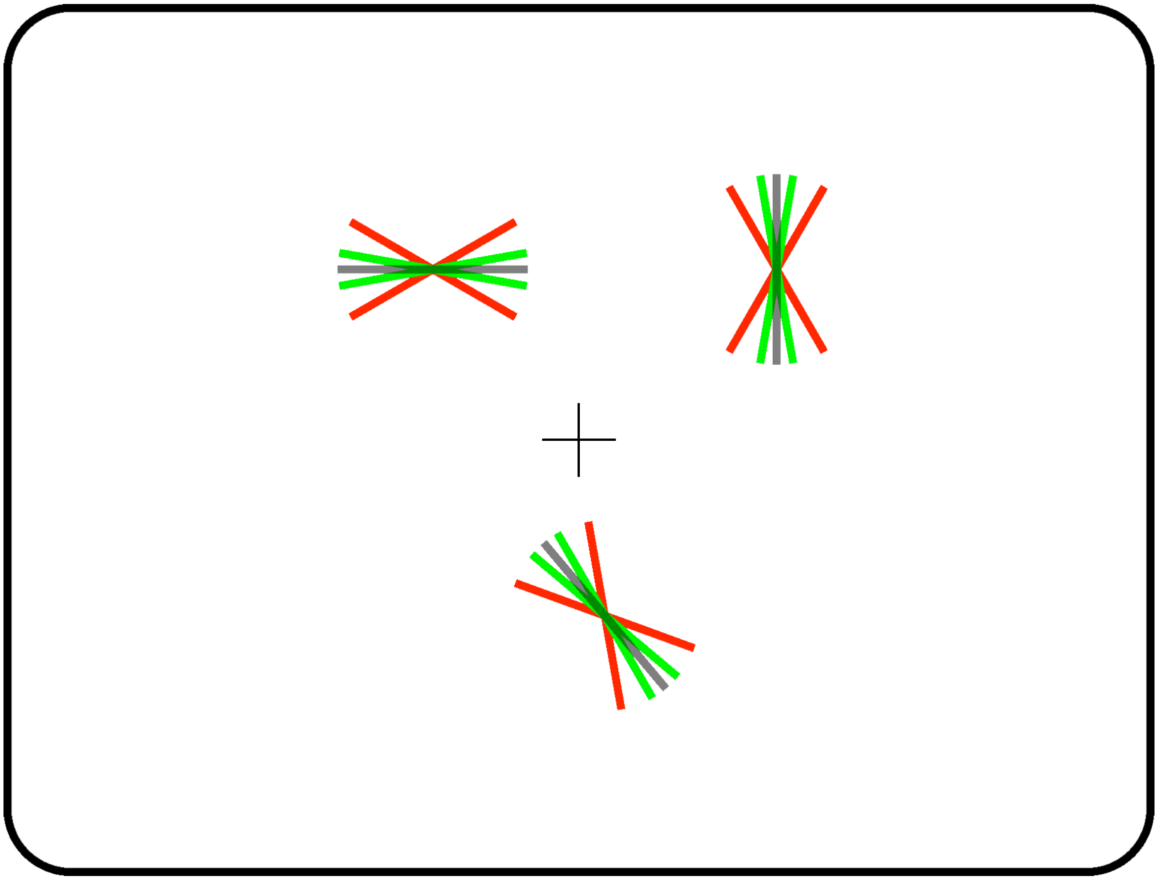

Figure 23. Family and Near-Family Arrays: Schematic of possible family array elements (green) and non-family array elements (red) generated with respect to the reference array (black). One element was selected at each position to create family or non-famiy arrays as appropriate for task difficulty.

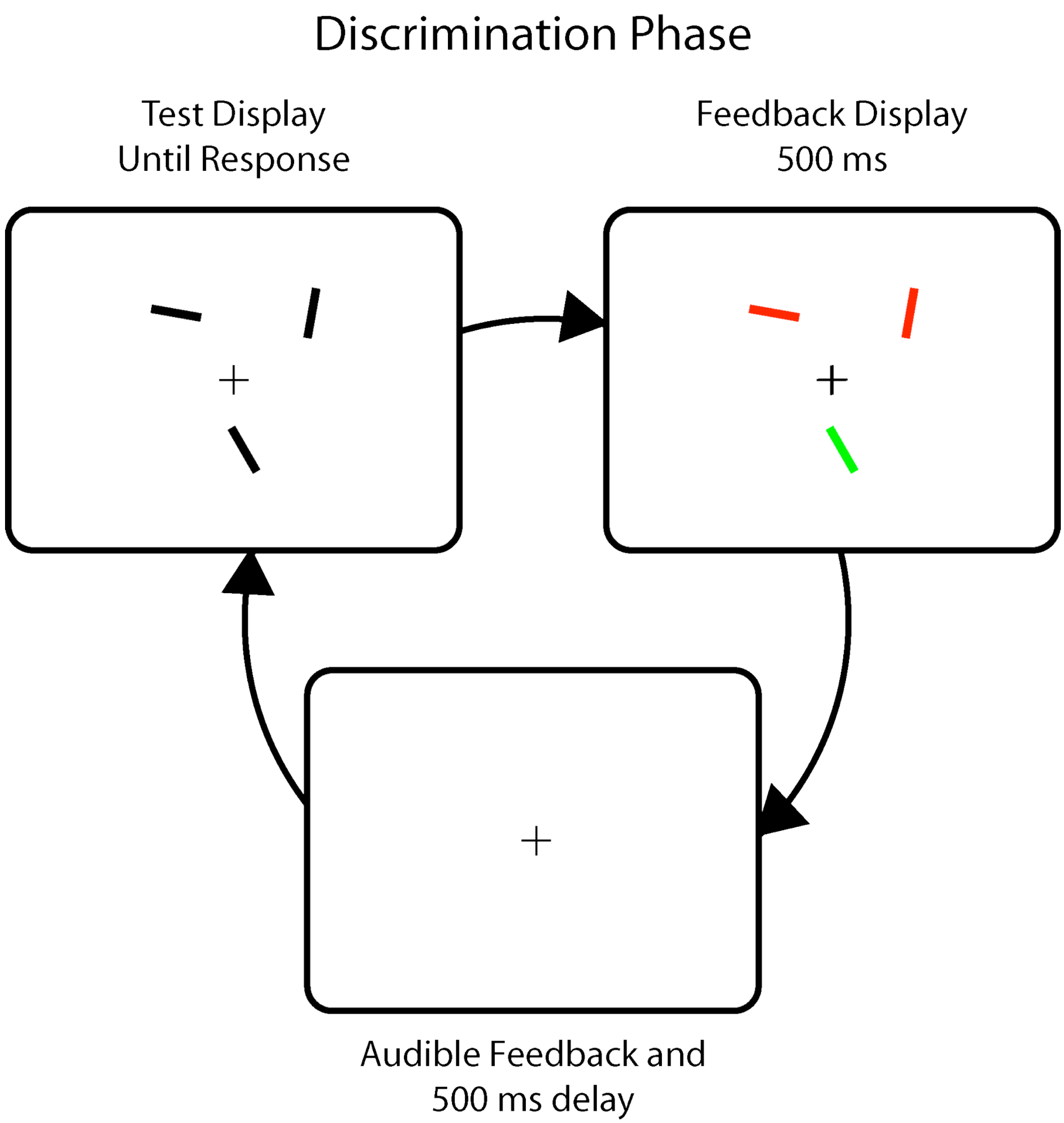

Figure 24. Family discrimination training: Schematic of the stimulus events that occurred during a single training trial. Participants first saw the test display, made a response, then saw the answer key (feedback display) for the trial, and finally received audible accuracy feedback.

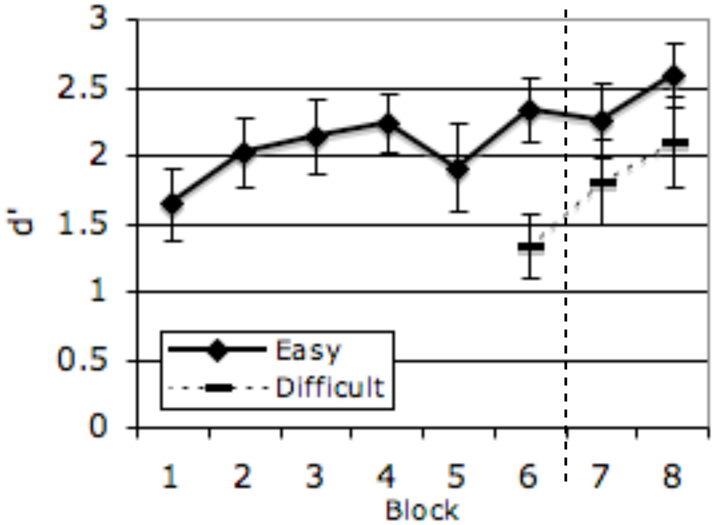

Figure 25. Experiment 4 Training d' (n=18): The first 6 blocks of the easy task were presented on the first day, and the final two were presented on the second. Starting after block 5 of the easy task, the three blocks of the difficult task were interleaved between blocks of the easy task. The broken line indicates a break between days of training.

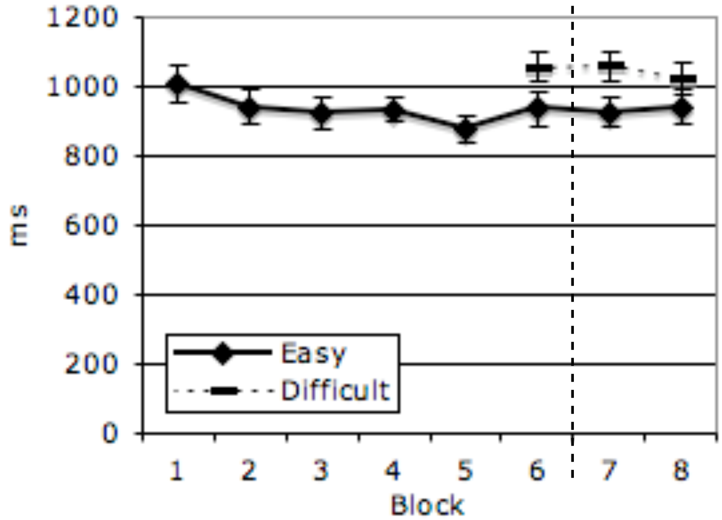

Figure 26. Experiment 4 Training RT (n=18): Participant RT performance remained stable for both tasks across blocks of training. The broken line indicates a break between days of training.

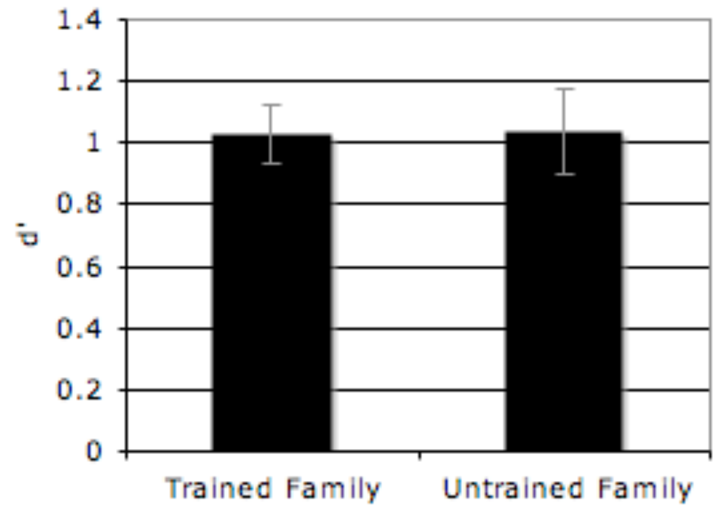

Figure 27. Experiment 4 Test d' (n=18): The change detection task was administered on the third day and showed no performance difference between the trained and untrained conditions.

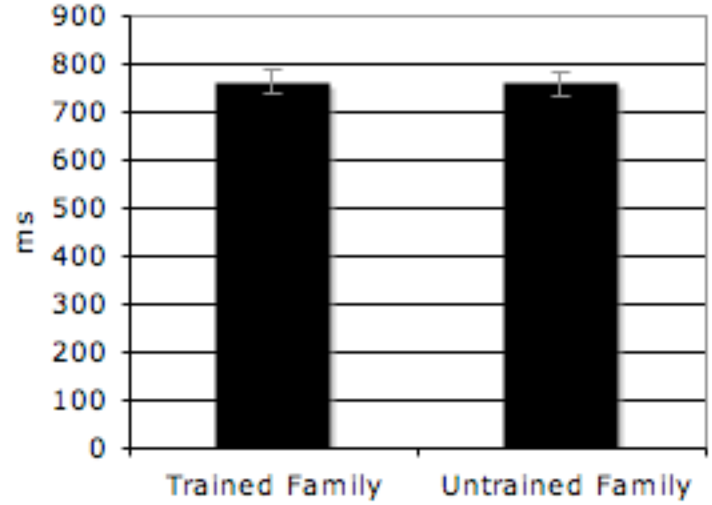

Figure 28. Experiment 4 Test RT (n=18): There was no performance difference between the trained and untrained conditions in the RT domain.

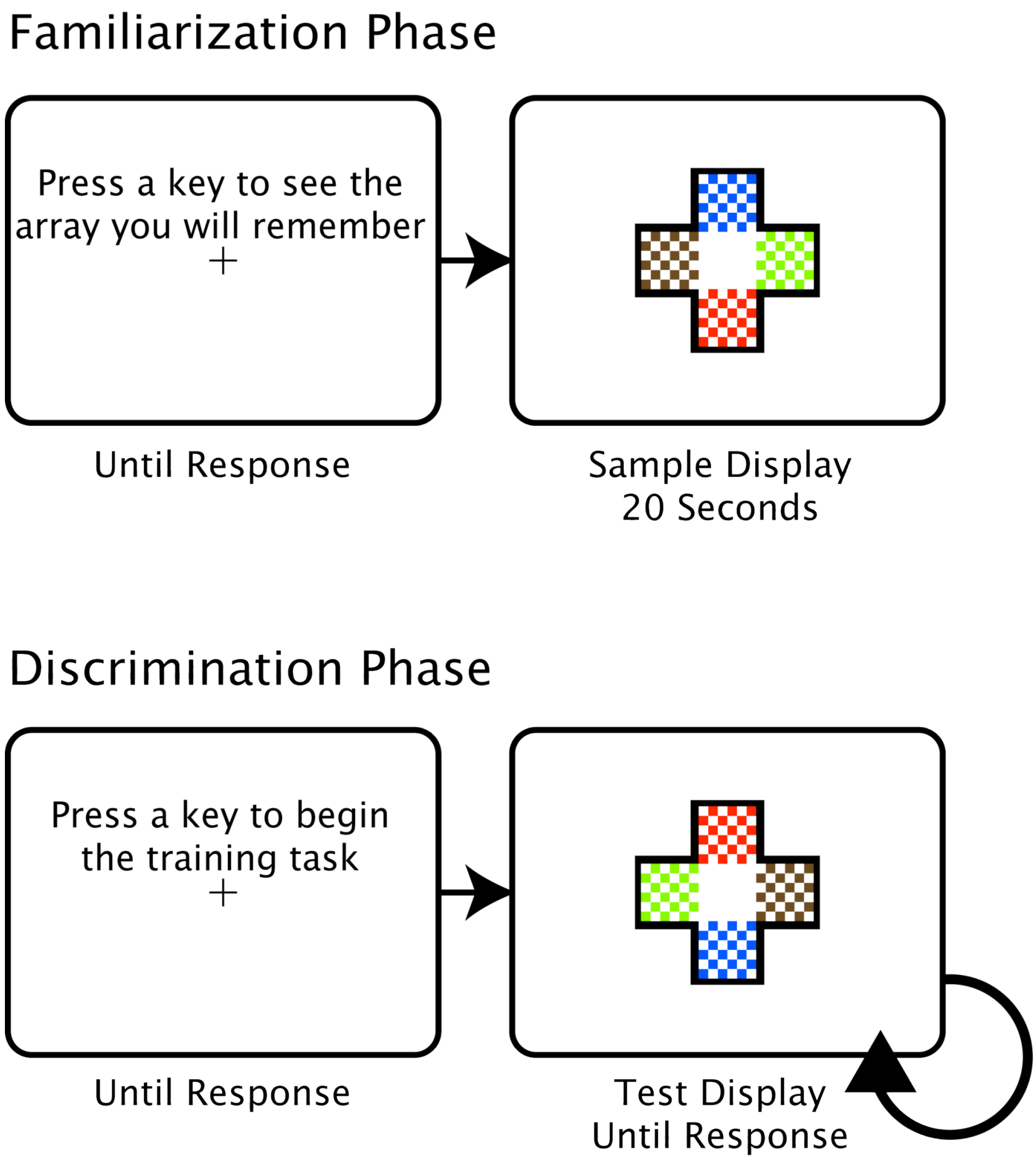

Figure 29. Familiarization and Discrimination in Experiment 5: The two phases of the color discrimination training task. The familiarization phase was a passive viewing period for the trained array. The trained and novel propellers were randomly presented in the discrimination phase, and participants were asked to distinguish between them.

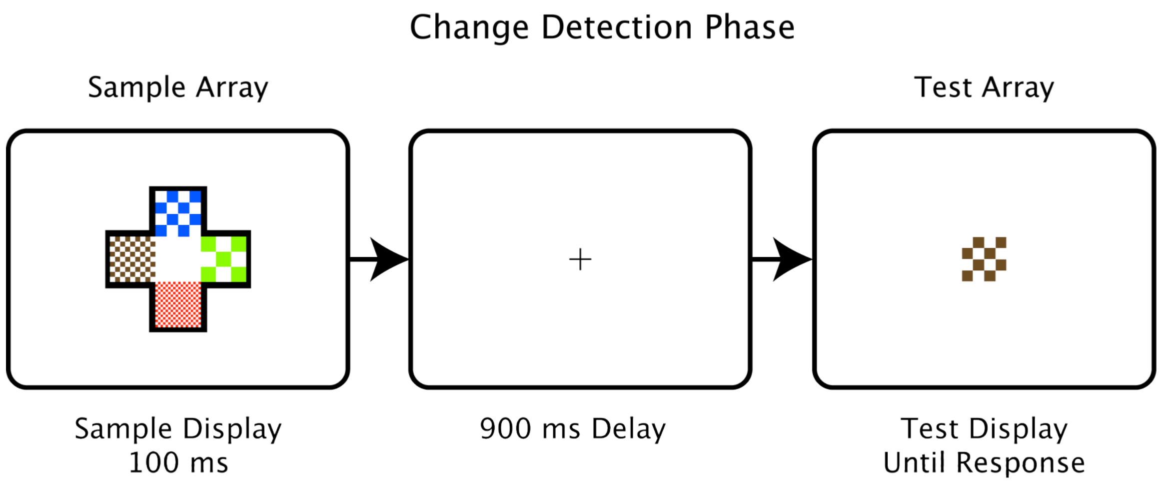

Figure 30. Change Detection Test in Experiment 5: Although the sample display contained a complete propeller, participants were presented with only one blade at test. This ensured that participants would need to use their color memory (the trained representation) to perform the texture change detection task.

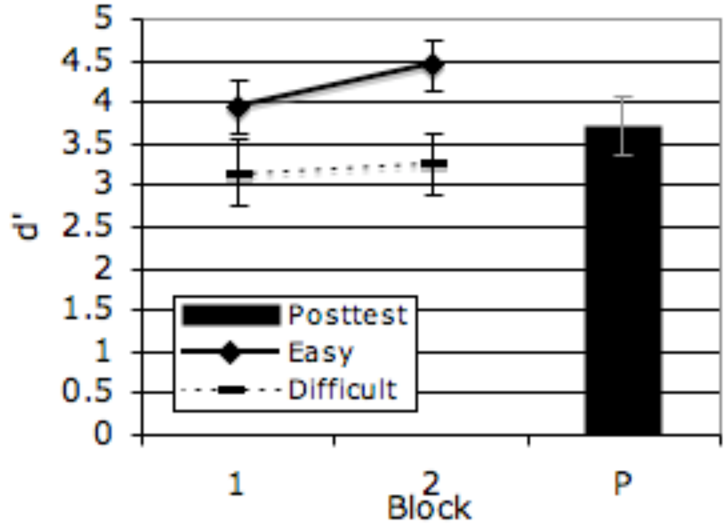

Figure 31. Experiment 5 Training and Posttest d' (n=9): Participants showed no significant improvement in d' during training, though they performed well above chance on the posttest.

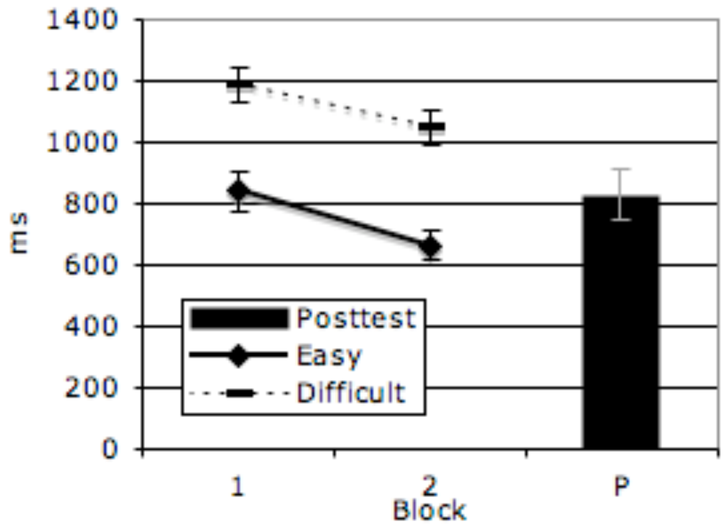

Figure 32. Experiment 5 Training and Posttest RT (n=9): Participants showed significant improvement in RT during training.

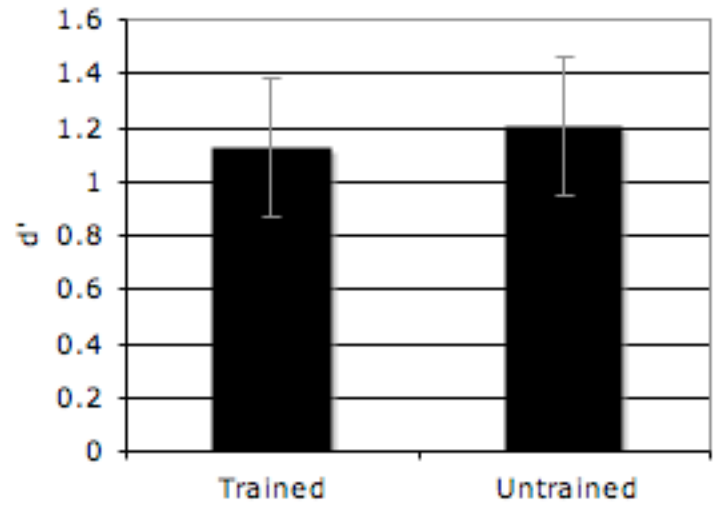

Figure 33. Experiment 5 Test d' (n=9): Participants showed no significant performance difference between the trained and untrained conditions.

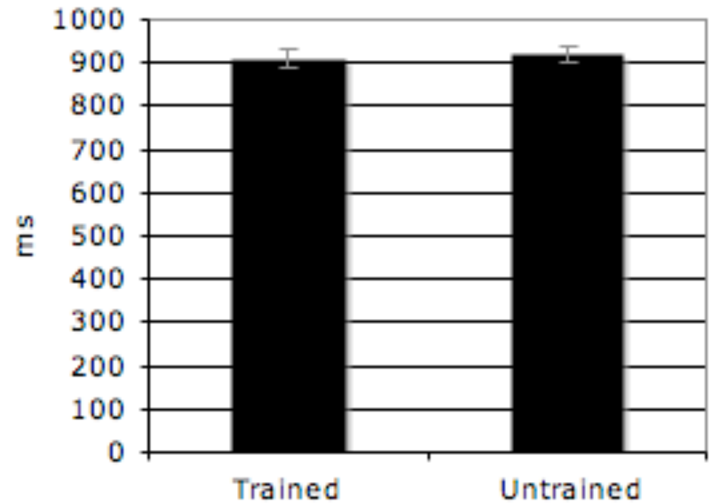

Figure 34. Experiment 5 Test RT (n=9): Participants showed no significant performance difference between the trained and untrained conditions.

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