The Prospective Power of Memory on Recall and Attentional Orienting

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Abstract

Memories are built from past experiences, but they continue to carry meaning and weight through to the present and future. The way in which we learn impacts not only how we remember but also how we perceive in the present moment. It is well established that memory is important for attentional guidance, as is attention for directing selective retrieval, yet these two abilities have primarily been studied separately. Therefore, our understanding of how memory guides recall compared to attentional orienting is lacking. In this thesis, I measured the formation of associative memories between target objects and scenes during visual search tasks and then probed how variations in learning parameters impacted subsequent performance. The search tasks differed based in the number of targets associated with each scene (Chapter 2), the type of spatial association (Chapter 3), or the spatial predictability of targets and distractors (Chapter 4). Recall and/or attentional-orienting tasks tested the relative influence of these different learning manipulations on future performance. Contrary to my hypotheses, competition among items associated with the same scene had little impact on memory recall. The type of association and predictability of items associated with scenes had significant impacts on both subsequent recall and attentional-orienting tasks. Interestingly, the patterns of influence were functionally dissociable. Memory recall was versatile: different types of associations and spatial expectations facilitated memory recall depending on the congruency between learning and recall demands. Instead, the pattern of memory-guided attentional orienting was more consistent and strongly dependent on spatial expectations pertaining to target objects. The thesis opens with a literature review on the relationship between visual search, memory recall, and attentional orienting (Chapter 1). The empirical chapters follow (Chapters 2 through 4). The final chapter discusses the implications of the studies and how they can facilitate future research.

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Chapter 1: General Introduction

When we think about the moments that make up our lives, we often turn our mental lens back in time to revisit past chapters of our life book. But, rather than staying as fixed writing on a page, our memories take a life of their own from the moment they are encoded – continuing to impact our behaviour into the yet unwritten pages of our book (Hardt et al., 2013; Nader & Hardt, 2009; Nobre & Stokes, 2019). The purpose of our memories is not just to store what has occurred in our lives for subsequent recollection (remembering past behaviour), but to use these occurrences to adaptively guide our future behaviour (applying learning to how we behave today or tomorrow). Put simply, this prospective power of memory allows us to learn from our past to empower the way we act in the present (Bar, 2009; Stokes & Nobre, 2012). For example, without the ability to build on prior experience, the visual system would treat every visual feature, object, and scene as novel, struggling to recognize and respond to recurring properties in the environment (Turk-Browne et al., 2013). Though these notions are not new (Helmholtz, 1867), memory research often focuses on the backwards-facing purposes of memory, studying how we reconstruct past events in our lives using different types and timescales of memory (Nobre & Stokes). Instead, this thesis will focus on the prospective influences of memory, investigating how we use our memories to guide our attention to the external world as well as to recollect past events.

1.1. Terminology and Theoretical Background

The prospective influences of memory can originate from a range of timescales (Nobre & Stokes, 2019). For example, behaviour is influenced by long-term (Aly & Turk-Browne, 2017; Nobre & Mesulam, 2014), intermediate (Chun & Jiang, 1998; Jiang, 2018), and short-term (Desimone & Duncan, 1995; Stokes et al., 2009) memory traces. Once memories are formed, they can also impact our ongoing and future behaviour in many ways.

For example, via explicit retrieval (Foerde & Shohamy, 2011), biasing future perception through attention (Nobre & Mesulam, 2014), guiding decision-making (Biderman et al., 2020), or helping us to imagine the future (Schacter et al., 2008). Therefore, how the brain stores information in anticipation of upcoming needs and then selects the necessary information flexibly and adaptively to respond to upcoming behavioural goals is cognitively complex. In my thesis, I will focus on the influences of long-term memory (LTM; memories retained for minutes or hours rather than seconds or milliseconds) on attentional guidance and memory retrieval.

Within this thesis, memory "retrieval" will act as an umbrella term representing: the cue-induced behavioural expression of a memory (Frankland et al., 2019). Retrieval may occur in scenarios where we intentionally attempt to recover a memory related to a specific cue (e.g., when in the vegetable aisle at the grocery store, trying to remember if you ran out of onions). Alternatively, retrieval can also be spontaneously triggered by a cue (e.g., passing by the bananas in the fruit aisle and remembering you ate the last one this morning). Within memory retrieval, there is an important further distinction between memory "recognition" versus "recall" (Squire et al., 1993). This distinction is important because, for example, certain patient groups (e.g., schizophrenics) have shown disproportionate recall compared to recognition deficits, pointing to different mechanisms and substrates involved in these processes (Aggleton & Shaw, 1996; Bauman & Murray, 1968; Migo et al., 2012). Recognition memory is a judgement as to whether a stimulus seen at that moment has previously occurred (e.g., deciding if a stimulus is old or new; Bastin & Linden, 2003; Migo et al.; Wagner et al., 2005). Whereas, during memory recall, participants do not make a choice, instead they are asked to recall the memory to the best of their ability (e.g., recall the location of the target; Frankland et al., 2019; Tulving & Pearlstone, 1966). For example, after learning a list of names, a participant could be shown a name and asked to recall as many

names from the list as possible (free recall) or cued to recall only the names that start with ‘M’ (cued recall). In my thesis experiments, I only measure recall using cued tasks (e.g., recall the location where the target appeared in this specific scene). Therefore, throughout this thesis, when I use the term ‘memory recall’ I am referring specifically to ‘cued memory recall’. However, I measure recognition memory in different ways that are important to distinguish.

“Dual-process” models have argued for the distinction of recognition memory into two processes termed “familiarity” and “recollection” (Aggleton & Brown, 2006; Mandler, 1980; Tulving, 1985; Yonelinas, 1994, 2002). Recognition and recall can be defined as tasks whereas familiarity and recollection are memory processes (Migo et al., 2012). Recollection is a cued "recall-like” process that refers to the retrieval of qualitative information about a specific studied episode (e.g., seeing a friend and remembering that you last saw them at the beach; Bastin & Linden, 2003; Gardiner, 1988; Gardiner & Java, 1990; Johnston et al., 1985), whereas familiarity (e.g., that feeling that you have met someone before, without necessarily retrieving where/when) is a more global measure of memory strength or stimulus recency (Moscovitch et al., 2016; Yonelinas et al., 2010). Recollection memory has been associated with “yes-no” recognition tasks in which items are presented one at a time and participants must respond whether they are ‘old” or “new’ (e.g., Wolfe, 2012) as well as with cued recall tasks where participants must recall where an item occurred (Migo et al.). On the other hand, familiarity memory is often associated with “forced-choice” recognition tasks where a target item is presented with one or more distractors and the participant must choose which item they have seen before (Aggleton & Shaw, 1996; Bastin & Linden, 2003; Parkin et al., 1994). However, whether in fact yes-no and forced-choice recognition differ in terms of the contribution of recollection and familiarity to performance is debated, with some arguing that recollection and familiarity contribute to the same extent to performance in both yes-no and

forced-choice tasks (Khoe et al., 2000). Others have argued that recollection and familiarity are not dissociable and may instead be driven by a single mnemonic process (Pratte & Rouder, 2012). These factors should be kept in mind when evaluating results from my experiments, which make use of both recognition (e.g., item memory) and cued recall tasks (e.g., location memory). The individual experimental chapters will elaborate more on these design considerations.

Attention is typically defined as the set of perceptual and cognitive processes that allows us to prioritize certain events for further analysis or action, meaning that attention is involved in a plethora of cognitive processes such as memory retrieval (Le Pelley et al., 2016). To clarify and delineate the relationship between the processes of attentional guidance and memory retrieval a taxonomy is helpful. Chun et al., (2011) lay out a crucial differentiation between external attention (the selection and modulation of sensory information) versus internal attention (the selection and modulation of internally generated information). Sitting on the train we can pay external attention to the passing scenery (the trees, mountains, and lakes in the external world). This sensory information can be organized into features or objects (perceptual groups or units), which can be the targets of external attention. Alternatively, we can pay internal attention to the swirling thoughts in our heads (the names and faces of the friends we will meet at our destination, deciding where you will go when you arrive, and how you will get there; Johnson & Hirst, 1992; Logan, 1996; Vecera & Behrmann, 2001). These items can be the contents of working memory, long-term memory, task sets, or response selection (Chun et al.). Other taxonomies of attention are also prominent and useful, such as divisions between exogenous or bottom-up and endogenous or top-down attentional control (Egeth & Yantis, 1997). These and other distinctions focus on differentiating specific mechanisms of attention, whereas the taxonomy I will use is based on the targets of attention, including all of its mechanisms and properties (Chun et al.). In

addition to being broad and all-encompassing, this taxonomy is useful to the studies in my thesis as they aim to investigate and delineate similarities and differences between the properties of internal versus external attention.

Both internal and external attention face the difficulty of overwhelming amounts of information or choices, but limited processing capacity, dictating a need for selection. For example, without attentional selection the external visual system would be crippled by irrelevant information competing for limited processing resources (it would be impossible to find your friend's face on the crowded train platform; Chun & Jiang, 1998; Turk-Browne et al., 2013; Wolfe, 1998). Similarly, it would be difficult to select a single internal memory trace for retrieval amongst the many competing alternatives (it would be impossible to retrieve what your friend at the train station looks like amongst your many other friends; Chun et al., 2011; Jeneson et al., 2011; Sprague et al., 2014). A primary goal of attention research and theory, and one that is important in my thesis, is to understand and outline which information is selected, how it is selected, and what happens to both selected and unselected information (Chun et al.,).

In their seminal theoretical piece, Desimone and Duncan articulate how the goal of attention is to bias competition in favour of a target object or expected event (1995). According to Biased Competition Theory: first, multiple visual stimuli compete for attention because only a small amount of information on the retina can be processed at any given moment in time (Desimone, 1996). Second, competition for attention is biased toward some stimuli over others based on either bottom-up stimuli (e.g., external information such as your friend’s cherry red jacket) or top-down sources (e.g., current behavioural goals such as your motivation to find a red object; Corbetta & Shulman, 2002; Desimone & Duncan, 1995; Vecera & Behrmann, 2001). Ultimately, both bottom-up and top-down factors dictate how spatial attention is directed towards objects that may be more salient or relevant for

behavioural goals than others (Awh et al., 2012; Kastner & Ungerleider, 2000; Vecera & Behrmann, 2001). Similarly, selecting a memory from other competing traces should also be viewed as an attentional operation, i.e., selective attention to an internal representation (Aly & Turk-Browne, 2017; Badre et al., 2005; Chun & Johnson, 2011; Wagner et al., 2005). In fact, forgetting often arises from memory retrieval failures (e.g., incorrect memory selection) rather than loss of information, heightening the importance of understanding the selection mechanisms involved in enhancing target memories compared to distractor memories (Aly & Turk-Browne, 2017). Though there are clear analogies between selection in the perceptual or attentional domain and selection during memory retrieval (Cabeza et al., 2008; Wagner et al., 2005), differentiating in which cases these two behaviours act similarly or differently is an open area of research (Chun & Turk-Browne, 2007).

In 2006, Eric Kandel proposed that one of the most important problems for 21st-century neuroscience is to understand how attention regulates the processes that stabilize experiential memories (Kandel, 2006). Yet, research on how attention influences memory processes in the brain is still in its early days (Aly & Turk-Browne, 2017). In fact, though attention and memory have been investigated frequently as separate topics, their interaction has been relatively neglected (Turk-Browne et al., 2013). Piecing apart what are the independent versus combined functions of memory and attention is difficult because of how intertwined these functions are - past experiences optimize external attentional selection just as attentional selection (both external and internal) is critical for successful retrieval (Aly & Turk-Browne, 2016; Chun et al., 2011; Tarder-Stoll et al., 2019). Taken together, there is a fundamental relationship between learning (i.e., the process of memory formation) and attention, where learning leads to the prioritization of stimuli that are likely to cue motivationally significant events. Further, attentional biases that develop from prioritized stimuli can then go on to modulate the rate of future learning of these stimuli, e.g. predictive

cues are subsequently learned about faster (Le Pelley et al., 2016). Contributing to our understanding of this process where memories are formed via learning and then go on to impact subsequent behaviour, whether it be retrieval or attentional guidance, is the primary goal of my thesis.

Focusing on the prospective powers of memory is an effective means to tease apart the similarities and differences between memory retrieval and attentional orienting for a few reasons. From a methodological standpoint, in my thesis experiments, I separated measures of learning from subsequent tests to allow for comparisons between how different learned associations can influence memory retrieval versus attentional orienting. Specifically, first, participants completed visual search tasks (see Section 1.2) where they use external attention to form associative memories of different types (e.g., learning contextual vs probabilistic associations). Then, I tested their internal attention with tasks that assess participants' ability to retrieve the correct object-scene associations against competing alternate traces (hereafter called memory retrieval tasks, with further delineation into recall or recognition tasks where relevant; see Section 1.3.1.). Also, participants completed external attention tasks where they had to detect and respond to objects that flash briefly in learned locations (hereafter referred to as attentional orienting tasks; See Section 1.3.1.). By manipulating the experimental variables at the learning phase and then measuring their subsequent implications, I could investigate research questions such as: Do spatial expectations alter the suitability of memories for attentional orienting compared to memory retrieval (Section 1.3.2)? Does increasing competition in memory make retrieval of specific associations more difficult (Section 1.3.3.)? Finally, do different types of memories (e.g., contextual versus probabilistic) have separate behavioural consequences (Section 1.3.4)? The following sections will delve deeper into the theoretical and methodological background that was considered when designing these studies, starting with the learning or visual search tasks.

1.2. Visual Search

Visual search is the process of searching for a target within a context, e.g., finding the lighthouse when you go to the beach. In real life, one can learn the associations between a given context (your favourite beach) and the location of items of interest (the lighthouse). By visiting related contexts (various beaches), it is also possible to learn regularities about certain items of interest (lighthouses are often on cliffs). It has been proposed that associations are the building blocks of predictions: by triggering a memory (walking back to the beach), information that is associated with that memory is retrieved, generating an expectation (where the lighthouse is likely to be; Bar, 2009; Schacter & Tulving, 1994). In this example, a memory for an episode in the past (the beach) influences behaviour in the present, for example, via retrieval of the object's location and attending to that point in the visual field (e.g., remembering where the lighthouse is located and directing your gaze accordingly). Therefore, even during the process of learning, memories are used to guide prospective behaviour adaptively (Nobre & Stokes, 2019).

Natural visual search behaviour has been approximated with a range of computer-based experimental paradigms using both simplistic (arrays of letters or numbers) and naturalistic contexts (objects in real-world scenes; Brockmole & Henderson, 2006; Chun & Jiang, 1998). Importantly, visual search has been shown to differ behaviourally and neurally based on whether targets are associated with a specific context (Chung & Jiang, 1998; Section 1.1.1.) or a probable location of appearance (Geng & Behrmann, 2002; Goldfarb et al., 2016; Section 1.1.2.).

1.2.1. Contextual Cueing

In one type of learning within visual search, known as contextual cueing, participants search for targets that are paired with specific contexts that repeat (Chun & Jiang, 1998).

Specifically, in the most basic version of contextual cueing experiments, targets (e.g., letters or numbers) that appear in fixed locations within repeating configurations of distracting stimuli are found more quickly than targets in new distractor configurations (Chun & Jiang, 1998; Endo & Takeda, 2004; Goujon et al., 2015). Importantly, responses become progressively faster each time a display is repeated (pairing of target and distractors in specific locations; Chun & Jiang, 1998). Notably, participants are unaware that some of the visual search displays are repeated. Also, the locations where targets appear are evenly distributed throughout the scene, therefore, participants cannot implicitly learn that targets are more likely to occur in a spatial area and use this to guide their search (Chun & Jiang, 1998). Instead, participants implicitly learn to use the specific spatial layout (e.g., the distractor locations) to facilitate their search for the target's location (Jiang, 2018). Despite the importance of these contextual clues for guiding search, participants perform at chance levels when tested on their recognition memory (e.g., 'old' or 'new'?) for the configuration of targets and distractors, suggesting that this form of learning is largely implicit (Jiang, 2018; though see Vadillo et al., 2016). Explicit attempts to memorize the repeated displays may even interfere with the facilitation of visual search by contextual cueing (Chun & Jiang, 2003). Importantly, evidence suggests that visual search in these simple paradigms differs markedly from search in naturalistic scenes (Brockmole & Henderson, 2006).

Much of our understanding of visual search comes from simple paradigms in which participants search for targets in random arrays of similar-looking distractors (Chun & Jiang, 1998; Goldfarb et al., 2016), yet search behaviour in these tasks differs markedly from searching for objects in naturalistic scenes (Wolfe et al., 2011). For example, in the seminal paper demonstrating the contextual cueing effect (Chun & Jiang, 1998), search times in repeated simple displays continued to decrease over 15-20 repetitions with a reaction time benefit of 60 to 80 ms compared to novel displays. In contrast, in Brockmole & Henderson

(2006), participants achieved the maximal cueing benefit of over 2s after only four repetitions of searching for targets in real-world scenes. A large contextual cueing effect has also been found in real-world scenes after only two exposures to the scenes (Becker & Rasmussen, 2008). Importantly, in contrast to the paradigms using simple stimulus arrays, learning object locations is explicit when searching through naturalistic scenes, and participants perform above chance when tested on their recognition memory for the scenes themselves (Brockmole & Henderson, 2006). Furthermore, whereas target locations are associated with the local context in simple arrays (objects spatially near the target; Jiang & Wagner, 2004; Olson & Chun, 2002), the explicit memory is driven by the global context in naturalistic scenes (the remainder of the scene that is not proximal to the target; Brockmole et al., 2006). Global context guides search effectively when it is specific and predictive, allowing the scene to be identified explicitly (Brockmole et al.). Therefore, how search is guided by naturalistic scenes is fundamentally different from search in simple target-distractor arrays based on differences in the speed of visual search, explicit knowledge, and utility of local versus global context.

In experiments using real-world scenes, the context provided by regularities in the natural scene is believed to provide an associative cue that directs attention to move to the location of the target (Chun & Jiang, 1998; Eckstein et al., 2002; Giesbrecht et al., 2013; Summerfield et al., 2006). In other words, memory for specific goal-relevant object-location associations (learned location of the lighthouse), as well as memory for the general context (the beach), feed forward to guide future behaviour (i.e., search for the lighthouse) adaptively (Aly & Turk-Browne, 2017; Võ & Wolfe, 2015). Eye-tracking results corroborate these findings by showing that contextual memory in natural scenes results in a more direct scan path to previously relevant object locations compared to novel locations (Becker & Rasmussen, 2008).

The visual features of the targets and distractors also have important implications for successful visual search. A variety of factors regulate the influence of targets and distractors on visual search, including "bottom-up" features such as visual similarity between targets and distractors (Duncan & Humphreys, 1989) and "top-down" features such as knowledge and long-term memory (Navalpakkam & Itti, 2006; Nobre & Stokes, 2019). For example, search is facilitated in "pop-out" tasks (e.g., green target amongst red distractors), whereas search is slowed when the target is more similar to distractors (e.g., orange target amongst red distractors; Treisman & Gelade, 1980). Similarly, the "extremeness" of features impacts search (e.g., faster search for a bright target amongst dark/medium distractors, and slow search for a medium target amongst dark or bright distractors; D'Zmura, 1991). Long-term memory and other "top-down" features work alongside these "bottom-up" visual features to guide visual search for specific items in scenes (Navalpakkam & Itti). For example, prior knowledge can facilitate search (e.g., search for a green shape target amongst distractors with similar shapes and different colours is faster if it is known that the target is green). Interestingly, though visual search is more difficult with less discriminability between targets and distractors, this may increase the reliance of visual search on memory, as demonstrated by a larger contextual cueing benefit for repeated scenes when targets are less discriminable from distractors (Solman & Smilek, 2012). These visual features (e.g., extremeness, discriminability, 'pop-out', etc.) interact with the spatial features of targets and distractors to simultaneously regulate search processes.

Though contextual cueing is defined by an association between a specific target location and a context, there is some flexibility to the spatial features of displays where visual search can be facilitated by contextual cueing. For example, contextual cueing benefits continue if the entire search display is spatially shifted or resized (Jiang & Wagner, 2004) or when only a subset of distractors are repeated (Olson & Chun, 2002). However, contextual

cueing benefits are eliminated if the location of the target location is swapped with a distractor location, even if the remaining distractors remain in their original locations (Makovski & Jiang, 2010; Oliva et al., 2004; Wolfe et al., 2000). Interestingly, in Higuchi et al., (2020), the locations of distractors in a contextual cueing task varied in repeated trials based on a low- or high-variability Gaussian distribution. Then, during a test phase in which visual search arrays were repeated, the distractors occurred at a novel location at the edge of the high variability distribution. Contextual cueing benefits were maintained in the high but not the low variability learning trials. Therefore, slight variability in the location of distractors has been shown to induce more generalizability in the possible configurations that will facilitate contextual cueing (Higuchi et al., 2020). Also, the benefits to search from contextual cueing increase at larger eccentricities (when objects were more spaced out from the centre or subtended a higher visual angle; Solman & Smilek, 2012). In other words, the increased cost of searching for targets that were more distant from the centre of the display meant that there was a greater advantage to guiding search based on contextual memory. This was demonstrated by a greater difference in search times between novel and repeated displays for high compared to lower degrees of eccentricity. Taken together, these results show that a range of visual and spatial factors have important consequences for contextual cueing. In addition, the role of memory in contextual cueing can vary based on different factors such as prior knowledge and cost or difficulty of searching de-novo compared to retrieving object locations based on memory. The role of memory in contextual cueing is backed by studies on the neural basis of this type of search facilitation.

The hippocampus is known for its role in explicit episodic memory (Scoville & Milner, 1957; Squire, 2004). More recent evidence has also supported its role in forms of implicit memory like contextual cueing (Chun & Phelps, 1999; Goldfarb et al., 2016). For example, patients with damage to the hippocampus and surrounding medial temporal lobe

(MTL) structures have impaired contextual cueing (Chun & Phelps; Squire & Manns, 2001). In imaging studies, MTL activity has been shown to correlate with contextual cueing even a week after initial learning (Kasper et al., 2015). It has been proposed that the reaction-time advantage in contextual cueing originates from two mechanisms: learning the repeated context and allocating attention to the associated target location. In principle, the two mechanisms may depend on different neural systems. For example, the hippocampus and MTL structures may support context learning, but a separate set of brain areas may implement the attentional shift (Giesbrecht et al., 2013).

1.2.2. Probabilistic Cueing

A parallel strand of research examines how learned habits guide attention. Whereas contextual cueing taps into unique associations between the location of a target within a given context (the lighthouse at your favourite beach) habit-based learning stresses consistent regularities across contexts (lighthouses are often on cliffs). In one type of habit learning, known as probability cueing, participants develop a habit of searching in locations that have previously contained target stimuli (Seger, 2018). Typically, in probability cueing tasks, targets (e.g., a letter or a shape) occur more frequently in one region of space (e.g., the top-left quadrant of the visual field). Over the course of many trials, participants become faster at finding the target in the high probability region (Druker & Anderson, 2010; Geng & Behrmann, 2002; Hoffmann & Kunde, 1999). This search facilitation – termed probability cueing - is driven by environmental statistics that guide attention to the likely target location (Salovich et al., 2018). Unlike contextual cueing, probabilistic learning is not context specific, therefore the distractor locations are unrelated to the location of target appearance (Druker & Anderson). Probability learning is described as habitual because it is implicit, acquired gradually, and persists for days after initial learning (Seger & Spiering, 2011), even

in absence of a reward (Jiang, Swallow, Rosenbaum, et al., 2013) The persistence of this bias differentiates probability cueing from goal-driven habits (where explicit knowledge cues attention) which are more flexible (Addleman et al., 2018), more reward-driven, and thus devalue faster (Hong & Kim, 2022; Seger, 2018). For example, if an attentional bias is learned for a region of space where targets are more likely to occur (e.g., higher chance of occurring in the top-left of the screen display), and then the target probability changes to be even across all points in space (e.g., 25% chance of occurring in any quadrant of display), the attentional bias for the top-left region is observed to persist for over a week (Jiang, Swallow, Rosenbaum, et al., 2013). Finally, probability cueing can transfer between similar tasks, indicating that the attentional bias is not necessarily situation-specific (Salovich et al., 2018). A number of factors make probabilistic location learning similar and different from other forms of habit.

The development of a habit is usually considered an associative learning of a stimulus-response relationship. Research on habits tends to focus on the 'response' side of this relationship, which emphasizes the impact of habit on motor systems (Wilson, 2014). Probability cueing is not strictly a motor habit, since moving one's eyes to a quadrant is not necessary for the learning to develop (Jiang, 2018). For example, in Jiang & Swallow, (2013), the search display was presented too quickly for a saccadic eye movement to occur (180 ms), and yet participants were still more accurate at responding to targets in the high probability region by using covert attention (Jiang & Swallow, 2013).

Evidence suggests a strong dissociation between goal-based attention and probability cueing. In support of the habitual nature of probability cueing, learning occurs even when it is counterproductive to goals (Le Pelley et al., 2015). Furthermore, goals can interfere with developing a probabilistic search habit (Jiang & Sisk, 2019). For example, valid endogenous cues (an arrow) that point to a region that has a high chance of containing the target, diminish

probabilistic cueing (Jiang, Swallow, & Rosenbaum, 2013). Therefore, the attentional habit that develops from probability cueing is unique in that it is different from both motor habits and goal-driven attention and is also markedly different from other forms of spatial learning such as contextual cueing.

Yet, as in contextual cueing, targets and distractors in probabilistic learning have a complex and intertwined relationship. Studies have manipulated the probability of both target and distractor locations, finding interdependence between the effects of target selection (attending to target locations) and distractor suppression (ignoring distractor locations). For example, some studies have found that a high probability of targets occurring in an area of space can enhance visual search for targets but may also enhance the distracting effects of distractors that occur in the high probability region (Ferrante et al., 2018; Zhang et al., 2022). This effect is graded: with every 10% increase in the probability of a target occurring, the reaction time benefits for search in the high-probability target locations compared to low-probability locations grows (Zhang et al.). Simultaneously, the distracting effects of a distractor occurring at the high-probability locations also increase. But when the difference between high and low probability locations is small (30% or less), participants do not learn the contingencies and gain no performance benefit from the high probability location (Zhang et al.). Other work has shown that if distractors occur in a specific location with high probability, this attenuates their ability to distract from the target (Failing et al., 2019; Ferrante et al., 2018; Wang et al., 2019). Alternatively, if distractors appear in different locations, research has suggested that their ability to interfere with visual search for the target is heightened (Ferrante et al., 2018; Kelley & Yantis, 2009).

Despite results showing interdependence between target selection and distractor suppression, research has supported that these forms of attentional guidance may act differently during probability cueing tasks and may even have separate neural correlates.

Namely, a range of findings contradict the assertion that target selection and distractor suppression act on the same cognitive and neural mechanisms (Couperus & Mangun, 2010; Hickey et al., 2009). For example, studies have found that manipulating the probability of target locations may not impact the attentional capture effects of salient distractors (Failing et al., 2019). Also, there may be no reaction-time cost to search when targets occur at frequent distractor locations compared to rare distractor locations (Zhang et al., 2019). Another study found that probabilistic learning of target location is a long-lasting attentional bias (persisting after a 24-hr delay), whereas suppression of distractor location is relatively short-lived (disappearing after a 24-hr delay). Di Caro & della Libera (2021) argue that, whereas target selection history (probabilistic cueing) may depend on lasting changes to representations of visual space, distractor suppression history effects depend on functional plasticity, which is transient and constantly updated. FMRI evidence has also supported that cueing distractor locations acts on different mechanisms than cueing target locations (Reeder et al., 2017, 2018). Overall, under different circumstances, target selection and distractor suppression can interact or act independently to facilitate probabilistic learning, yet there is no definitive consensus on whether attentional guidance based on targets or distractor probability represent two outcomes of a single mechanism or are independent (Chelazzi et al., 2019). Further, there is a need for additional work that examines whether these target and distractor guidance mechanisms act similarly or differently in simplistic versus naturalistic settings.

Most work on probabilistic cueing, including the studies reviewed up until this point, has been based on tasks using simple stimulus arrays. However, some recent work has examined whether probabilistic cueing can develop in naturalistic settings (Addleman et al., 2019; Jiang, Swallow, et al., 2014). For example, in Jiang et al., (2014) participants became faster at finding a target in a high-probability quadrant during a search task that was based on a single naturalistic scene. Interestingly, part-way through the experiment, the monitor was

rotated 90 degrees, and the target probability was made consistent throughout the scene. Despite the environment rotating, the learned attentional bias persisted for the viewer-centred quadrant participants had learned (e.g., learned preference for the top-left of the screen persisted despite scene rotation). Therefore, probabilistic learning may prioritize attentional biases relative to the viewer's perspective rather than relative to the environment (e.g., the part of the scene that was the original high probability quadrant). Interestingly, some research has also measured probabilistic learning in real and virtual 3D environments (Jiang, Won, et al., 2014; Smith et al., 2010). For example, in Sisk et al., (2021), participants searched in a large virtual 3D environment devoid of complex visual cues that could act as landmarks. Once again, participants showed evidence of probabilistic learning, but only when the high probability region was located in their initial field of view when they began searching. The authors argued that probability learning may be disrupted for information outside of the initial field of view, particularly in environments where there is an absence of rich visual cues (Sisk et al.). Given that search in computer-based paradigms that utilize 2D naturalistic scenes does not require head movement, these results may support that probabilistic learning in 3D environments may not differ markedly from search in 2D environments.

Neuroscience research links probabilistic cueing to the striatum. Forming response-outcome associations relies on the striatal network (Delgado et al., 2005; Frank, 2005; Freedberg et al., 2020). For example, striatal activity has been related to learning to direct attention to visual features or regions of space during probability cueing (Anderson, 2016; Goldfarb et al., 2016; Seger, 2018). In contrast to the MTL and hippocampus, responsible for rapid learning, the striatum partakes in gradual learning across many trials (Hiebert et al., 2014; Moody et al., 2004). Learned habits have been shown to interfere with or supersede more explicit memories (Packard & McGaugh, 1996). Specifically, an initial hippocampal-dependent contextual spatial strategy (Spaak & Lange, 2020) may transition to a striatal-

dependent response strategy once attentional habits have formed (Ferbinteanu, 2016). Under different circumstances, the hippocampus and striatum may work cooperatively (Duncan et al., 2018; Sadeh et al., 2011) or competitively (Foerde & Shohamy et al., 2011; Voss et al., 2020) to facilitate learning and memory. To date, most studies that have measured the relation between striatal and hippocampal memory systems have focused on learning associations (Dickerson et al., 2011), rather than utilising the learning for subsequent behaviour.

1.2.3. Scene Semantics

Scene semantics (i.e., what objects naturally belong where within a scene) have important implications for naturalistic search processes (Draschkow et al., 2014; Konkle et al., 2010; Yarbus, 1967). For example, the differences in how naturalistic scenes guide visual search compared to simple stimulus arrays have to do with the ways in which scene semantics impact the search process (Brockmole & Henderson, 2006a). Generally, any collection of objects or shapes can be considered a scene. However, real-world scenes differ from simple scenes in that they contain a large variety of meaningfully or predictably arranged items and can be divided into foreground and background elements (Biederman et al., 1982; Brockmole et al., 2006b; Draschkow et al., 2014). In the context of this thesis, one further distinction is important: a scene is often a specific viewpoint of a real-world environment (Malcolm et al., 2016). For example, a scene could be a photograph of a professional football pitch. Within this imagined scene, as might be predicted, there is a football in the foreground on green grass, with white lines, goal posts, and stands in the background. A scene like this contains a wealth of information that can be used to guide search effectively, such as the scene's basic category – football pitch (Greene & Oliva, 2009), its spatial layout – goal posts on the ends, stands surrounding the pitch (Oliva & Torralba,

2001), and the distribution of visual features like colour (grass is green, posts are white) and orientation (flat and horizontal; Chong & Treisman, 2003). This information can be combined to reduce the difficulty of visual search in scenes. For example, possible target locations can be reduced by using our knowledge of the typical locations where certain objects occur (scene semantics) to guide search (Ehinger et al., 2009; Torralba et al., 2006; Võ & Wolfe, 2012) and this ability may persist into old age (Ramzaoui et al., 2021). For example, if a goalpost is your search target, you would search on the ends of the pitch, not in the sky. However, visual search can also be guided by specific memories, for example, via contextual cueing (Brockmole & Henderson, 2006a). Therefore, during repeated search (search in scenes that repeat from block to block) there is competition between a de-novo search through plausible target locations vs. a search through memory for the remembered location of targets (Võ & Wolfe, 2012).

During repeated search tasks, under what circumstances de-novo search is preferred compared to memory-guided search is an ongoing topic of debate. Scene semantics have the potential to guide search so effectively that the usefulness of episodic memory is minimized (Võ & Wolfe, 2013). For example, search guidance by naturalistic scene semantics can act extremely quickly (50 – 75 ms; Võ & Henderson, 2011), potentially resulting in the object being found before memory for the context can be used to facilitate search (Võ & Wolfe, 2015). However, some results demonstrate that objects that occur in locations that follow scene semantics (plausible locations), not only benefit search (Bravo & Farid, 2009; Castelhano & Heaven, 2010; Henderson & Hollingworth, 1999; Maxfield & Zelinsky, 2013; Spotorno et al., 2015) but support stronger memory representations compared to objects that occur without the involvement of semantic guidance (Atienza et al., 2011; Buuren et al., 2014; Draschkow et al., 2014). These findings appear to conflict with other research (Greve et al., 2017; Hunt & Worthen, 2006; Tulving & Kroll, 1995; Von Restorff, 1933) which

suggest that events that are incongruent with our expectations are remembered better. For example, decreasing the availability of semantic information by placing objects in unexpected locations (e.g., toilet hanging on the wall) has been found to increase the use of episodic memory in guiding search in 3D images based on a larger reaction time benefit to repeated compared to novel display trials (Võ & Wolfe, 2013). Therefore, scene semantics have important implications for visual search, even if the functions linking semantic congruency with memory retrieval have not been fully resolved and are likely to be complex.

Another important factor that impacts attentional selection in scenes is the prevalence of perceptual versus semantic factors. Perceptual salience is composed of the "bottom-up" factors which dictate how much each scene location differs from its surroundings (Desimone & Duncan, 1996; Ramzaoui et al., 2021; Vecera & Behrmann, 2001). Whereas semantic factors measure how well an object fits into its surrounding context (Draschkow et al., 2014; Konkle et al., 2010; Yarbus, 1967). Some have argued that perceptual salience predominates over semantics, asserting that attentional selection in scenes proceeds first from the most perceptually salient point (Itti & Koch, 2000; Parkhurst et al., 2002). For example, some research has shown that when an object is highly salient, the effects of semantic consistency are less prominent (Coco et al., 2014; Spotorno & Faure, 2011). Yet, others have asserted that semantic factors predominate or even override perceptual salience. For example, demonstrating that semantically relevant objects may be prioritized even when they are lower in perceptual salience than semantically unimportant objects (Chen & Zelinsky, 2006; Tatler et al., 2011; Underwood et al., 2008). Further, there seem to be contradictions between literature on whether strong agreement with expectations (semantically consistent) about object occurrence (Coco et al., 2014; O'Regan et al., 2000; Spotorno & Faure) or strong disagreement with expectations (semantic inconsistent) results in greater object prioritization for selection (Bonitz & Gordon, 2008; Cornelissen & Võ, 2017; Stirk & Underwood, 2007;

Underwood et al., 2007). A recent study by Spotorno and colleagues manipulated semantic informativeness, consistency with expectations, and perceptual salience of objects in scenes (2017). They demonstrated that semantically inconsistent objects are not prioritized over expected and informative objects (i.e., objects which help to diagnose the gist of the scene). Further, not only are unexpected objects looked at later, but when they are perceptually salient, they slow down how quickly the expected and informative objects are selected. Finally, interestingly, perceptual salience affected the attentional selection of consistent objects (regardless of informativeness) but not of inconsistent objects (Spotorno & Tatler, 2017).

However, in cases where objects are either semantically consistent or inconsistent, goal-relevant cues can facilitate visual search. For example, in their 2015 study, Spotorno et al. created a visual search task with semantically consistent and inconsistent scenarios. In the consistent scenario, all objects occurred in plausible locations. In the inconsistent (switched) scenarios, the target object occurred in an implausible location while the distractor occurred in the location where a participant may expect to find the target. In both scenarios, the target object template was cued prior to search by either a pictorial cue (picture of the target object) or a word cue (name of target object). They found that, though placing an object in an implausible location increased the difficulty of searching for it, semantically inconsistent targets were still found with higher probability than inconsistent distractors. Therefore, they assert that prior information about the target (i.e., a pictorial, precise cue) gives stronger guidance to attention than predictions about where to find the target. In fact, the only scenario in which the inconsistent distractor was preferentially selected was when it was the largest object in the region, favouring its quick selection on a perceptual basis (Spotorno et al., 2015). Therefore, though there are significant differences in how visual searched occurs in

semantically consistent and inconsistent scenes, goal-relevant cues may guide search effectively in both cases.

In the studies within this thesis, though naturalistic images were used (i.e., photographs of real-world settings) as backgrounds, objects were superimposed in semantically inconsistent locations and object scene pairs were incongruent. Therefore, throughout the different visual search tasks, it is likely that objects were found more slowly than if semantically consistency was maintained due to ineffective contextual guidance disrupting search (Spotorno et al., 2015). Without contextual guidance, selection of inconsistent objects would likely be determined by a combination of bottom-up and top-down features, or by chance (Gareze & Findlay, 2007; Malcolm & Henderson, 2010; Spotorno et al.). This design choice was purposeful, as I wanted participants' learning to begin from the moment they began the study. Otherwise, participants would be using their understanding of 'what usually goes where' (scene semantics) while simultaneously learning 'what goes where in this scene context' (associative learning; Draschkow et a., 2014). If both factors were at play, it would have been difficult to parse the contribution of associative learning versus semantic guidance to search performance. Also, without contextual guidance, participants' reliance on memory to facilitate search was heightened (Võ & Wolfe, 2013), aligning with my goal of studying similarities and differences between how different types of memories are formed and utilized. Other design choices were made to increase the difficulty of visual search, further heightening participants' reliance on memory (Võ & Wolfe, 2012). For example, keeping objects small (all Chapters), well-immersed in the scene by reducing opacity (Chapter 3), and making objects and scene greyscale to reduce the "pop-out" of objects against their background (Chapter 4). Further, to further reduce bottom-up guidance, within each Chapter all objects were equated in terms of size, and no objects with extremely bright or recognisable features were used.

Though the arrangements of scenes and objects used in my thesis are not naturalistic to the degree of some other work (e.g., Draschkow et al., 2014; Spotorno et al., 2015), my task designs are improvements on the simple paradigms where much of the research on memory and attention processes are based. Much of the longstanding understanding of how different types of spatial predictability guide search processes and engage different neural systems comes from animal and human studies in simplistic settings where scene semantics do not apply to the same extent (Võ & Wolfe., 2015). Even at the most basic level, objects do not have a semantically consistent location in simplistic scenes, e.g., there is no equivalent for the goalposts belonging on the ends of the pitch for arrays of random letters or shapes. Therefore, the extent to which the understanding of visual search that is based in simplistic settings will continue to be relevant to behaviour in naturalistic settings is unclear (Võ & Wolfe). In the case of my experiments, I have chosen a middle ground where, though semantic congruency is compromised by pairing objects with scenes that are incongruent, participants still must search through real scenes for real objects. This design choice was made to increase participants' reliance on memory during learning, allowing me to more adequately address my research questions about memory formation and utilization. Therefore, though the tasks in my thesis are closer to real-world search than designs utilizing simple displays, they are not perfect analogies for naturalistic search, limiting their ecological validity.

1.2.4. Intentionality and Explicitness of Learning

Intentionality and explicitness are two closely related dimensions that have important implications for the design of the tasks in my thesis. It might be predicted that intentional learning, i.e. viewing a scene with the purpose of finding and remembering the objects within, would improve performance compared to incidental learning, i.e., simply searching

for the objects within the scene (Vo & Wolfe, 2015). Indeed, some evidence supports that memory for objects that are learned intentionally is better than for incidentally learned objects (Tatler & Tatler, 2013). In contrast, Draschkow et al., (2014), directly compared incidental memorization of search targets in naturalistic scenes with intentional memorization of the same scenes. They found that memory was actually better for searched objects compared to objects that participants had intentionally tried to memorize. This study is significant as its overall design is similar to the tasks in my thesis in important ways. Specifically, for the objects that were searched for, participants were not explicitly asked to memorize objects and did not know there would be a subsequent memory test. Similarly, all of the learning tasks in my thesis are incidental in that participants are not given explicit instructions to learn the objects or scenes for any subsequent purpose, instead, they are simply told to complete the search task by finding the embedded object in each scene and that another task will follow. However, it is important to note that in Draschkow et al. memory benefits for incidental compared with explicit learning only occurred in semantically congruent scenes, i.e., these benefits were lost when objects were presented against uniform, non-scene backgrounds. Therefore, in my study, where naturalistic scenes are used as backgrounds but the objects within are semantically incongruent, these same benefits from incidental memorization may not occur, or not to the same extent.

Incidental and implicit learning tasks are used throughout my thesis for a number of reasons. Throughout my thesis, I kept participants blinded to the conditions underlying the different learning tasks as well as to the fact that they would be subsequently tested on their learning. This is because if participants were initially, explicitly instructed to learn the objects in the different scenes for the purpose of performing a subsequent memory test, it is more likely that they would have attempted to develop strategies to optimize their performance. In fact, past research has found that using ‘active’ strategies (actively attempting to find the

search target) as opposed to ‘passive’ strategies (intuitive search) inhibits the contextual cueing effect (Lleras & Von Mühlenen, 2004). In particular, when search is more difficult, passive strategies appear to be more effective than active strategies (Smilek et al., 2006). This could be because under more active strategies that result from explicit instruction, participants may try to actively control and direct their attention, potentially blocking guidance from implicitly learned information such as context. Additionally, if using a more active strategy, participants may have attempted to learn if there were patterns underlying the object locations in the different scenes. If they became explicitly aware of the rules that dictated object-location occurrence (e.g., in the probabilistic condition that objects in ocean scenes occur on the right side of the screen), this would potentially negate the need for further learning. Further, during the memory retrieval segment they could rely on the heuristic to recall the target location rather than using their memory. I was more interested in researching how we implicitly form and flexibly use associative memories of different types for retrieval and attentional orienting. Because, though we have a relatively strong understanding of how intentionally attending to or focusing on facts/events enhances the likelihood of later memory (Aly & Turk-Browne, 2016; Tarder-Stoll et al., 2019), it is less clear how attention modulates and enhances implicit memories (Chun & Turk-Browne, 2007). Of course, despite no explicit instructions, it is possible that participants could become explicitly aware of the repeating locations of objects in scenes (Brockmole & Henderson, 2006b). In fact, to a certain extent, this is an unavoidable consequence of having participants complete repeated search for objects in unique and distinguishable naturalistic scenes. Yet, participants becoming aware of rules naturally is still a learning process, which would be negated by explicitly telling them these rules.

Another related design choice I made was to assess participants with distinct learning, explicit retrieval, and attentional-orienting tasks. I have reviewed how memories are formed

through the process of visual search, and how these memories can guide search in subsequent repeating displays (Section 1.2). Many of the studies described in this Section take reductions in reaction time during visual search as a measure of facilitation of attentional guidance by memory, yet they never test memory or attentional orienting explicitly (Draschkow et al., 2014; Vo & Wolfe, 2015). An explicit test of memory would assess participants on their ability to retrieve the environments, object identities, or object locations they learned, whereas an attentional orienting test would assess participants' ability to orient to targets that occur briefly in learned or novel locations. In both cases, explicit recall and attentional orienting tests are distinctly not repeats of the learning task – participants are required to use their learning in a novel way. This difference between implicit and explicit testing has important implications for our understanding of learning and memory guidance in naturalistic scenes. For example, the finding that semantic consistency facilitates memory by Draschkow et al. (2014) seems to conflict with the finding by Võ & Wolfe (2013) that memory was facilitated when semantic expectations were broken. However, in Draschkow et al., memory was measured explicitly by having participants draw the learned scenes and the objects within, whereas in Võ & Wolfe, participants' use of memory was demonstrated via reaction time benefits during the visual search task. Therefore, there may be important differences in the way that memory is used during visual search compared to during explicit retrieval and even in memory-guided attentional orienting (Hutchinson & Turk-Browne, 2012). Determining whether these differences exist is crucial, as in daily life we do not simply repeat our learning, we use our memories in novel situations where different types of learning may be more or less useful to the tasks at hand (Nobre & Stokes, 2019; Vogel & Schwabe, 2016).

1.3. Uses of Memory for Explicit Retrieval and Attentional Orienting

A range of studies in recent years have employed designs with two phases: a learning phase and a subsequent test phase to measure the utility of the learned associations. Typically, these studies have focused on the consequences of associative learning for either memory retrieval (Foerde & Shohamy, 2011) or memory-guided attentional orienting (Summerfield et al., 2006; Stokes et al., 2012). However, the impact of spatial expectations regarding target and distractor locations (Section 1.3.2), the influences of memory set size (Section 1.3.3.), and the relative consequences of different types of learned associations (e.g., contextual or probabilistic learning, Section 1.3.4.) for attentional orienting compared to memory retrieval remain unclear (Goldfarb et al., 2016; Hutchinson & Turk-Browne, 2012; Nobre & Mesulam, 2014). Over the three empirical chapters of my thesis, I aimed to address these gaps in our understanding with targeted studies. Investigating this topic has important implications for ongoing debates and theories regarding the extent to which attentional orienting (external attention) and memory retrieval (internal attention) are similar or different cognitively and neurally (Cabeza et al., 2008, 2011; Chun et al., 2011; Hutchinson et al., 2009b). Therefore, researching the similarities and differences between these two forms of behaviour will contribute to our understanding of the relationship between the external visual world and the internal world where we store representations of what we see (Tarder-Stoll et al., 2020). It will also help us to explore the possibility that the process of learning may not only differ markedly from retrieval or attentional orienting but that the way in which we learn may have important consequences for use in these subsequent behaviours (Nobre & Stokes, 2019).

1.3.1. Relating Associative Learning to External and Internal Attention

Recent research has expanded on Chun et al.'s taxonomy dividing attention into external and internal components (2011). For example, proposals have been made that memory encoding requires externally orienting attention to the visual world, whereas memory retrieval requires internally oriented attention to prioritize and select information from working or long-term memory (Long et al., 2018; Nobre & Stokes, 2019; Poskanzer & Aly, 2022). During encoding, attentional selection (e.g., looking at the lighthouse) has been shown to be important for subsequent successful episodic memory retrieval (Aly & Turk-Browne, 2016; Tarder-Stroll et al., 2019). Then, during memory retrieval, selective attention may promote retrieval of targets while overcoming competition from distractors that are stored in memory (e.g., when shown the beach, remembering the lighthouse is on the cliff and not in the bay as in another beach scene; Chun et al., 2010; Chun & Johnson, 2011). Therefore, attentional orienting is important both during the initial learning phase or encoding, as well as during the retrieval phase. Similarly, memory guides attention during learning (e.g., remembering the lighthouse is found on the cliff and attending accordingly) as I have reviewed with the contextual cueing literature (Brockmole & Henderson, 2006a), but memory can also guide attention during subsequent behaviours that differ from the initial learning (e.g., flashing targets in learned or novel locations and having participants respond if the target was present or absent, see Section 1.3.4.; Summerfield et al., 2006). Therefore, internal attention (memory retrieval) has important consequences for external attention (perception) and vice versa. In this Section (1.3.), I will further investigate the similarities and differences between these mutually beneficial types of behaviour and identify gaps in our understanding of them.

In an fMRI study, Aly & Turk-Browne (2016) elegantly showed how attentional selection during learning is crucial for successful retrieval. They had participants view unique

images of rooms with paintings during an incidental encoding task. In art blocks, participants looked for two paintings in a row by the same artist, whereas in room blocks participants looked for two rooms in a row with the same layout. Because each image contained a painting and a specific layout, top-down attention was needed to select relevant information to the current block and ignore irrelevant information. In this task, they measured the extent to which the hippocampus was in the correct attentional state by calculating the pattern correlation with the template (pre-calculated hippocampal activity pattern) that was relevant for the current block (e.g., art block) versus the irrelevant block (e.g., room block). Finally, participants completed a recognition memory ('old' or 'new') test for the paintings in the art block and the layouts in the room block. They found that the hippocampus had stronger representations for task-relevant attentional states during the encoding of items that were subsequently remembered compared to forgotten (Aly & Turk-Browne, 2016). This finding is in line with the biased competition model, which argues that information that is selected for attention is more robustly represented in sensory systems than unselected information (Desimone, 1998; Desimone & Duncan, 1995). Selected information is then more likely to be sent to the hippocampus for further processing as an item to be encoded or as a retrieval cue for existing memories (Aly & Turk-Browne, 2017). Therefore, selective attention to targets during encoding or visual search can signal the importance of encoding the target such that subsequent retrieval is facilitated.

The consequences of selective attention on memory have also been examined during the retrieval phase. For example, in the study by Wimber et al (2015), participants learned a series of word-image associations. Each word was separately paired with two images (e.g., the word sand might be paired with a hat and then later with an image of Obama). Then, during a retrieval phase in fMRI, participants were shown the cue word and had to retrieve whether the first image that had been associated with the word was a face, object, or scene.

Each target word was shown four times, requiring four repetitions of retrieving the associated image from memory. Interestingly, as the repetitions increased, the percentage of intrusions (retrieving a face even though the word had been associated with an object) decreased. This finding suggests that the competing memories may have been weakened over time due to the attentional selection of the target image. Importantly, a recognition test after the fMRI session revealed that participants had lower recognition accuracy for competing images in memory (Obama) compared to baseline images that were not shown during the retrieval phase (e.g., a pair of boots). This study, therefore, provides evidence that attending to and retrieving one item among competitors facilitates memory for the attended item (Wimber et al., 2015). In support of this assertion, fMRI activity linked to the competing memory in the ventral visual cortex decreased as the target memory was retrieved more frequently. However, these results should be taken with caution as follow-ups with similar designs failed to find a difference between competing memories and baseline memories (Potter et al., 2018).

Despite difficulties with replication, the study by Wimber et al. (2015) effectively illustrates the well-established concept of retrieval-induced forgetting, where repeated retrieval of a target memory reduces competition for retrieval against alternatives (Bjork, 1988; Levy & Anderson, 2002; Tarder-Stoll et al., 2020). In other words, at the retrieval phase, selective attention to targets in memory facilitates recollection compared to competing memories and may even attenuate memory for the competing distractors. This literature is important as it demonstrates that the way in which targets and distractors are learned has implications for their uses in subsequent behaviour, e.g., associating a target and a distractor with the same image during learning had important consequences for memory for the target as well as memory for the distractor (Wimber et al., 2015). One goal of this thesis is to determine if these consequences may differ for memory retrieval compared to memory-

guided attentional orienting. For example, one factor which may differ in its utility for memory retrieval compared to attentional orienting is learned spatial expectation.

1.3.2. Impact of Spatial Expectations on Subsequent Behaviour

In their review, Le Pelley et al., outline the importance of predictiveness during associative learning on subsequent attentional guidance (2016). A predictive cue is a stimulus that is a consistent and reliable indicator of events that will follow (e.g., green light means the cars will go). Whereas a nonpredictive cue is one that provides no information or unreliable information on the events that will follow (e.g., whether or not a car will appear when you round an upcoming blind turn). They break down the relationship between these cues and attention as the predictiveness principle (attention is preferentially allocated to cues when their outcome is predicted; Mackintosh, 1975) and the uncertainty principle (attention is preferentially allocated to cues when their outcomes are surprising; Pearce & Hall, 1980). For example, responses to a target are faster when it appears in a location cued by a predictive stimulus compared to a location cued by a nonpredictive stimulus (Le Pelley et al., 2013). These findings suggest that predictive stimuli can capture participants' spatial attention and resultingly speed response to events that occur in the predictive location, even when not required or adaptive to task completion. Similarly, spatial predictable targets and distractors have well-established impact benefits for visual search (Ferrante et al., 2018), and these learned consistencies can facilitate performance on subsequent attentional orienting (Summerfield et al., 2006, 2012). Alternatively, compared to animal studies, there is much less support in human research for the uncertainty principle (Pearce & Mackintosh, 2010; Le Pelley et al., 2016). However, Le Pelley et al., argue that if participants were more strongly encouraged and motivated to explore all potential sources of information, then evidence for the uncertainty principle in humans could be stronger (2016). Relatedly, Beesley et al.

(2015), have proposed that whereas the predictiveness principle can be described as attentional exploitation (cognitive resources focus on exploiting the most predictive source of information), the uncertainty principle is characterized more by attentional exploration (cognitive resources are used to explore uncertain but potentially useful sources of information that may help predict future events).

In my thesis, I investigate the consequences of attentional exploitation versus exploration for attentional orienting and memory retrieval. For example, though object location memory is facilitated by attentional exploitation of targets which occur in predictable spatial locations during repeated search (Stokes et al., 2012), would memory for the scenes also benefit from this kind of learning? It might instead be predicted that finding targets which occur in unpredictable or variable locations requires greater attentional exploration, causing more of the background scene to be attentionally captured. Therefore, does greater attentional exploration facilitate scene memory? Alternatively, it is well established that targets which occur in predictable spatial locations are exploited during visual search (Becker & Rasmussen, 2008; Chun & Jiang, 1998; Geng & Behrmann, 2002) and attentional orienting (Salvato et al., 2016; Stokes et al., 2012; Summerfield et al, 2006). Therefore, will a different pattern occur for internal (scene memory) versus external (visual search and attentional orienting) attention, where external attention is facilitated by attentional exploitation rather than exploration? The role of predictability in attentional capture by distractors is even less clear. Although the retrieval-induced forgetting literature suggests that memory for distractors is suppressed upon retrieval of targets, memory for distractors is still significantly present (i.e., above chance levels; see Wimber et al., 2015). Other work has also shown that distractors are reliably encoded during learning (Castelhano & Henderson, 2006; Draschkow & Võ, 2016). But, if predictable distractors are discounted more easily, and unpredictable distractors are more distracting (Ferrante et al., 2018), what are the consequences of this

distractibility on subsequent attentional orienting and memory retrieval? We might predict, for instance, that if unpredictable distractors capture attention more easily, they might be remembered better. In this sense, attentional exploration (attending to the uncertain distractor), could benefit memory for distractors. Addressing these questions is the purpose of the fourth chapter of my thesis where I investigate the behavioural implications of spatial predictability in memory. Finally, in the literature that I reviewed in this section, the impact of competition between two associations in memory (i.e., target and distractor) was measured (Wimber et al.,). However, further increasing the number of competing memories may have important implications for memory encoding and subsequent utility.

1.3.3. Impact of Memory Set Size on Subsequent Behaviour

In the first section of this introduction, I discussed Desimone and Duncan's biased competition model where different sources of external information (e.g., top-down and bottom-up factors) can compete for attentional selection (1996). Just as increasing the amount of external stimulus can make attentional selection of relevant information difficult (Chun & Jiang, 1998; Wolfe, 1998), increasing the number of competing memories (set size) during a learning task has been shown to have consequences on attentional selection during retrieval. For example, in a study by Sohn et al. (2003), participants learned person-location associations in the form of sentences (i.e., the fireman is at the station). The number of locations associated with each person was either one, two, or three, and each location was also associated with one, two, or three people. In a subsequent recognition test, participants were presented with one of the original person-location pairs (e.g., fireman-station), or a re-paired version that was not studied during the learning phase (e.g., fireman-bank), and had to indicate if the pair was studied or new. Recognition performance was less accurate and slower for item pairs that had a larger number of associations. Also, during the recognition

test, bilateral dorsolateral and ventrolateral prefrontal cortex activity was higher for associations with a high vs. a low number of associations (Sohn et al., 2003). This activity pattern may reflect the role of the prefrontal cortex in controlling the attentional selection of to-be-retrieved memories in the face of competition (Tarder-Stoll et al., 2020). Finally, this evidence showing reduced memory retrieval performance with a higher degree of competition (higher set size) ties into ongoing discussions regarding the ways in which LTM is retrieved into working memory.

As the set size of objects associated with a single setting or scene increases, there is more competition between the items to be remembered, interfering with the process of retrieval (Jeneson et al., 2011; Sprague et al., 2014). Interference is the primary obstacle to successful memory retrieval – it occurs due to the overlap between associative memories (Anderson, 2003; Kuhl & Wagner, 2009). The majority of research showing that increases in the set size of objects increase interference with retrieval has been conducted in visual working memory (WM) paradigms. For example, in a study by Jeneson et al., (2011), participants were shown an array with differing numbers of coloured squares (1, 2, 3, 4, or 6) and, after a delay (1, 3, 4, or 8 seconds), participants saw another array. When this array appeared, a square was cued and participants had to determine if the colour in the cued square matched the colour in the original array. Interestingly, controls performed similarly to patients with MTL damage until the number of items to be maintained exceeded 3 at a delay of 3 s or longer. Jeneson et al. argue that, once the number of items and the delay were increased, patients' performance was impaired because hippocampal-dependent LTM mechanisms were necessary to aid WM for successful retrieval. Therefore, they argue that at higher set sizes and longer delays, WM relies on LTM mechanisms for successful retrieval. Relatedly, others have argued that LTM can guide attention via retrieval into working memory (Atkinson & Shiffrin, 1968; Rosen et al., 2014).

Recent proposals have been made that if visual LTM is retrieved into working memory, it must abide by the same capacity limits as visual working memory (3-4 objects in memory; Fukuda & Vogel, 2019). Limited research has supported this account, showing that increasing set size beyond 3-4 objects in memory impairs LTM retrieval (Fukuda & Vogel, 2017). However, other results have found a "massive" capacity for objects (over 100) stored in LTM (Brady et al., 2008; Potter & Levy, 1969). In Chapter 2 of my thesis, I investigate these differing accounts to determine whether retrieval of individual object-scene associations from LTM must act via WM (and is therefore held to its set size limits) or may operate directly via LTM (in which case it may not be impacted by increasing set size). This investigation also sheds light on whether memory retrieval (internal attention) in this case acts similarly to attentional orienting (external attention). For example, if internal attention during memory retrieval is analogous to external attention during perception (Chun et al., 2011), retrieving a memory for a single object from a scene that was associated with multiple objects might be similar to searching for a target object amongst a set of distractors. If in fact these two operations act similarly, then an increase in set size would lead to decreased memory retrieval performance, just as attentional selection is slower as the number of distractor objects increases (Chun & Jiang, 1998; Sisk et al., 2019; Wolfe., 1998). Alternatively, as in other findings (Hutchinson et al., 2009), if these operations are dissociable then increased set size will not lead to worse memory retrieval. Therefore, in Chapter 2, I aim to contribute new evidence to research suggesting that there are both similarities and differences between memory retrieval and perception (Tarder-Stoll, 2020).

1.3.4. Uses of Contextual and Probabilistic Learning for Subsequent Behaviour

In the visual search section (1.2.1.), I reviewed how contextual associations can provide expectations that guide perception during learning. In turn, context can also modulate

subsequent behaviour: memory and attentional orienting can be improved when the encoded context is reinstated at retrieval (Bar, 2004; Salvato, Patai, & Nobre, 2016). A range of experiments in recent years investigated the implications of contextual associations stored in long-term memory on subsequent behaviour. In these studies, participants begin by completing a learning task that is akin to contextual cueing paradigms: they search for objects occurring in repeating locations of specific naturalistic scenes (Summerfield et al. 2006). Then, participants are tested in an attentional orienting task where they must detect the presence of targets in learned or novel locations. Behaviourally, participants show higher perceptual sensitivity and faster reaction time to targets that occur in learned compared to novel locations (Doallo et al., 2013; Patai et al., 2012; Summerfield et al., 2006). Further, excitability is enhanced in visual cortex in anticipation of the appearance of orienting targets in learned locations (Summerfield et al., 2011; Stokes et al., 2012). Activations in the hippocampus suggest its involvement in LTM-based attentional orienting (Stokes et al.; Summerfield 2006). These results suggest a bidirectional relationship between attention and contextual learning, whereby attention influences the learning of contextual associations, and the learning of these regularities influences how attention is deployed in the future (Long et al., 2018). Therefore, it is possible that the neural mechanisms associated with externally cued attention are also used for biasing perception based on past experiences stored in LTM, with the hippocampus and other areas involved in spatial contextual memories providing the link between systems (Nobre & Mesulam, 2014). However, there is a lack of work on whether the mechanisms involved in habit-based memories can also support LTM-guided attention.

As I have reviewed (Section 1.2.2.), probability cueing is an attentional habit that facilitates learning during visual search, with behavioural benefits linked to striatal activity (Goldfarb et al., 2016; Jiang, 2018; Seger, 2018). However, the implications of probabilistic

location learning for subsequent retrieval and memory-guided attentional orienting are unknown. For example, though participants may implicitly learn that targets are more likely to appear in one quadrant of the screen (Jiang et al., 2013; Jiang et al., 2014; Jiang, 2018), can this learning facilitate performance in attentional-orienting tasks (e.g. responding to targets that flash in predictive versus non-predictive quadrant) or during memory recall (e.g., recalling which quadrant the target appeared in when shown the scene)? Much of our understanding of habit-based attention is based on visual tasks in which participants search for targets that are more probable at certain locations, without needing to use this learning in novel circumstances. Thus, probability learning, attentional focusing, target selection, and distractor inhibition may all be playing a role. I am aware of only one study that has measured the implications of probabilistic location learning (search for a target in an array of letters) for behaviour in a separate, related task (search for a target in a naturalistic scene; Salovich et al., 2018). In their task, participants began by searching in a simplistic array where targets were more likely to appear in one quadrant. After probability cueing was established, participants completed a scene search task. In this task, they searched for a target in a natural scene, but the target was equally likely to appear in any quadrant of the screen. Despite the equal distribution of targets, participants were faster at finding targets in the previous high-probability quadrant, demonstrating maintenance of the attentional habit despite the context shifting. Importantly, in this task, the authors measured the transfer of the same learned behaviour (probability cueing) to a novel context, but not the application of this learning to a different behaviour such as explicit recall or attentional orienting. Therefore, there is a significant gap in research examining the consequences of probabilistic learning on subsequent behaviour.

There is also a paucity of work that simultaneously measures different types of learning and their relative utility for subsequent behavioural tests (Hutchinson & Turk-

Brown, 2012). One study has measured the relative benefits of probabilistic and contextual associations to visual search using simple stimulus displays, demonstrating that both forms of learning similarly facilitated search compared to a baseline condition (Goldfarb et al., 2016). Interestingly, the attentional benefit was carried by dissociable neural systems. Striatal activity correlated with benefits in probability cueing whereas hippocampal activity correlated with benefits in contextual cueing. However, again, the implications of the two types of learning were not tested on separate measures of subsequent behavioural utility. Another study has investigated differences between striatal and hippocampal-dependent retrieval. In a study by Shohamy and Wagner (2008), participants learned face-scene associations that included partial overlap between associative pairs, allowing for integration across the shared features during encoding. Then, a test phase measured participants' ability to retrieve the original associative pairs and to generalize their learning to novel contexts. The striatum was active during the retrieval of inflexible stimulus-response associations during retrieval. Instead, the hippocampus was active during flexible generalization to novel contexts for retrieval (Shohamy & Wagner). Notably, this task only measured the implications of a single type of learning on subsequent behaviour. Therefore, although there is research on the acquisition of learning in different memory systems (Goldfarb et al.) and the use of different systems during retrieval (Shohamy & Wagner), work that links these two inter-related behaviours in a single paradigm is lacking.

In one recent study, different types of learning were tested in memory-guided attention and memory retrieval tasks (Rosen et al., 2018). First, participants completed separate learning tasks that were specific to the experimental conditions of the study (LTM-guided attention condition, a stimulus-guided attention condition, and a retrieval condition). In the LTM-guided attention training they learned to anticipate objects at specific locations based on a cued word, in the LTM retrieval training they learned word-category pairings, and

in the stimulus-guided attention training they covertly detected objects and determined if they were members of the cued category. Then, they completed a task during fMRI scanning where they were tested on each type of learning in separate blocks. In the test (a target detection task), they were cued with a category word and then were asked to detect the presence/absence of an associated object in a briefly presented probe array of objects. Depending on the block, they would be cued by an arrow pointing to an object location and would have to say if the object was a member of the cued category (stimulus-guided attention), use their memory to retrieve the category associated with the cued word and report if the centrally presented target was a member of this category (LTM retrieval condition), or use their memory to retrieve the location associated with the cued word and report if an exemplar of the named category appeared at that location (LTM-guided attention condition). Participants demonstrated greater activation in bilateral posterior parietal and subcortical (including dorsal striatum) areas for LTM-guided visuospatial attention compared to LTM retrieval and stimulus-guided attention. Rosen et al. argued that these regions are involved in integrating information retrieved from LTM to support attentional guidance. However, each type of learning was tested with matched retrieval and attention tasks, therefore, the implications of different types of learning on both retrieval and attentional orienting were not measured (e.g., stimulus-guided learning for memory retrieval). As a result, the neural regions that Rosen et al. have reported to be involved in LTM-guided attention may be specific to the type of learning that was measured. Therefore, it is unclear if the pattern of neural activity they found would differ if another type of learning, such as location probability learning, was also tested on LTM-guided attention (Hutchinson & Turk-Browne, 2012). This lack of comparison between the effects of learning type supports the need for follow-up studies that measure the relative benefits of different types of learning to retrieval and LTM-guided attention.

1.4. Aims

Our knowledge of how different types of memory associations distinctively impact memory retrieval and attentional orienting is limited. Accordingly, the goal of my thesis is to investigate similarities and differences in the ways in which different types of associative spatial learning can subsequently facilitate memory retrieval compared to attentional orienting. First, in Chapter 2, I examine how increasing the set size of objects associated with a specific scene context impacts explicit retrieval of the objects' identities and locations. This chapter sheds light on whether retrieval from long-term memory is impacted by competition among associations and is restricted by standard capacity limits of visual working memory. Next, in Chapter 3, I directly compare how contextual and probabilistic associations are learned using a single experimental framework. I then measure the relative consequences of these different types of associations for performance in subsequent memory retrieval and attentional-orienting tasks. Finally, in Chapter 4, I vary the spatial predictability of target and distractor locations in a single learning task. I then assess the utility of spatial predictability for subsequent explicit retrieval and attentional orienting tasks probing performance for targets and distractors. This emphasises the importance of considering the behavioural purpose of the task when assessing the utility of memory traces for guiding future behaviour. Overall, this work demonstrates the prospective implications of manipulating the load, association type, or purpose of spatial learning on memory retrieval and attentional orienting. The final chapter in the thesis, Chapter 5, draws together the main findings across all the empirical studies, considers them in light of the literature, acknowledges limitations, and proposes directions for future investigation.

Chapter 2. Examining the Effects of Within-episode and Between-episode Competition on Memory Retrieval

Abstract

Past events, or episodes, often share easily confusable features. These overlapping features can occur within and between memory episodes and generate competition among the items to be remembered. I tested long-term memory (LTM) for object-scene associations to investigate the individual and joint effects of within-episode and between-episode competition on memory retrieval. In Experiment 1, participants completed a learning task where they searched for objects within scenes over five testing blocks. Each combination of a set of objects and a specific scene represented a single memory episode. I tested within-episode competition by varying the number of target objects (set size) associated with each scene. Afterwards, participants completed an explicit retrieval task where they had to retrieve the identity and location of the learned objects. I tested between-episode competition by requiring participants to retrieve object-scene pairs with varying spatial overlap between the target and a lure from a different learned scene. There was no effect of within-episode or between-episode competition on retrieval performance in LTM, though participants were significantly better at identifying novel lures. In Experiment 2, I investigated whether retrieval ability in LTM would be impaired at set sizes beyond the hypothesized 'capacity' of visual working memory. Similar to Experiment 1, I did not find effects of varying set size on retrieval performance. Finally, in Experiment 3, participants were exposed to each unique objects-scene pairing just once during learning, but still showed no effects of set size on retrieval performance. Overall, the findings question whether increasing set size up to 7 items within a memory episode has demonstrable effects on LTM performance.

2.1. Introduction

Our capacity to remember past events is often complicated by the comparable or overlapping features of our memories (M. C. Anderson, 2003; M. C. Anderson et al., 1994; Favila et al., 2016). For example, when trying to remember each friend we ran into at the store, we may find ourselves mentally flipping through our friends to remember who was featured in that episode (Colgin et al., 2008). Intuitively, this task may seem particularly daunting if you ran into a group of ten of your friends at the store. Despite how commonplace this sort of recollection challenge may be, the way in which an increasing number (set size) of to-be-remembered features compete for and subsequently interfere with our successful recollection remains poorly understood (Drew et al., 2016; Jeneson et al., 2011).

Competition between items in memory for successful retrieval can arise from many sources. For example, it has been found to root from semantic distraction (Melcher & Murphy, 2011), visual distraction (Draschkow et al., 2019; Wais et al., 2010), spatially competing information (Chanales et al., 2017), overlapping associations (Kuhl et al., 2010, 2011), and set size (Drew et al., 2016; Sprague et al., 2014), to name a few. For the purposes of this study, I will divide these many sources of competition into two broad categories: competition between episodes and competition within episodes. Competition between memory episodes occurs when the features of one memory episode overlap with the features of a separate memory episode (Colgin et al., 2008; Favila et al., 2016; Kyle et al., 2015). For example, trying to remember whether you skateboarded to the park and then scootered to the store, or vice versa. These would be considered separate memory episodes as they occurred within different settings (Wood et al., 2000). However, the similarities between these memories may make retrieving specifics difficult (Colgin et al., 2008). For example, if you keep your scooter in the same location as your skateboard, it may be more difficult to remember which you took to the store versus the park. In contrast, competition within

memory episodes occurs when features within one memory episode compete for and subsequently interfere with successful retrieval (Sprague et al., 2014). Going back to the example at the beginning of this section, we can consider going to the store as a single episode. When you got there, the number of friends you ran into could dictate the degree of within-episode competition, with more friends increasing the difficulty of retrieving a specific friend (Jeneson et al., 2011).

Most research into competition in LTM has focused on between-episode competition, leaving less known about within-episode competition. Studies investigating between-episode competition typically start with participants viewing a large number of scenes or objects one by one, thus separating them into individual episodes. Next, participants are presented with the scenes or objects they have seen in the past, one after another, during a two alternative forced choice (2AFC) tasks where they make a distinction as to whether each item is "old" vs "new" (Schurgin & Flombaum, 2018b; Standing, 1973). In these recognition memory tasks, Visual LTM has been found to have a "massive" capacity for thousands of detailed representations such as scenes and objects (Schurgin, 2018). For example, visual search is efficient up to 100 objects in memory (Wolfe, 2012). These findings are in line with evidence for the role of the hippocampus as a rapid encoder of single-trial associations with sensory regions (i.e., memory episodes; McHugh et al., 2007; Nakazawa et al. 2003, 2004; Rolls, 2018; Rolls & Treves, 1998). For example, it is easy to reflect back on a long day and remember many separate visual episodes. These individual episodes often share overlapping representations in the neocortex, but through pattern separation their hippocampal coding is kept orthogonal, drastically reducing competition (Bakker et al., 2008; Hardt et al., 2013b; Kirwan & Stark, 2007a; Rolls, 2013; Sadeh et al., 2014). Though the hippocampus is effective at reducing competition between episodes, it remains unclear whether increasing set size within a memory episode (e.g. the number of friends at the store) increases the difficulty

of pattern separation and leads to decreased LTM performance (e.g., greater difficulty remembering who specifically you saw at the store; Fallon et al., 2016; Hardt et al., 2013; Rolls, 2018).

Some recent evidence has supported that increasing the set size of learned associations decreases LTM retrieval performance. Modal models of memory hypothesize that when information is first stored it is held actively in short-term memory before long-term storage (Atkinson & Shiffrin, 1968). Therefore, it has been asserted that during retrieval of visual LTM into working memory (WM), LTM faces the same capacity bottleneck as visual working memory (~3-4 objects; Fukuda & Vogel, 2019). Specifically, at set sizes above 3-4 objects, there is predicted to be a rapid decrease or plateau in LTM performance because more objects cannot be simultaneously held actively in WM. To test this prediction, Fukuda & Woodman (2017) had participants learn arrays which contained 1, 2, 4, or 8 coloured squares. After seeing the array, participants were shown an associated letter and had to press one of eight possible coloured buttons to indicate the colour that had appeared at a probed location. During a subsequent retrieval task, first the associated letter was shown, acting as a memory cue, and then participants had to retrieve the colour of the object at the learned location. Results demonstrated that the speed of retrieval slowed as set sizes increased, plateauing after a set size of 4 items. Based on these results, the authors argued that the amount of information retrieved into long-term memory from working memory has a limited "bandwidth" (Fukuda & Vogel). Other research has also found reductions in long-term memory retrieval performance after increasing set size within a memory episode in older healthy adults and in age-matched APOE ε4 carriers (Zokaei et al., 2019).

In their study, Zokaei et al., (2019) demonstrated that manipulations to memory set size may be sensitive to early signs of AD-related impairments. Older adults (mean of 68 years of age) who participated were split into three groups based on their APOE ε4 allele

status (APOE ε3/ε3, ε3/ε4, and ε4/ε4). APOE ε4 confers the highest genetic risk for Alzheimer's disease (AD; Winblad et al., 2016). The experiment started with a visual search task where participants had to search through scenes (photographs of outdoor and indoor spaces) and find and click on either one or two non-semantically congruent objects that were embedded within. Once this learning task was complete, participants had a 20-minute break before beginning a surprise explicit retrieval task which assessed their memory for the object-scene associations they had learned. In each trial, participants were presented with an object from the learning phase (target) and a novel object (foil) below the scene where the target occurred in the learning task. Their task was to recognize the target object (recognition memory) and drag it to the location or where they recalled it occurring in the scene (cued location recall). Interestingly, APOE ε4 carriers performed worse at localizing the object compared to ε3 carriers, but only when recalling the target location for scenes associated with two objects in memory. In addition, all participant groups were worse at both recognition memory and cued location recall for scenes associated with two objects versus one object in memory. These findings raised a few relevant questions. For example, were the effects of manipulating set size on memory retrieval in healthy older adults (ε3 carriers) exacerbated by the effects of ageing? In other words, would the consequences of manipulated set size be less in younger adults? Also, this study and others have manipulated either within or between episode competition in separate tasks (Chanales et al., 2017; Fukuda & Woodman, 2017; Sohn et al., 2003), but would the interfering effects of competition compound if these sources of competition were manipulated simultaneously?

Over three experiments, I examined the impact of within and between-episode competition on memory retrieval ability in healthy young adults. In each experiment, participants completed an implicit learning task where they searched through scenes for embedded target objects. Then, after a break, they were tested with a surprise (incidental)

explicit retrieval task. This task tested long-term memory by measuring participants' performance on object recognition and cued recall of the object-scene associations they had learned. Within-episode competition was manipulated by varying the number of objects associated with scenes during learning. In Experiment 1, between-episode competition was scaled during explicit retrieval by varying the spatial overlap between the learned locations of probed objects (e.g., a high degree of spatial overlap would mean that two objects had occurred in similar locations in different learned scenes). Therefore, during the explicit retrieval task, participants' performance could be simultaneously impacted by within-episode (set size) and between-episode (spatial overlap) competition. In Experiments 2 and 3, I focused on measuring the effects of within-episode competition on explicit retrieval by increasing the set size of objects-per-scene (Experiment 2) and decreasing the number of learning blocks (Experiment 3). I hypothesized that increasing both within-episode and between-episode competition would decrease memory retrieval performance in a stepwise fashion (Fukuda & Woodman, 2017). In other words, with each increase in set-size, there would be a corresponding decrease in memory retrieval performance. Also, this decrease in memory performance would be compounded when moving from a low to a high degree of spatial overlap between the learned object locations (Chanales et al., 2017).

2.2 Experiment 1: Combined Effects of Between-episode and Within-episode Competition on Memory

The goal of the first experiment was to manipulate within-episode and between-episode competition to measure their independent and shared impacts on explicit retrieval performance. Further, this experiment would test whether Zokaei et al.'s findings that increasing set size below 'WM capacity' impacts explicit retrieval performance is specific to older adults, or if younger adults' memory retrieval abilities can also be impacted by

increasing within-episode competition in this manner (2019). In the experiment, participants first learned the identities and locations of 1, 2, or 3 unique objects within unique scenes. After a break, they then performed a retrieval task in which they had to recognize which of two objects was repeated from the learning task and then place the selected object in its remembered location (Migo et al., 2012). I hypothesized that, in both measures of memory retrieval, participants would perform worst for scenes associated with 3 objects during the learning compared with learning 1 or 2 objects. Also, retrieval performance would be worse when the probed objects had similar compared to different learned locations.

2.2.1. Methods

2.2.1.1 Participants. The study was approved by the Central University Research Ethics Committee of the University of Oxford code: R63062/RE001. Participants (age range = 18-40) were recruited separately to complete the task in the lab (on departmental computers in-person) or online (on their personal computers). In-lab participants were recruited using SONA (Oxford Psychology Department participant recruitment platform). Online participants were recruited using Gorilla, an online crowdsourcing and experiment-testing platform (www.gorilla.sc). They were compensated £10 per hour and invited to participate based on the following criteria: age 18-40, fluent in spoken and written English, and normal or corrected eyesight.

Following procedures from a similar study (Zokaei et al., 2019), a suggested sample size of 20 participants per group was determined. To yield the combined sample size of 40 participants (20 in-lab and 20 online), 45 individuals were initially recruited. All completed the task using the online platform (Gorilla), but 20 did so in the lab, while 25 completed the task online. Five online participants were excluded from the analysis. Of the five, three were excluded because they did not follow the instructions during the explicit retrieval section of

the task; one because they took a long break between different parts of the task (200 minutes rather than 20) and one because they had missing data. Full demographics for all experiments are shown in Table 2.1.

Table 2.1

Task timings and Demographics for Experiments 1, 2, and 3

Experiment	Mean Learning time (min)	Mean Rest Time (min)	Mean Retrieval Time (min)	Mean Total Time (min)	Age (mean/SD)	Age (min; max)
Exp. 1 Online	49	22.5	10	84	25.6 /5.7	18; 38
Exp. 1 In-Lab	40.5	21	9	72.5	24.3 /5.4	19; 35
Exp. 2 Online	65.3	22.3	9.6	97.2	21.7 /2.5	19; 26
Exp. 3 Online	23.6	22.1	10.2	55.8	23.6 /3.6	19; 30

Note. Table 2.1 shows how long each segment of the experiments took as well as demographic information for the Online and In-lab groups that completed Experiment 1, and the Online groups that completed experiments 2 and 3.

2.2.1.2. Stimuli. The experiment was programmed jointly in Matlab (The Math Works, Inc., 2019) and Gorilla (www.Gorilla.sc). Gorilla is largely GUI-based, with has some coding capabilities using the TypeScript programming language. Gorilla collects two different screen-specific metrics from the user: monitor size and viewport size (the portion of the screen that does not include the browser panel at the top of the screen). The size of the scene and objects scaled with the size of the viewport (Viewport size reported in Table 2.2). The viewport is composed of the scene, a panel at the bottom where instructions occurred, and white panels on the left and right sides of the scene. Objects were small and covered only

approximately 8% by 8% of the entire scene. This ratio was maintained regardless of the viewport size. Within the scene, 110 possible object locations were manually created in the Gorilla builder: 10 rows of 11 side-by-side locations. They were spaced out evenly such that the locations were non-overlapping. Also, surrounding the four sides of the possible locations, there was a designated space where objects could not occur. This space was equivalent in size to one object's width or height (approximately 8% of the width or height of the scene). Additionally, within the same scene, objects could not occur within one object's width and height from another object. The possible object locations were created in this way to maximize the possible locations where objects could occur on the screen, while excluding the edges and making it easy to define where objects could and could not occur.

Table 2.2

Descriptive Statistics for Screen Dimensions in Experiment 1

Variables	**Viewport X Axis**	**Viewport Y Axis**
Median Online (pixels)	1440	784
Median In-lab (pixels)	1163.50	932
W	333	80
p	<.001	<.001

Note. Mann-Whitney U tests comparing screen dimensions for the different task segments between the online and in-lab groups in Experiment 1. Viewport X axis was larger Online whereas Viewport Y axis was larger In-lab.

Objects were taken from the UCSD Vision and Memory Lab stimuli set (Brady et al., 2008). From this set, 180 objects were chosen for maximum distinctiveness and

differentiability (e.g., there would be only one teddy bear in the entire object set). Also, as much as possible, objects were chosen to be easily identifiable. White square backgrounds were removed from these objects so that they would appear embedded in their surrounding scenes. Finally, all objects were resized to the same dimensions (8% by 8% of the scene size).

Scenes were taken from an in-lab dataset containing photographs of outdoor scenes taken by lab members in countries throughout the world. Generally, scenes were chosen specifically to maximize diversity (e.g., different types of buildings, seasons, climates, and weather conditions) and distinctiveness (the Discussion section elaborates on the importance of distinctiveness for this experiment). For example, no two scenes were very evidently from the same geographic location, so that they would not potentially be confused. As much as possible, all the scenes also contained a diversity of visual information, e.g., photographs of the ocean or the sky were avoided. Utilizing scenes such as this could result in a 'pop-out' effect, where objects are very easily distinguishable, and the scene itself may not be as well encoded (Draschkow et al., 2014). Also, no scenes contained easily recognizable landmarks (e.g., Big Ben) that may contribute to memorability.

For Experiment 1, the in-lab group completed the task using a monitor with 1920x1080 pixel resolution. Participants who completed the task Online completed a display calibration where they were instructed to resize their viewport until a visually presented box fit snugly in the bottom right corner of the scene. This calibration ensured some viewport size consistency to control for their varying monitor sizes. See Table 2.2. for a comparison of viewport size between the groups in Experiment 1.

2.2.1.3. Procedure. Participants completed the entire experiment on the Gorilla platform (www.Gorilla.sc). After reading a description of the study, participants provided informed consent. Before starting the learning task, participants were familiarized with the

task through a set of instructions, an example video, and a set of ten practice trials using scenes and objects that did not re-occur during the main task.

2.2.1.3.1. Learning Task. The learning task was a modified version of the procedure used in Zokaei et al. (2019; Figure 2.1). At the beginning of each trial, 1, 2, or 3 objects appeared centrally with a white background. Once participants were familiarized with the objects, they clicked a button that said 'next' at the bottom of the screen to continue. Participants were given as much time as they needed to familiarize themselves. If they chose to, they could take longer when there were more objects (further commentary on encoding timings and their implications can be found in the Discussion section). Also, because each participant had to click "next" to continue onto the search task, across participants, the mouse began in the same location in each visual search trial. This was followed by a fixation period (250 ms) before a scene containing the objects was presented. Participants had up to ten seconds to find (and click) on all the objects in the scene. They could click on the objects in any order. If they found all the objects before the time limit, they were instructed to press the spacebar to continue. Otherwise, the task continued automatically when the ten seconds had elapsed. A 250 ms fixation period preceded the next trial.

Figure 2.1

Learning Task Procedure



Note. A schematic of the learning task. The task began with a preview of the visual search target objects. Then, after a short fixation, participants had 10 seconds to search for and click each of the objects. When they had clicked them all, they could press space to continue immediately onto the next trial.

Participants completed 4 blocks of learning trials, each consisting of 90 object-scene combinations (30 trials each of 1, 2, or 3 objects). Within each block, the combinations were presented in a random order, and each participant received a unique set of object-scene pairs. The first time the objects appeared, when participants had the chance to familiarize themselves with the object identities prior to search, they appeared in a random order from left to right. After this first block of trials, the original order of the objects reoccurred in the remaining test blocks. Also, object locations were chosen randomly from amongst the 110 possible locations at the beginning of the experiment but were consistent from block to block. Therefore, the locations where the objects occurred in block 1, would reoccur in the remaining blocks. Between blocks, participants had a 1-minute break.

This learning task was identical in structure but had some differences in timings compared with the learning task in Zokaei et al., (2019). The significant differences were that in Zokaei et al., participants had only 4 seconds to familiarize themselves with the objects during the initial viewing. In my study, participants had as much time as they needed because I wanted to equate encoding strength as much as possible and then see if increasing the set size reduced memory retrieval performance (see Discussion section for further review of implications of encoding strength). Also, in Zokaei et al., participants had 120 seconds to search and click the objects, whereas in my study they had only 10 seconds. Because my study was online, I reasoned that giving participants the same large time window might lead to them becoming distracted more easily (Sauter et al., 2020) and was unnecessary given the search speeds in Zokaei et al. (5.5-6 seconds on average even when they needed to find two objects).

2.2.1.3.2. Retrieval Task. Once participants completed the learning phase (Figure 2.1), they were instructed to take a 20-minute break. This was followed by a surprise memory test for the learned object identities and their locations (Figure 2.2). This task was identical in structure and timings to the retrieval task in Zokaei et al., 2019. Participants completed 90 trials in total – one for each learned scene. In each trial, participants were presented with a scene and two objects at the bottom of the display. Participants were asked first to choose the object that was previously associated with the scene (identification) and then to click its remembered location within the scene (localisation). Participants were encouraged to take their time in identifying the correct object and placing it precisely in the location where they remembered it occurring. Therefore, though I have included response times for identification and localisation in the analysis, response time was not a primary measure of interest as responses were not speeded.

Figure 2.2

Explicit Memory Retrieval Task



Note. A schematic of the Memory Retrieval task. The task began with a memory identification response, where participant had to choose the object that matched the scene out of two possibilities: a learned target and a lure. Once they selected, they had to click the location in the scene where the object had occurred during the learning task.

During the identification response, participants were asked to recognize the target object out of two possibilities. One of the objects was previously associated with the scene (target) while the other was a lure. The location (i.e., left or right side of the screen) where each occurred was counterbalanced. If more than one object was associated with the scene during learning, one of the learned objects was chosen randomly to be the target during the retrieval phase. The lure object came from 1 of 3 categories: same-location in a different scene, different-location in a different scene, or completely novel. Specifically, an object would qualify as a same-location lure if it occurred at a location that was within the width of one object (8% of the screen x or y axes) from the target location, but within a different

learned scene. Since the objects could only occur in predefined possible locations, a partial fulfilment of this rule was impossible. In other words, another object could only be totally within the square next to the original object, or outside of this allowance entirely. Different-location lures were from a different location (any location that did not qualify as a same-location) than the target and learned in a different scene.

2.2.1.4. Data Analysis. Parametric analyses were applied, transforming the data when necessary to conform to the required assumptions. In cases where the interactions of main effects were significant, Tukey HSD tests were applied. Tukey tests were used to control for multiple comparisons as numerous variables in the analysis had 3 or more levels. Greenhouse-Geisser correction was applied when the sphericity assumption was violated. Throughout the experiment, to account for within-participant comparisons (i.e., between association conditions), procedures from Morey were followed (2008).

Data were processed and graphed using Matlab (The Math Works, Inc., 2019). All analyses were conducted using RStudio (Version 1.1.463) by the R core team (2022). Descriptive statistics and Tukey HSD tests were conducted using the "stats" package in (R core team, 2018). Within-participant ANOVAs were conducted using the "e" package when necessary to aggregate data (Version 4.4-0; Lawrence, 2016).

2.2.1.4.1. Online vs. In-lab. In addition to the main dependent variables in this Experiment, I was also interested in exploring whether the online and in-lab groups differed on other measures such as how long they took to do the experiment and their demographics (Table 2.1).

2.2.1.4.2. Learning Task. To analyse performance on the learning task, target identification accuracy (% of correctly identified targets) and response time (time at which the first target was clicked in each scene) were tracked over the 4 blocks. The independent variables of interest were set size (1, 2, or 3) and block (1-4) as within-participants variables, and group (online or in-lab) as a between-participants variable. The Box-Cox procedure (Box & Cox, 1964) tested the distribution and residuals of response-time values. Based on this, I applied an inverse square-root transformation to response times to approximate the normal distribution and meet ANOVA assumptions. Trials in which response times were shorter or longer than 2 standard deviations from the participant-specific mean across all conditions were excluded from response time analysis (~4% of trials).

2.2.1.4.3. Retrieval Task. Object identification accuracy and response times were used to examine explicit retrieval performance for learned object-scene associations. To do so, separate mixed ANOVAs were conducted with identification accuracy and response times for object identification as dependent variables, group (online or in-lab) as a between-participants factor, and set size and lure type (same, different, new) as within-participants factors. Trials in which response times were shorter or longer than 2 standard deviations from the participant-specific mean were excluded from analysis (~4% of trials). Based on Box-Cox lambda, I applied an inverse square-root transformation to the identification response time data. Also, to make encoding strength and exposure time between objects in the different set-sizes as similar as possible, only trials in which participants correctly clicked the target during the final learning block were included in the retrieval analysis.

I examined localisation performance by measuring localisation error (normalized distance between response location and target location) for trials in which participants correctly identified the target. I calculated the distance in two-dimensional space between the

centre of the target locations in each of the 5 learning blocks and the participants' responses during the location retrieval phase. To simplify error values from the raw Gorilla output coordinates, error values were divided by the maximum possible localisation error, which gave me normalized percentage error out of 100. This is the value that appears as 'normalized localization error' in my figures (e.g., Figure 2.4a-b). Maximum possible localisation error was calculated as the maximum distance between a possible target and a possible response, i.e., the Euclidian distance from the limit of possible target appearance in the top left to the bottom right of the visual display – the most distant possible response. Finally, a mixed ANOVA was conducted with localisation error as the dependent variable, group (online or in-lab) as a between-participants factor, and set size and lure type (same, different, new) as within-participants factors. Based on Box-Cox lambda, a square-root transformation was conducted on the localisation error data.

2.2.2. Results

2.2.2.1. Descriptive Statistics. To compare the In-lab and Online groups that completed Experiment 1, I ran Mann-Whitney U tests on learning time, break time, retrieval time, total experiment time, and viewport size (dictated the size of the scene and objects). Participants were significantly slower across all parts of the experiment in the online study (Table 2.3), their viewport x axis was also larger, though their y-axis was smaller (Table 2.2).

Table 2.3

Descriptive Statistics for Task Timings in Experiment 1

Variables	Learning Time	Break Time	Retrieval Time	Total time
Median Online (min)	49	22.5	10	84
Median In-lab (min)	40.5	21	9	72.5
W	295	291	270.5	330
p	.01	.01	.05	<.001

Note. Mann-Whitney U tests comparing timings for the different task segments between the online and in-lab groups in Experiment 1.

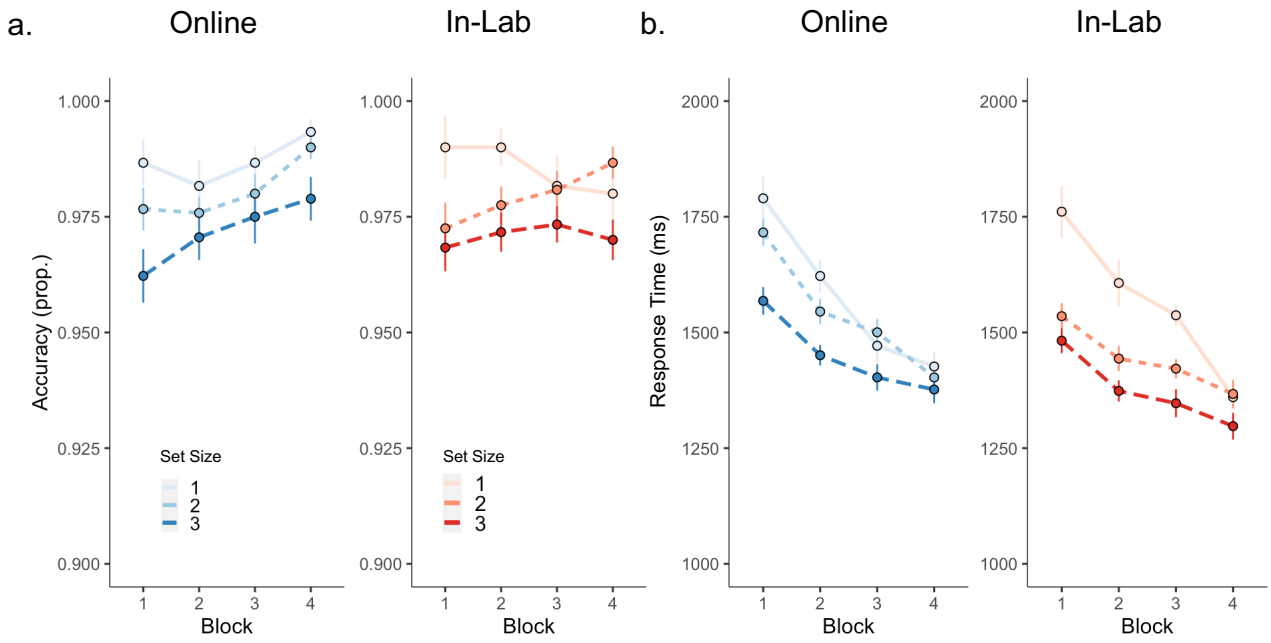
2.2.2.2. Learning Results.

2.2.2.2.1. Search Accuracy. A two-way mixed ANOVA with Set Size and Block as within-participant factors and Group (in-lab vs online) as a between-participants factor demonstrated better performance for smaller set sizes and an overall improvement in accuracy over time. There was a significant main effect of Set Size ($F(2,76) = 46.04$, $p < .001$, $\eta^2_p = 0.27$, Figure 2.3a) and a main effect of Block ($F(2.07, 78.55) = 3.35$, $p < .05$, $\eta^2_p = 0.01$), but no main effect of Group ($F(1, 38) = 0.03$, $p = .86$, $\eta^2_p < .01$). Means for Set Size were 98% for 1 object (*SD* = 12%), 98% for 2 objects (*SD* = 10%), and 97% for 3 objects (*SD* = 10%). Tukey's HSD demonstrated that participants were more accurate on trials with a Set Size of 1 compared to 3 objects ($p < .001$) and 2 objects ($p < .001$). Though near-significant, there was no difference in performance between 2 and 1 object trials ($p = .05$). Therefore, generally, participants' learning accuracy decreased as Set Size increased. Participants' accuracy was 97% for Block 1 (*SD* = 11%) and 98% for Block 4 (*SD* = 10%),

with the related Tukey HSD not coming out as significant (p = .104). No significant interactions occurred between Group and Block (F(2.22, 78.55) = 0.90, p = .44, η^2_p < .01), Group and Set size (F(2,76) = 0.04, p = .96, η^2_p < .01), Block and Set Size (F(6,228) = 1.65, p = .14, η^2_p = 0.01), or between Group, Block, and Set Size (F(6,228) = .31, p = .93, η^2_p < .01).

Figure 2.3

Learning task Performance for Online and In-lab groups



Note. (a) Search accuracy across the 4 blocks of the learning task. Results are split by whether participants searched for 1, 2, or 3 objects (Set Size) and whether they completed the task Online (blue) or In-Lab (red). Participants were more accurate on 1 than 3 object trials. (b) Search response times for the first object clicked in each trial. Participants responded faster during learning as Set Size increased and as Blocks progressed. Data sets for Online and In-Lab groups are split to exemplify the lack of group differences. Error bars correspond to standard error of the mean.

2.2.2.2.2. Search Response time. A two-way mixed ANOVA with Set Size and Block as within-participant factors and Group as a between-participants factor demonstrated that Response times for the first object clicked became faster as the learning proceeded. There were significant main effects of Set Size ($F(1.48, 28.86) = 16.36$, $p < .001$, $\eta^2_p = 0.01$, Figure 2.3b) and Block ($F(2.28, 28.86) = 90.56$, $p < .001$, $\eta^2_p = 0.10$), but no main effect of Group ($F(1, 38) = 0.72$, $p = .40$, $\eta^2_p = 0.02$). Means for Set Size were 1571 ms for 1 object (*SD* = 803), 1491 ms for 2 objects (*SD* = 607), and 1412 ms for 3 objects (*SD* = 489). Tukey's HSD tests demonstrated that participants were faster at clicking an object on trials with a Set Size of 3 compared to 1 ($p < .05$). However, there were no significant differences in response time when comparing trials with a Set Size of 2 versus 1 ($p = .47$), or a Set size of 3 versus 2 ($p = .30$). Also, response time decreased from Block 4 to Block 1 ($p < .001$). Means were 1642 ms for Block 1 (*SD* = 718) and 1371 ms for Block 4 (*SD* = 512).

The interaction between Block and Set Size also reached significance ($F(2.05, 77.75) = 2.82$, $p < .05$, $\eta^2_p < .01$, Figure 2.3b). Tukey HSD tests on the interaction between block and set size were examined. Within trials with a Set Size of 1, participants' response times were faster in Block 3 than Block 1 ($p < .05$), and in Block 4 than Block 1 ($p < .001$), but no difference was found between Blocks 1 and 2 ($p = .74$), nor between any of the other Block with Block comparisons (e.g., 1:2, 2:3, 3:4 etc.). Within trials with a Set Size of 2, participants' response times were faster in Block 4 than in Block 1 ($p < .001$), but none of the other Block with Block comparisons were significant. Within trials with a Set Size of 3, participants' response times were faster in Block 4 than in Block 1 ($p < .05$), but none of the other Block with Block comparisons were significant. Also, within each of the Blocks, there were no significant differences when comparing response times between each of the set sizes (e.g., within Block 1, between set sizes 3 and 1 there was no significant difference ($p = .86$)).

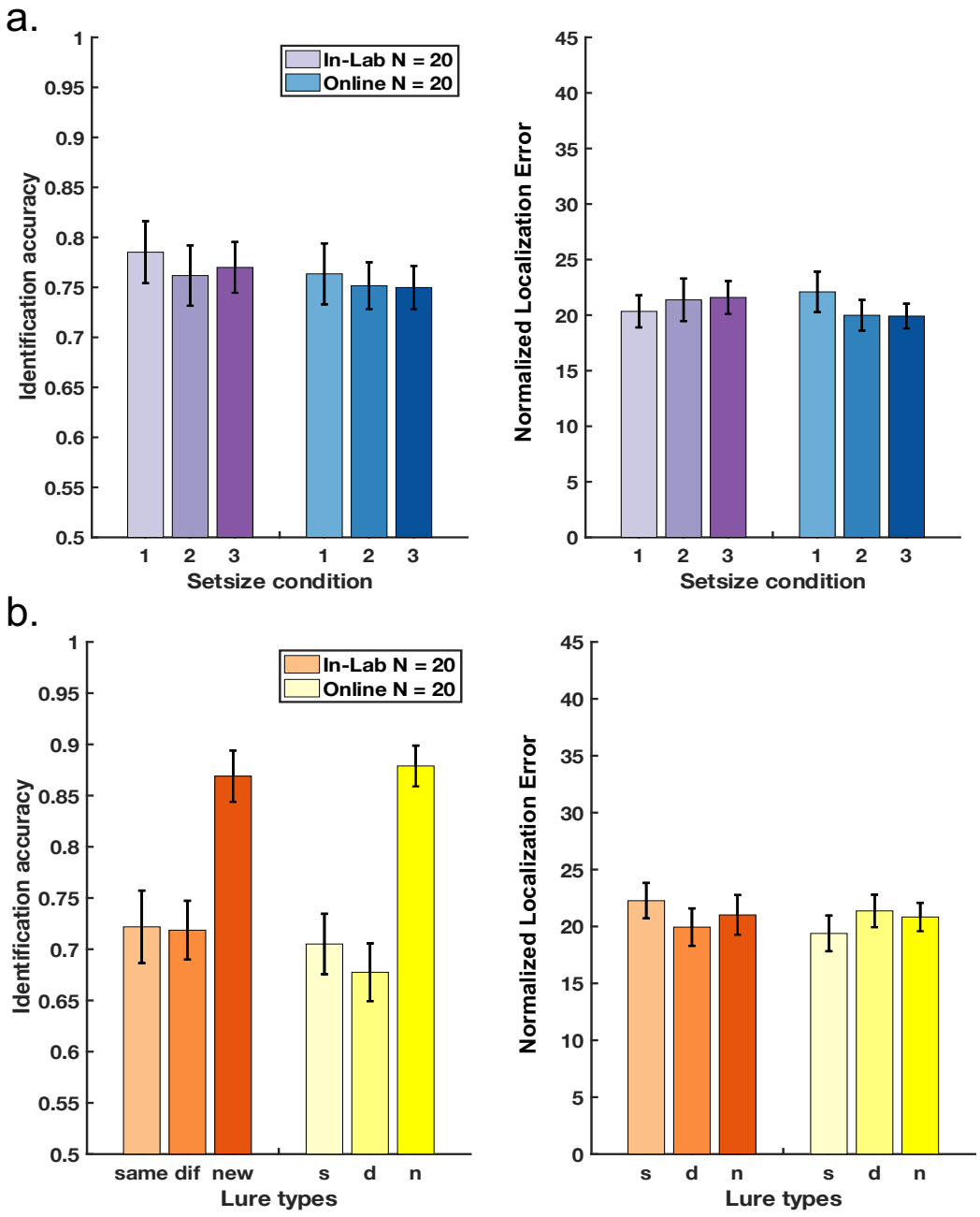
It is possible that the study was underpowered to find an effect within these single condition comparisons. Due to the sheer number of comparisons, and the lack of theoretical implications for these non-significant results, I have not included the p-values for these comparisons. Finally, there was no significant interaction between Group and Block ($F(1.54, 58.35) = 0.94$, $p = .40$, $\eta^2_p < 0.01$), Group and Set Size ($F(1.64,62.45) = 1.66$, $p = .20$, $\eta^2_p < 0.01$, or between Group, Block, and Set Size ($F(2.05, 77.75) = 0.55$, $p = .71$, $\eta^2_p < .01$).

2.2.2.3. Retrieval Results.

2.2.2.3.1. Identification Accuracy. A mixed ANOVA was conducted with Group (Online or In-lab) as a between-participants factor, and Set Size (1, 2, or 3 objects) and Lure Type (Same, Different, Novel) as within-participants factors. There was a significant main effect of Lure Type ($F(2, 76) = 49.65$, $p < .001$, $\eta^2_p = 0.18$, Figure 2.4b) but no main effect of Set Size ($F(2, 76) = 0.35$, $p = .70$, $\eta^2_p < 0.01$, Figure 2.4a) or of Group ($F(1, 38) = 0.05$, $p = .82$, $\eta^2_p < .01$, Figure 2.4). Mean accuracy by Set Size was 77% (*SD* = 6%) for Set Size 1, 76% (*SD* = 7%) for Set size 2, and 76% (*SD* = 7%) for Set Size 3. Mean accuracy by Lure Type was 72% (*SD* = 9%) for Same, 70% (*SD* = 6%) for Different, and 87% (*SD* = 8%) for Novel location lures. Tukey's HSD revealed that participants were more accurate on trials where the Lure was completely Novel compared to trials with Same ($p <.001$) or Different location ($p < .001$) lures. There was no difference in accuracy between trials with Same or Different location lures ($p = .58$; Figure 2.4b). There was no interaction between Group and Set Size ($F(2, 76) = 0.28$, $p = .76$, $\eta^2_p < .01$), Group and Lure Type ($F(2, 76) = 1.64$, $p = .20$, $\eta^2_p < 0.01$), or between Group, Set Size, and Lure Type ($F(4, 152) = 0.71$, $p = .59$, $\eta^2_p = 0.01$).

Figure 2.4

Explicit Retrieval Performance Across Set Size and Lure Type



Note. (a) No effect of set size on identification accuracy or localisation error was found for trials in which the learned scene had 1, 2, or 3 objects. (b) Identification accuracy and Localisation error during explicit retrieval for trials in which the participants had to choose

between a target, and lures that were from a similar, different, or novel location. Participants performed significantly better at identifying the target when a novel lure was present, but no difference in localisation error was found between lure types. Localisation error was measured for trials where participants correctly identified the target. Normalized localization was calculated by taking the Euclidian distance between participants' responses to the target location and its actual location and dividing this by the maximum possible error. Error bars correspond to the standard error of the mean.

There was an interaction between Set Size and Lure Type ($F(4, 152) = 3.24$, $p < .05$, $\eta^2_p = 0.03$). Tukey HSD tests were used to examine the interaction between Set Size and Lure Type. Within trials with a Set Size of 1, participants were more accurate when lures were Novel compared to from Same ($p < .001$) or Different ($p < .001$) locations in old trials. Within trials with a Set Size of 2, participants were more also accurate when lures were Novel compared to from Same ($p < .05$) or Different ($p < .001$) locations in old trials. The same pattern was true for trials with a Set Size of 3 - participants were more also accurate when lures were Novel compared to from Same ($p <.001$) or Different ($p <.001$) locations in old trials. Within the Set Sizes, none of the other comparisons between lure types were significant (e.g., at set size 1, no significant performance difference with same and different location lures). Also, within the Lure Types, none of the comparisons between performance in the different set sizes were significant (e.g. within same location lures, no significant differences at set sizes 1, 2, or 3). Due to the sheer number of comparisons, and the lack of theoretical implications for the results, I have not included the p-values for these non-significant comparisons.

Due to the unexpected finding that Set Size had no significant effect on identification accuracy, I ran a subsequent Bayes Factor analysis to confirm whether the main effect of Set Size was insignificant. First, I estimated a Bayes factor using Bayesian Information Criteria (Wagenmakers, 2007), comparing the fit of the data under the null vs. alternative hypotheses. An estimated Bayes factor for Set Size (BF = .04) suggested that the data were 1:.04 (null x alternative) in favour of the null hypothesis, or rather, 25 times more likely to occur under a model excluding an effect of Set Size, rather than a model including it. This result indicates strong evidence that the main effect of Set Size was insignificant.

2.2.2.3.2. Identification Response Time. Again, a mixed ANOVA was conducted with Group (Online or In-lab) as a between-participants factor and Set Size (1, 2, or 3 objects) and Lure Type (Same, Different, New) as within-participants factors. There was a significant main effect of Lure Type ($F(2,76) = 4.96$, $p < .01$, $\eta^2_p = .01$, Figure 2.4b), but there was no significant main effect of Set Size ($F(2,76) = 0.25$, $p = .78$, $\eta^2_p < .01$, Figure 2.4a) or of Group ($F(1,38) = 0.05$, $p = .82$). Tukey HSD tests did not reveal any differences between Lure Type pairs (Same vs Different, $p = .39$; Same vs New, $p = .17$, Different vs New, $p = .87$). It is possible that the study was underpowered to detect differences between the levels of Lure Type. For example, the main effect of Lure Type, though significant, had a small effect size ($\eta^2_p = .01$). The possibility that this and subsequent studies were underpowered is discussed in more detail in the Discussion section. Finally, there was no interaction between Group and Set Size ($F(2,76) = 1.18$, $p = .31$, $\eta^2_p < .01$), Set size and Lure Type ($F(4,152) = 1.93$, $p = .11$, $\eta^2_p = 0.01$), Lure Type and Group ($F(2,76) = 2.69$, $p = .075$, $\eta^2_p = 0.01$), or between Group, Set Size, and Lure Type ($F(4, 152) = 1.19$, $p = .31$, $\eta^2_p = 0.01$).

2.2.2.3.3. Localisation Error. A mixed ANOVA was conducted with Group (Online or In-Lab) as a between-participants factor and Set Size (1, 2, or 3) and Lure Type (Same, Different, New) as a within-participants factor. There was no significant main effect of Set Size ($F(2, 76) = 0.48$, $p = .62$, $\eta^2_p < 0.01$, Figure 2.4a), Lure Type ($F(2, 76) = 0.84$, $p = .43$, $\eta^2_p < 0.01$, Figure 2.4b), or Group ($F(1, 38) = 0.07$, $p = .79$, $\eta^2_p < 0.01$, Figure 2.4a-b). Further, there was no interaction between Group and Set size ($F(2, 76) = 1.19$, $p = .31$, $\eta^2_p < .01$), Group and Lure Type ($F(2, 76) = 1.98$, $p = .14$, $\eta^2_p = 0.01$), Set size and Lure Type ($F(4, 152) = 1.77$, $p = .14$, $\eta^2_p = 0.01$), or between Group, Set Size, and Lure type ($F(4, 152) = 0.46$, $p = .76$, $\eta^2_p < 0.01$); Figure 2.4a-2.2b). Mean localization error by Set Size was 22.46 ($SD = 3.01$) for Set Size 1, 22.68 ($SD = 3.32$) for Set size 2, and 22.61 ($SD = 2.98$) for Set Size 3. Mean localization error by Lure Type was 22.02 ($SD = 3.54$) for Same, 23.86 ($SD = 3.41$) for Different, and 21.87 ($SD = 2.50$) for Novel location lures.

Again, due to the unexpected finding that Set Size had no significant effect on localisation error, I ran a subsequent Bayes Factor analysis to confirm whether the main effect of Set Size was insignificant. First, I estimated a Bayes factor using Bayesian Information Criteria (Wagenmakers, 2007), comparing the fit of the data under the null hypothesis and the alternative hypothesis. An estimated Bayes factor for Set Size ($BF = .05$) suggested that the data were 1: .05 (null x alternative) in favour of the null hypothesis, or 20 times more likely to occur under a model excluding an effect of Set Size, rather than a model including it. This result indicates strong evidence that the main effect of Set Size was insignificant.

2.2.3. Conclusion.

In Experiment 1, I found that despite increasing within-episode competition, both online and in-lab groups did not show decreased LTM performance for object-scene

associations (Figure 2.4a). However, both groups showed effects of between-episode competition on object identification accuracy based on whether the lure was novel or associated with another scene (Figure 2.4b). Additionally, the absence of discernible performance disparities between in-lab and online groups lends evidence to favour the viability of online testing for conducting LTM experiments (Figure 2.4a-b).

First, participants demonstrated learning by identifying the targets more accurately and quickly as the experiment proceeded (Figure 2.3). Also, there was an effect of set size for both learning accuracy and RT, indicating that participants were slightly less accurate when they had more objects to search for, but were slightly faster at finding an object. This result for search time likely reflects the fact that, regardless of what is guiding search (i.e., top-down or bottom-up influences), participants' gaze would more quickly cross paths with an object if there are more filling up the screen. Also, it is more likely for an object to be closer to the starting point of participants' gaze when there are 3 spaced out around the scene rather than one, contributing to the increased search speed at higher set sizes. Finally, response time results are naturally noisier in online experiments where different devices are used (Sauter et al., 2020), therefore it is encouraging that the in-lab and online groups did not differ significantly in this metric. This was one of the important results that provided evidence in favour of the continued use of online testing in my subsequent studies.

Contrary to my initial hypothesis, there were no significant differences in memory retrieval performance based on manipulations to within-episode competition. During the explicit retrieval portion of the task, for both object recognition and cued recall, participants' performance was not impacted by manipulations to set size, i.e., the number of objects associated with the learned scenes (Figure 2.4a). Therefore, regardless of the memory process being tested (e.g., familiarity vs recollection), participants' retrieval performance was not impacted by scaling within-episode competition. Overall, these were surprising results given

past findings that increasing the set size of objects within a scene reduces long-term memory retrieval performance (Fukuda & Vogel, 2017). Given that past experiments with very similar tasks have detected effects of set size (Zokaei et al., 2019), it was also unlikely that the task was not sensitive to these effects. Two possible explanations of these results seemed viable based on existing evidence: 1. Decrements to LTM retrieval performance related to set size are exacerbated in older age groups as in Zokaei et al., 2019, or 2. LTM performance was not impacted when set size was only increased below "WM capacity" (Fukuda & Vogel, 2019). In the subsequent experiment of this chapter, I tested the second theory by increasing set sizes beyond the maximum of experiment 1.

Although participants' performance was not impacted by between-episode competition as predicted (i.e., by the same or different location lure condition), participants were much more accurate at identifying the target on trials where the lure was completely novel compared to when the lure was from a similar or different location than the target (in another scene; Figure 2.4b). This may demonstrate that participants could recognize the novel lure as non-familiar, allowing them to discount it as a potential target and increase their accuracy at identifying the actual target (Migo et al., 2012). Alternatively, it is possible that the same and different location lures were more familiar to participants due to their appearance in other learned scenes, potentially interfering with participants' ability to recognize that the target was associated with the current scene and reducing their overall performance (Reagh & Yassa, 2014). Interestingly, the comparative increase in identification accuracy when the novel lure was present did not translate to a decrease in localisation error for trials with novel lures compared to trials with same or different location lures. Therefore, discounting the novel lure as a potential target based on a lack of familiarity did not facilitate participants' ability to recollect the location where the target had occurred in the scene. This may be further support for the literature on differences between familiarity and recollection

memory (Aggleton & Brown, 2006; Mandler, 1980; Tulving, 1985; Yonelinas, 1994, 2002), in that a situation where participants' ability to use their familiarity memory was enhanced did not translate to better memory recollection. Future studies could also include a confidence rating scale, as it is possible that when there is a novel lure present (compared to an old lure), participants may be more confident in responding to the target.

Nevertheless, the results reported in this experiment stand in contrast to the literature demonstrating that the degree to which lures spatially overlap with a target can lead to increased competition and subsequent interference (Chanales et al., 2017; Pertzov & Husain, 2014). One possible explanation for this discrepancy in findings is that, unlike in Chanales et al., where spatial overlap occurring in the same setting led to an increase in between-episode competition and reduced memory performance, spatial overlap in my task occurred in the same screen location but in different scenes. Therefore, scene-based overlap may differ from screen-based overlap, i.e., two objects occurring in the same screen location in different scenes may be easier to pattern separate than two objects occurring in the same location on the same scene, but in different trials. If this is the case, my manipulation to between-episode competition based on scaling whether lures were from the same or different screen location as the target may not have been an effective manipulation of competition. Although further studies on between-episode competition, for example manipulating screen-based or scene-based overlap, would have been an interesting next step, this inquiry would have been more difficult due to additional design changes required and less guidance from existing literature than my hypothesis on within-episode competition. Therefore, in the subsequent two studies, I focused my efforts on investigating the role of within-episode competition on LTM performance.

2.3. Experiment 2: Comparing Effects of Within-episode Competition beyond WM 'Capacity'

After finding the surprising result that within-episode competition did not have a significant effect on LTM performance in the first experiment, in my second experiment I investigated if this lack of effect was due to the set sizes in Experiment 1 being within the hypothesized WM "limit" of four visual targets (Cowan, 2001; Fukuda & Vogel, 2019; Fukuda & Woodman, 2017). Therefore, in my second experiment, I used an identical learning and retrieval task but increased the set sizes during the learning task to go above the standard capacity limit in some cases (3, 5, or 7 objects were paired with each scene). Importantly, despite increasing the maximum possible number of objects in each scene, the amount of time participants had to find them (10 s) was kept the same. Therefore, participants had the same amount of time to search as in Experiment 1 but had more objects to find during this time period. With this experiment, I hoped to contribute new evidence to support or weaken proposals that retrieval from visual LTM faces working memory's capacity limits (Brady et al., 2013; Cowan, 2001; Fallon et al., 2016; Fukuda & Vogel, 2019). This study focused on within-episode competition. Therefore, the retrieval segment did not contain the same manipulation of between-episode competition as Experiment 1.

2.3.1. Methods

2.3.1.1. Participants. Participants were recruited online on the Gorilla platform. The same recruitment criteria were used as in Experiment 1. To yield the suggested sample size of 20 participants, 24 individuals were initially recruited. Four individuals were excluded from analysis, all for not following the study instructions (e.g., for not completing the retrieval task in the correct order (sporadically clicking the target location then identifying which object was the target) or not taking the required amount of break time between the learning and

recall task). For those included (19 females and one male), the average age was 21.71. Full demographics for this experiment are shown in Table 2.1.

2.3.1.2. Stimuli. Stimuli matched those in Experiment 1 in all aspects except for the number of objects. The overall number of scenes was the same (90), but more objects were used to match the increase in set size per scene. These objects came from the same online set as in Experiment 1 (Brady et al., 2008), and the same criteria was used in their selection.

2.3.1.3. Procedure. Participants completed the entire experiment on the Gorilla platform (www.Gorilla.sc). After reading a description of the study, participants provided informed consent. Before starting the learning task, participants were familiarized with the task through a set of instructions, an example video, and a set of 10 practice trials using scenes and objects that did not occur in the main task.

2.3.1.3.1. Learning Task. The learning portion of the task was identical to Experiment 1, but participants were presented with 3, 5, or 7 objects in each scene. Importantly, they still had only 10 s to click all the objects.

2.3.1.3.2. Retrieval Task. The explicit retrieval task was identical to that used in Experiment 1, except all lures were novel – not seen before during the learning task.

2.3.1.4. Data Analysis. Procedures for analysis replicated Experiment 1.

2.3.1.4.1. Learning Task. The only difference in analysis from Experiment 1 were the experimental variables. To analyse performance on the learning task, target identification

accuracy (% of correctly identified targets) and response times (for first clicked object) were tracked over the 4 blocks. The independent variables of interest were set size (3, 5, or 7) and block (1-4). Based on Box-Cox procedures, I applied an inverse square-root transformation to response times to approximate the normal distribution and to meet ANOVA assumptions. Trials in which response times were shorter or longer than 2 standard deviations from the participant-specific mean across conditions were excluded from analysis (~4.5% of trials).

2.3.1.4.2. Retrieval Task. Object identification accuracy, response times, and localisation error were used to examine explicit retrieval performance for learned object-scene associations. To do so, separate ANOVAs were conducted with identification accuracy, identification response times, and localisation error as dependent variables and set size as a within-participants factor. Responses that were shorter or longer than 2 standard deviations from participant-specific means were excluded from analysis (~3% of trials). Based on the Box-Cox lambda, I applied an inverse square-root transformation to the identification response time data. Also, only trials in which participants correctly clicked the target during the final learning block were included in the retrieval analysis. Again, based on the Box-Cox lambda, a square-root transformation was conducted on the localisation error data.

2.3.2. Results

2.3.2.1. Learning Results.

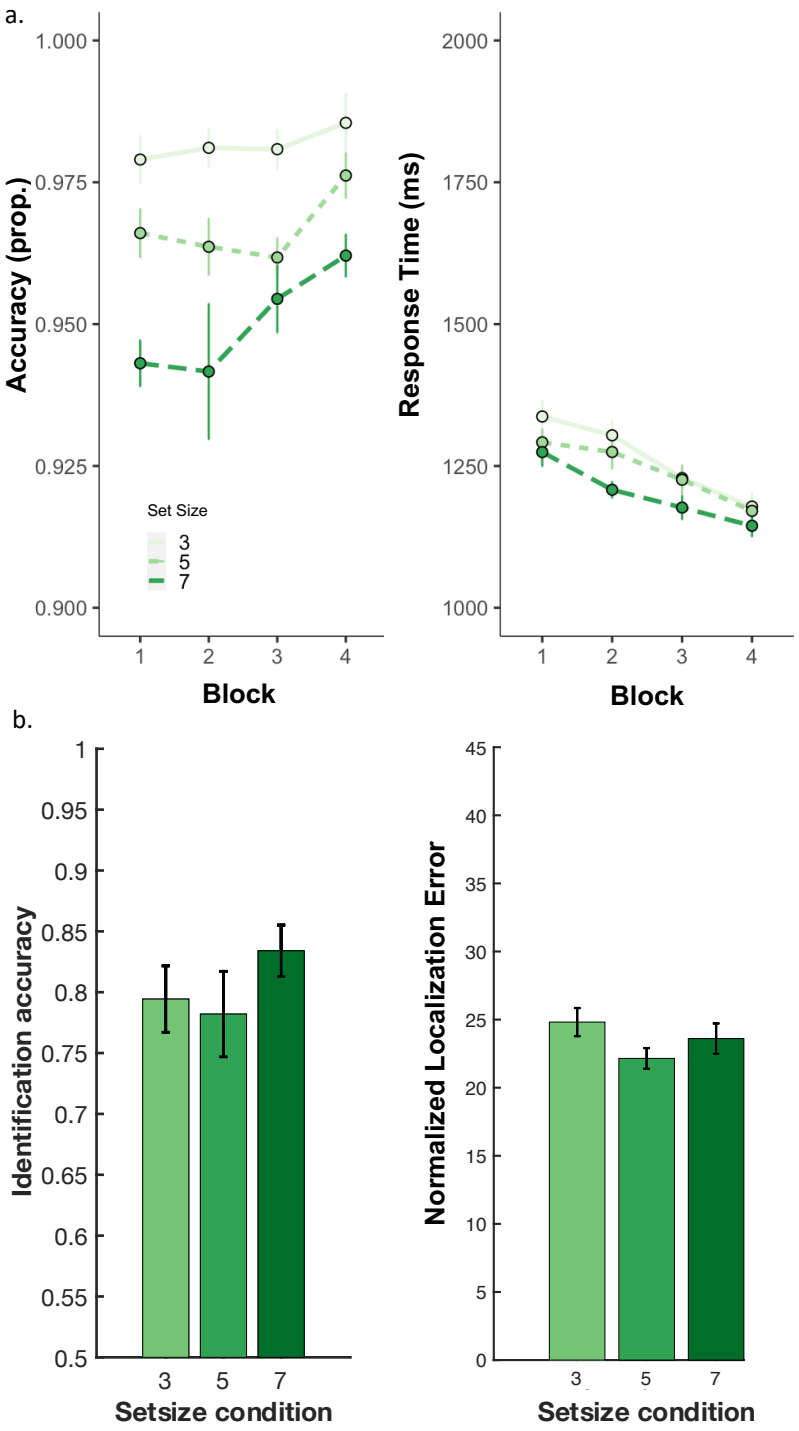
2.3.2.1.1 Search Accuracy. There was a main effect of Set Size ($F(1.2, 11.4) = 18.03$, $p = <.001$, $\eta^2_p = 0.12$, Figure 2.5a). However, there was no main effect of Block ($F(3, 57) = 2.41$, $p = .08$, $\eta^2_p = 0.02$) and no significant interaction between Block and Set Size ($F(6, 114) = 1.68$, $p = .13$, $\eta^2_p = 0.01$). Means for Set Size were 97% for 3 objects (SD = 9%), 96% for 5 objects (SD = 10%), and 94% for 7 objects (SD = 10%; Figure 2.5a). Tukey's HSD tests

were run to compare performance at the different set sizes. Participants were significantly more accurate on trials with a set size of 3 objects compared to 7 objects ($p < .001$) and on 5 object trials compared to 7 object trials ($p < .05$). However, there was no significant difference in performance between 3 and 5 object trials ($p = .10$).

2.3.2.1.1. Search Response Time. There was a main effect of Set Size ($F(1.34, 12.73) = 6.29$, $p = .01$, $\eta^2_p = 0.07$, Figure 2.5a) and Block ($F(2.1, 10.83) = 29.79$, $p < .001$, $\eta^2_p = 0.06$). However, there was no significant interaction between Block and Set Size ($F(3.80, 72.27) = 0.64$, $p = .69$, $\eta^2_p < .01$). Means for Set Size were 1262 ms for 3 objects ($SD = 452$), 1240 ms for 5 objects ($SD = 468$), and 1200 ms for 7 objects ($SD = 425$). Tukey HSD t-tests found no significant differences between response time at the different set sizes: Set Sizes 3 vs 5 ($p = .84$), Set Sizes 3 vs 7 ($p = .24$), and Set Sizes 5 vs 7 ($p = .54$). However, there was a significant difference in response time between Blocks 1 and 4 ($p < .05$). Means were 1301 ms for Block 1 ($SD = 396$) and 1164 ms for Block 4 ($SD = 408$).

Figure 2.5

Learning and Retrieval Performance in Experiment 2



Note. (a) Search accuracy and response time across the 4 blocks of the learning phase for trials with 3, 5 or 7 objects. Across Set Sizes, response times for the first object clicked

became faster as the Blocks progressed. (b) Identification accuracy and localisation error during explicit retrieval for trials in which the memory array had 3, 5, or 7 objects. No effect of set size on identification accuracy or localisation error was found. Error bars correspond to standard error.

2.3.2.2. Retrieval Results.

2.3.2.1.1. Target Identification. Response times and accuracy for object identification were examined during retrieval. To do so, separate ANOVAs were conducted with identification accuracy and response times for object identification as dependent variables and Set Size as a within-participants factor. During object identification, there was no effect of Set Size on response time ($F(2, 38) = 1.21$, $p = .31$, $\eta^2_p < .01$, Figure 2.5b) or accuracy ($F(2, 38) = 2.53$, $p = .09$, $\eta^2_p = .02$). Means for Set Size were 79% for 3 objects (SD = 8%), 78% for 5 objects (SD = 7%), and 83% for 7 objects (SD = 7%).

Due to the unexpected finding that Set Size had no significant effect on identification accuracy, I ran a subsequent Bayes Factor analysis to confirm whether the main effect of Set Size was insignificant. An estimated Bayes factor on Set Size (BF = .95) suggested that the data were 1:.95 (null x alternative) in favour of the null hypothesis, or rather, or 1.05 times more likely to occur under a model excluding an effect of Set Size, rather than a model including it. This result indicates that there is not strong evidence for or against an effect of Set Size on identification accuracy.

2.3.2.1.1. Localisation Error. Analysis of localisation errors revealed a main effect of Set Size ($F(2,38) = 3.72$, $p < .05$, $\eta^2_p = .07$, Figure 2.5b). Mean localization error by Set Size was 26.34 ($SD = 3.99$) for Set Size 3, 23.94 ($SD = 3.02$) for Set Size 5, and 24.92 ($SD = 3.93$)

for Set Size 7. However, Tukey HSD tests did not reveal any significant differences between levels of the Set Size variable (5 vs 3 objects: p = .14, 3 vs 7: p = .67, 3 vs 7: p = .54).

2.3.3. Conclusion

After Experiment 1, I hypothesized that, in younger adults, detrimental effects of set size on memory retrieval may only occur above 'working memory capacity'. Experiment 2 tested this hypothesis by examining participants' performance on object recognition and location recall tasks for scenes that were associated with 3, 5, or 7 objects during the learning task. In this online experiment, participants were effective at learning up to 7 object-scene associations over 4 blocks of learning (Figure 2.5a). Participants' search accuracy decreased as the set size increased, but this did not translate to deficits in retrieval performance. Also, in contrast to Experiment 1, there were no significant differences in response time at differing set sizes. One plausible explanation is that participants' response times for the first object clicked gained less advantage when set size was increased between 3 and 7 in Experiment 2 compared with 1 and 3 in Experiment 1. Alternatively, it is possible that this Experiment 2 was underpowered to detect this effect compared to Experiment 1. Both possibilities are also not mutually exclusive. Issues with statistical power are discussed in more detail in the Discussion section. Finally, as in Experiment 1, participants' object recognition and cued recall performance were not impacted by scaling within-episode competition (Figure 2.5b). Set size did have a significant effect on localisation error, however, the differences did not reach significance in group-level comparisons with Tukey HSD tests.

These findings contrast with assertions that there is a "limit" of four visual targets during the retrieval of visual LTM into working memory (Cowan, 2001; Fukuda & Vogel, 2019; Fukuda & Woodman, 2017). For example, In Fukuda & Woodman (2017) participants learned 4 spatial arrays composed of a segmented grey background with 1, 2, 4, or 8 coloured

squares overlaid in unique locations, which acted as “simplified scenes”. During a subsequent LTM retrieval task, where participants were cued on which array to recall (See Section 2.1 for more details on this study), participants’ retrieval performance dropped off sharply above a set size of 4 items. However, it is important to note that the grey background itself was identical between each of the scenes, therefore, it is likely that participants faced between-episode competition from identical backgrounds in addition to the within-episode competition from increased set size during retrieval. This raises the possibility that the more complex and unique real-world scenes used as backgrounds in my task may have contributed to participants' ability to recognize object identities and recollect their locations despite the increasing set size, e.g., because of an increased ability to pattern separate each of the object-scene associations (Bakker et al., 2008; Kirwan & Stark, 2007b; Rolls, 2013). Indeed, in these complex settings, young adults in my study were able to recognize objects and recall their locations of appearance from scenes associated with up to 7 objects. However, around the time my study was completed, results from a similar study suggested that another relevant factor may impact memory retrieval performance: encoding strength. In their study, Čepukaitytė et al. gave participants just one opportunity to learn object scene associations and found that in this circumstance there were detrimental effects of increasing set size on memory retrieval performance (2023). Therefore, in the final experiment of this chapter, I similarly reduced encoding opportunities to determine if reduced encoding strength would induce effects of set size on memory retrieval in young adults.

2.4. Experiment 3: Within-episode Competition after One-Shot Learning

The goal of this experiment was to determine whether detriments to LTM retrieval would scale with set size (within-episode competition) after only one exposure to object-scene associations. In Čepukaitytė et al., after only one opportunity to learn object-scene

associations, participants demonstrated effects of set size on memory performance during a subsequent explicit retrieval task (2023). In the study, participants completed a learning and retrieval segment very similar to that in Experiment 2. There were two critical differences: during the learning segment, participants were exposed to two different types of learning trials: a short-term memory (STM) trial and an encoding trial. During the STM trials, they were shown 1 or 3 objects in a scene for 5 seconds and, after an 8-second delay, they then had to identify the target vs. a novel lure and localize it in the scene (just like my explicit retrieval phase). In encoding trials, they were also shown 1 or 3 objects in a scene, but, after the delay, they only had to click a green arrow in the middle of the scene. Then, after a 20-minute delay, participants completed an explicit retrieval task that was identical to my design. In this explicit retrieval task, young adults performed worse at localizing targets from scenes that contained 3 objects during the learning compared to one object.

The key difference between Čepukaitytė et al. (2023) and Experiment 2 that I focused on was the number of exposures to the object-scene associations. In their study, participants only had one chance to learn these associations, whereas in my study they had four chances spread out throughout the learning task. I reasoned that the increased number of exposures in my study could have resulted in participants reaching their performance ceiling during the learning task, potentially precluding a decrease in long-term retrieval performance for scenes associated with a larger set of objects. Therefore, in my third and final experiment of this chapter, I decreased the number of learning blocks to one to investigate if reducing the number of encoding opportunities would unveil an effect of set size (within-episode competition) on long-term memory retrieval.

2.4.1. Methods

2.4.1.1. Participants. As in Experiments 1 and 2, participants were recruited on Gorilla following the same inclusion and exclusion criteria. Twenty-two data sets were collected in total. Following the same procedures from Experiment 1, two individuals were excluded from the analysis for not following the study instructions. For those included (12 females and 8 males), the average age was 23.64. Full demographics for this experiment are shown in Table 2.1.

2.4.1.2. Stimuli. Stimuli matched those in Experiment 2 in all aspects.

2.4.1.3. Procedure. Participants completed the entire experiment on the Gorilla platform (www.Gorilla.sc). After reading a description of the study, participants provided informed consent. Before starting the learning task, participants were familiarized with the task through a set of instructions, an example video, and a set of 10 practice trials using scenes and objects that do not occur in the main task.

2.4.1.3.1. Learning Task. The learning portion of the task was identical to Experiment 2, but participants completed only one block of learning.

2.4.1.3.2. Retrieval Task. The explicit retrieval task was identical to that used in Experiment 2.

2.4.1.4. Data Analysis. Procedures for analysis followed Experiments 1.

2.4.1.4.2. Learning Task. Two separate ANOVAs were performed with accuracy and response time for the first clicked object as the dependent factors and set size as a within-participants factor. Based on the Box-Cox lambda, I applied an inverse square-root transformation to response times to approximate the normal distribution and to meet ANOVA assumptions. Trials in which response times were shorter or longer than 2 standard deviations from the participant-specific mean across all conditions were excluded from analysis (~4.8% of trials).

2.4.1.4.3. Retrieval Task. Object identification accuracy, response times, and localisation error were used to examine explicit retrieval performance for learned object-scene associations. To do so, separate ANOVAs were conducted with identification accuracy, identification response times, and localisation error as dependent variables and set size as within-participants factors. Responses that were shorter or longer than 2 standard deviations from the participant-specific mean were excluded from analysis (~4.4% of trials). Based on the Box-Cox lambda, I applied an inverse square-root transformation to the identification response time data. Also, only trials in which participants correctly clicked the target during the learning block were included in the retrieval analysis. Based on the Box-Cox lambda, a square root transformation was conducted on the localisation error data.

2.4.2. Results

2.4.2.1. Learning Results.

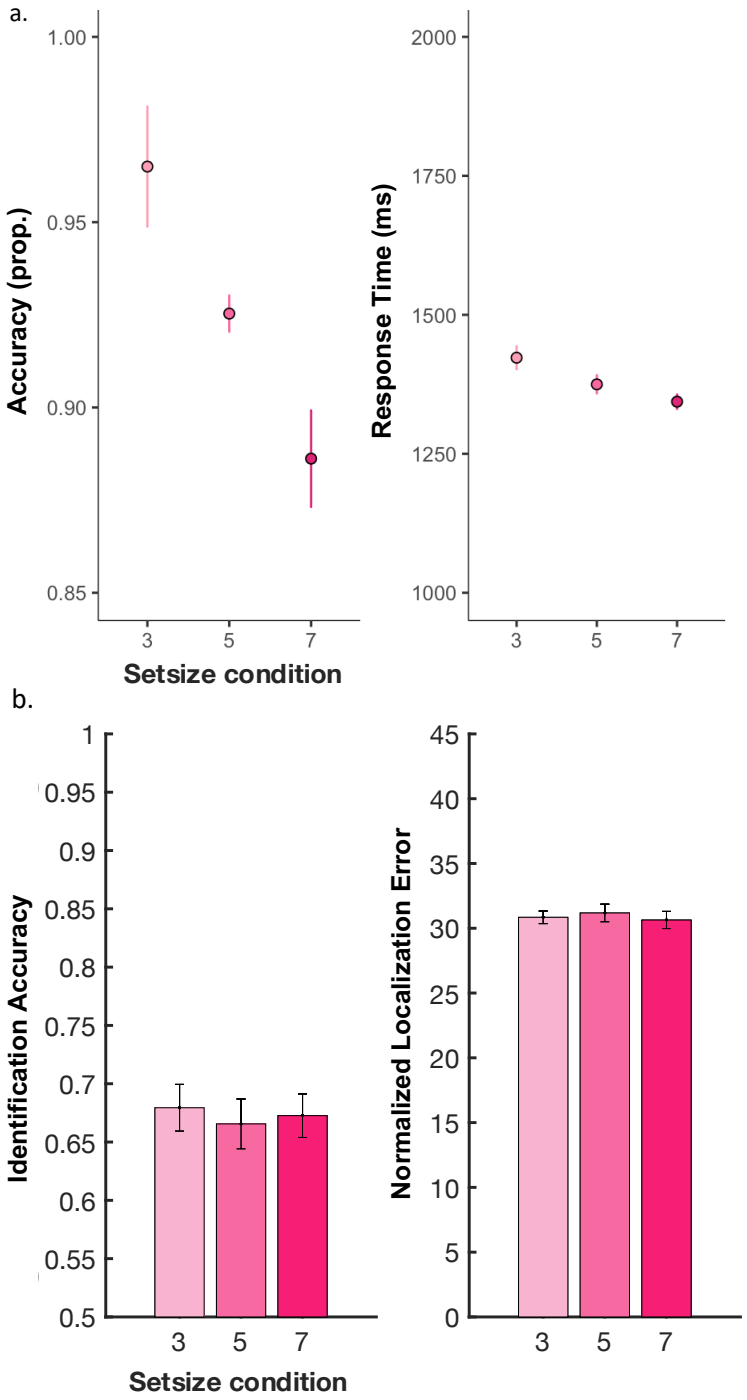
2.4.2.1.1. Search Accuracy. There was a main effect of Set Size ($F(1.14, 21.71) = 9.11$, $p < .01$, $\eta^2_p = 0.13$, Figure 2.6a). Means for Set Size were 96% for 3 objects (SD = .11), 92% for 5 objects (SD = .14), and 88% for 7 objects (SD = .16). Tukey's HSD tests were run to compare performance at the different set sizes. Participants were significantly more

accurate on trials with a set size of 3 objects compared to 7 objects (p <.001). However, there was no significant difference in performance between 5 object trials compared to 7 object trials (p = .28) or between 3 and 5 object trials (p = .29). Therefore, participants' learning accuracy decreased from the lowest to the highest set size.

2.4.2.1.2. Search Response Time. There was a main effect of Set Size ($F(2, 38) = 7.18$, $p < .01$, $\eta^2_p = 0.02$, Figure 2.6a). Means for Set Size were 1422 ms for 1 object ($SD = 431$), 1374 ms for 5 objects ($SD = 444$), and 1343 ms for 7 objects ($SD = 398$). Tukey HSD tests found no significant differences when compared response times at the difference set sizes: 5 versus 3 objects ($p = .68$), 7 versus 3 objects ($p = .71$), and 7 versus 5 objects ($p = 1$).

Figure 2.6

Learning and Retrieval Performance in Experiment 3



Note. (a) Search accuracy and response time over one block of the learning phase for trials with 3, 5, or 7 objects. Participants accuracy significantly decreased at higher set sizes. (b)

Identification accuracy and localisation error during explicit retrieval for trials in which the memory array had 3, 5, or 7 objects. No effect of set size on identification accuracy or localisation error was found. Error bars correspond to standard error of the mean.

2.4.2.2. Retrieval Results.

2.4.2.2.1. Target Identification. Response times and accuracy for object identification were examined during retrieval. Separate ANOVAs were conducted with identification accuracy and response times for object identification as dependent variables and Set Size as a within-participants factor. There was no effect of Set Size on response time ($F(2, 38) = 1.57$, $p = .22$, $\eta^2_p < .01$, Figure 2.6b) or accuracy ($F(2, 38) = 0.20$, $p = .82$, $\eta^2_p < .01$) for object identification. Means for Set Size were 68% for 3 objects (SD = 7%), 67% for 5 objects (SD = 9%), and 67% for 7 objects (SD = 10%).

Due to the finding that Set Size had no significant effect on localisation error, I ran a subsequent Bayes Factor analysis to confirm whether the main effect of Set Size was insignificant. First, I estimated a Bayes factor using Bayesian Information Criteria (Wagenmakers, 2007), comparing the fit of the data under the null hypothesis and the alternative hypothesis. An estimated Bayes factor on Set Size (BF = .16) suggested that the data were 1:16 (null x alternative) in favour of the null hypothesis, or 6.25 times more likely to occur under a model excluding an effect of Set Size, rather than a model including it. This result indicates strong evidence that the main effect of Set Size was insignificant.

2.4.2.2.2. Localisation Error. Analysis of localisation errors revealed no main effect of Set Size ($F(2,38) = .007$, $p = .99$, $\eta^2_p = .00013$, Figure 2.6b). Mean localization error by

Set Size was 31.17 (*SD* = 2.12) for Set Size 3, 31.86 (*SD* = 4.03) for Set Size 5, and 31.71 (*SD* = 2.92) for Set Size 7.

An estimated Bayes factor on Set Size (BF = .13) suggested that the data were 1:.13 (null x alternative) in favour of the null hypothesis, or 7.69 times more likely to occur under a model excluding an effect of set size, rather than a model including it. This result indicates strong evidence that the main effect of Set Size was insignificant.

2.4.2.3. Comparing Retrieval Performance between Experiments. I ran independent samples t-tests to compare performance on object recognition and location recall between Experiments 1, 2 and 3. These analyses were run to investigate whether participants' performance was generally impacted by the experiment-experiment design changes such as increasing the total number of objects they had to learn via increasing set size (Experiment 2) or reducing the number of encoding opportunities (Experiment 3).To run these analyses, within each experiment, performance was collapsed across the set sizes to create averages for recognition and recall. In Experiment 1, performance was also collapsed between the in-lab and online experiments, and across the different lure conditions.

2.4.2.3.1. Target Identification. I ran independent samples t-tests to compare performance on object recognition between each of the Experiments. When collapsed across set sizes, Mean accuracy was 76% (*SD* = 4%) in Experiment 1, 81% in Experiment 2 (*SD* = 4%), and 67% in Experiment 3 (*SD* = 5%). Object identification accuracy was overall worse in Experiment 3 than in Experiment 2 ($t(36.43) = 3.35$, $p < .001$, Cohen's $D = 1.09$) and Experiment 1 ($t(30.76) = 2.56$, $p < .05$, Cohen's $D = .77$). There was no significant difference in object identification accuracy between Experiments 1 and 2 ($t(36.62) = 1.42$, $p = .16$, Cohen's $D = .40$).

2.4.2.3.2. Localisation Error. I ran independent samples t-tests to compare performance on location recall between each of the Experiments. Mean normalized localisation error was 22.3 in Experiment 1 (*SD* = 17.2), 24.83 in Experiment 2 (*SD* = 17.02), and 31.75 in Experiment 3 (*SD* = 16.74). Location recall performance was also overall worse in Experiment 3 than in Experiment 2 ($t(37.96) = 5.41$, $p < .001$, Cohen's $D = 1.75$) and Experiment 1 ($t(52.89) = 7.39$, $p < .001$, Cohen's $D = 1.81$). Performance was also worse in Experiment 2 than in Experiment 1 ($t(51.88) = 2.01$, $p < .05$, Cohen's $D = .50$).

2.4.3. Conclusion

In Experiment 3, though participants had only one chance to learn the object-scene associations, they showed no significant differences in their explicit retrieval ability at different set sizes. Participants were able to learn up to 7 items at high accuracy, though their search accuracy suffered as the set size increased (Figure 2.6a). Also, similar to Experiment 2, but in contrast to Experiment 1, there were no differences in response time at the different et sizes despite a main effect of set size. Once again, this finding points to either a weaker effect of manipulating higher set sizes (i.e., 3-7, rather than 1-3) on response time, or that the experiment itself was underpowered for this effect to come out. However, any detriments to learning accuracy did not translate to deficits at higher set sizes during explicit retrieval (Figure 2.6a). Therefore, the findings of this experiment did not replicate Čepukaitytė et al.'s finding that, after only opportunity to learn object-scene associations, there is a decrease in LTM retrieval performance at higher set sizes (2023). The discussion section considers this discrepancy in findings further by analysing the differences between the studies in greater detail. My alternative hypothesis, that the effects of increasing set size on retrieval performance are exacerbated by ageing, is also considered.

When comparing overall retrieval performance between the different experiments, participants performed overall worse in Experiment 3 than in Experiments 1 and 2. This pattern was matched for identification accuracy (object recognition) and cued recall (location recollection). Therefore, though reducing the number of opportunities that participants had to encode the objects did not lead to retrieval deficits that scaled with memory set size, overall retrieval performance was negatively impacted by fewer chances to make object-scene associations. There was also some evidence that participants performed worse at location recall on Experiment 2 compared to Experiment 1. Therefore, it is possible that increasing the total number of objects participants had to learn reduced their ability to remember specific object locations, even if this performance impediment did not scale with set size. This finding will also be discussed in more detail in the discussion section.

2.5. Discussion

Across three experiments, participants searched for a varying number of objects (set size) associated with scenes. Surprisingly, when tested on their ability to retrieve object identities and locations from memory, participants' performance did not diminish as a function of increasing within-episode competition (i.e., set size). This result was consistent regardless of whether set size was scaled below visual working memory 'capacity' (Experiment 1), above this 'capacity' (Experiment 2), or when participants were only given one opportunity to encode object-scene associations (Experiment 3). These results indicated that healthy, young adults can consistently recognize the identity and recall the location of an object, regardless of variations in the number of other objects that were associated with the same scene during learning. In the following section, I consider possible explanations for why these findings did not replicate others' results showing that increasing set size reduces LTM retrieval performance (Čepukaitytė et al., 2023; Fukuda & Woodman, 2017; Sohn et al.,

2003; Zokaei et al., 2019). Despite no evidence for effects of within-episode competition, between-episode competition reduced participants' performance on recognition memory trials when lures were learned (i.e., same or different location lures) versus novel. However, there was no significant difference in retrieval performance when probing lures from the same location as the target in other scenes as opposed to from a different location. Finally, results from participants who completed the study online (in Experiment 1) did not differ from results for participants tested in a controlled laboratory setting. This result provides additional evidence in favour of using online testing as a method to obtain data sets for behavioural tasks that have long runs times, such as learning over multiple blocks for long-term memory tests.

In the Experiments contained in this Chapter, I developed a task that promoted learning of varying numbers of objects embedded in scenes. This simple design allowed for careful manipulation of learning and retrieval conditions, such as the number of objects in the scenes (within-episode competition), the number of learning blocks (encoding opportunities), and the degree to which probed targets overlapped spatially with lures during LTM retrieval (between-episode competition). Measuring these factors in a single task allowed for assessing their independent and joint effects on retrieval performance. For example, at a set size of 1, there was no within-episode competition, so only the independent effects of between-episode competition impacted retrieval performance. Also, when assessing memory for targets compared to novel lures, there was no between-episode competition, so the effects of within-episode competition could be assessed independently. Alternatively, at set sizes higher than 1, the joint effects of within-episode competition from increased set size and between-episode competition from same- and different-location lures could be measured. It was also possible that within and between-episode competition would modulate each other’s effects on memory retrieval. For example, with higher set size, the likelihood increased that different location

lures occurred in the same location as one of the distractors from the current scene (a distractor would be another object that was paired with the current probed scene during learning but is not the retrieval target). However, in the groups of young adults who were tested, few of the manipulations to the learning task impacted participants' performance during explicit retrieval via independent or joint effects.

During the explicit retrieval task, participants' memory for the object-scene associations was measured for both object recognition and cued location recall. Participants' object recognition performance was not impacted by scaling the extent to which the targets' screen coordinates overlapped with lures from different scenes. Notably, other studies which have found effects of scaling between-episode competition on retrieval performance have manipulated the extent to which the scenes themselves overlapped between trials (Chanales et al., 2017). Alternatively, in my study, regardless of whether lures were from the same or different coordinates as the target, the scenes the lures appeared in were completely different from the target scene. Therefore, scene-based overlap may interfere more with memory retrieval than screen-based overlap (i.e., overlap based on screen coordinates). However, in Experiment 1 some effects of between-episode competition were evident based on whether lures were learned (i.e., either same or different location lures) or novel. Namely, participants performed worse at object recognition when same or different location lures competed with the target for retrieval compared to novel lures, which did not induce any between-episode competition. In the novel lure condition, participants were likely able to identify the novel lure as non-familiar, indicating that the other object was the target (Migo et al., 2012). Therefore, though participants object recognition memory was not modulated by the extent of screen-based overlap between the target and the lure from a different scene, the task of recognizing a target as belonging with the presented scene was generally made more difficult when a target from a different scene was presented as a lure due to between-episode

competition (Reagh & Yassa, 2014). However, these differences in performance based on lure novelty did not translate to differences in memory recall performance.

To assess memory recall, participants were asked to click the locations they remembered the target occurring within the associated scene. Calculating the resulting localisation error from the actual target location gave a continuous measure of participants' memory performance. This localisation error metric allowed for tracking how well participants remembered the target locations, rather than simply their ability to recognize the objects (which object is old or new) as in past studies (Čepukaitytė et al., 2023; Schurgin, 2018; Zokaei et al., 2019). However, other than in Experiment 1 where between-episode competition impacted object recognition but not recall, there were no significant differences in the pattern of effects when assessing participants' object recognition versus their recall. In Experiment 1, participants' increased accuracy at recognizing the target object did not translate to higher precision in localizing the target within the scene. It is possible that these results are related to differences in the processes involves in object recognition versus recall. Specifically, object recognition has been argued to be primarily a process driven by familiarity (Aggleton & Shaw, 1996; Bastin & Linden, 2003; Parkin et al., 1994), with varying extents to which recollection is involved based on the task (Cook et al., 2005; Sheridan & Reingold, 2012), whereas cued recall primarily involves recollection (Migo et al., 2012). Therefore, though there is some evidence that between-episode competition impacted participants' familiarity memory via differences in their ability to recognize objects as old or new (novel), there is less evidence that between-episode or within-episode competition significantly impacted participants' recollection memory in any of the experiments.

My results contrast with current reports regarding capacity limits on LTM retrieval into working memory. Modal models of LTM retrieval suggest that the capacity limit on WM (~3-4 objects) should also apply to LTM, as LTM retrieval occurs via retrieval into working

memory (Atkinson & Shiffrin, 1968; Cowan, 2001; Brady et al., 2013; Fukuda & Vogel, 2019; Fukuda & Woodman, 2017; Shiffrin & Atkinson, 1969). However, in my task, participants were able to remember objects from scenes associated with up to seven objects with no detriments compared to scenes associated with 3 objects or fewer. Notably, in my experiment, each of the learned scenes was a unique outdoor photograph, whereas in other studies on the relationship between set size and memory retrieval, participants have learned to associate objects with contexts that share overlapping components (Fukuda & Woodman, 2017). This contextual overlap likely induced between-episode competition for memory retrieval (Chanales et al., 2017), calling into question whether the reported detrimental effects of set size on memory retrieval were modulated by between-episode competition. However, in Čepukaitytė et al. (2023), young adults demonstrated reduced memory retrieval performance at higher set sizes, independent of between-episode competition. To investigate whether I could replicate this result, I altered a significant aspect of my study design to match theirs: number of encoding opportunities.

I hypothesized that effects of set size on LTM retrieval performance might be related to the number of encoding opportunities. There is a longstanding concept that retrieval failure, i.e. the inability to reproduce a memorized item, can stem from two sources: storage strength (how well an item was learned) and retrieval strength (how well an item can currently be accessed; Bjork & Bjork, 1992). Recent evidence suggests that memory retrieval performance in visual LTM is dependent on the former, storage strength. For example, increasing the number of encoding opportunities (one metric for storage strength) has been shown to increase retrieval performance (Fukuda & Vogel, 2019; Reagh & Yassa, 2014; Schurgin & Flombaum, 2018a). In their recent study, Čepukaitytė et al. (2023) demonstrated that after only one opportunity to associate either 1 or 3 objects with a naturalistic scene, young adults' abilities to retrieve the location of targets in the 3 objects condition were

impaired. Therefore, in Experiment 3, I manipulated storage strength by reducing the number of opportunities for participants to encode object-scene associations to just one block of learning. In line with other findings, reducing the number of exposures to the object-scene associations did decrease overall retrieval performance (Fukuda & Vogel, 2019; Reagh & Yassa). However, in contrast to Čepukaitytė et al., retrieval performance still did not scale with set size.

Another possible explanation for the lack of an effect of set size on LTM performance in my study is the relationship between the duration of exposure to individual objects in a set and retrieval performance. In my study, although the set size increased without a corresponding increase in available search time, participants could continue to the next trial whenever they had found all the objects. Therefore, if they had 1 target and found it in 1.5 s, they could continue immediately, making their search time 1.5 s. Alternatively, if they had 3 targets and found them in 4.5 s, then continued, that would still make the per object search time still roughly 1.5 s. Indeed, for trials with a set size of 3 objects, mean response times for the first object clicked were 1412 ms, then it took an additional 1192 ms to find the second object, and 1113 ms for the third, making total search time 3717 ms on average. Therefore, though search times for each object were not exactly proportional, they did not differ drastically with increased set size. Alternatively, in Čepukaitytė et al. (2023), participants had 5 s to encode the targets during the learning task but could not end the trial early when they found all the targets. They argued that the reduced time per object in the 3-object condition compared to the 1-object condition may have caused the reduced retrieval performance in the former, i.e., the 5 seconds would have been split by 3 in the 3-object condition (~1.6s per object), but, in the 1 object condition, they could attend to the single object for the entire duration (5s). This assertion is supported by evidence that increased fixation time on objects in naturalistic scenes relates positively to retrieval performance (Hannula et al., 2010;

Hollingworth & Henderson, 2002; Ryan & Shen, 2020; Schwedes & Wentura, 2016). Though it is likely that fixing the encoding windows in the same manner as Čepukaitytė et al. would have led to set size effects on LTM retrieval, this would have been because objects at higher set sizes would not have been encoded as well due to a shorter fixation duration, i.e., confounding the effects of within-episode competition. The same principle applies to the initial 'familiarization' window when participants first saw the objects and could take as much time as they needed to familiarize themselves with the objects. In this set of studies, I was more interested in investigating whether, after similar encoding strength between conditions (e.g., all objects in recall analysis were clicked on the final block of learning and a similar amount of time was spent initially viewing or searching for each object), does increasing the number of objects associated with a given memory episode lead to memory retrieval deficits? Over three studies, my results repeatedly showed that young adults' memory retrieval is not impacted by increasing within-episode competition in unique and complex object-scene associations.

Healthy, young individuals are uniquely equipped to handle the sort of memory challenges imposed by my task: resolving competition within and between memories (Hardt et al., 2013b; Jeneson et al., 2011). These tasks may prove more difficult in older age groups. For example, in a task nearly identical to Experiment 2, healthy, older adults showed an increase in localisation error with a rise from only 1 to 2 objects in memory (Zokaei et al., 2019). Further, age-matched, healthy, APOE ε4 carriers (the most common and highest risk genetic phenotype for Alzheimer's disease (AD)) showed worse overall retrieval performance and higher set size effects than ε3 carriers (less risk for AD development; Winblad et al., 2016; Zokaei et al.,). Given evidence that the ability to resolve competition between memories (pattern separation) decreases in function with age and with risk for or onset of dementia (Dillon et al., 2017; Hardt et al., 2013b; Jeneson et al., 2011; Xu et al., 2008; Yassa

et al., 2011), effects of set size on long-term memory may be easier to measure in older or clinical groups as in Zokaei et al.. Accordingly, the lack of effects of set size on LTM performance may have been related to using a young and healthy participant group in which the ability to pattern separate items within and across memories was intact. In my studies, further analysis was not run on age (e.g, including age as a factor or covariate), as all participants were within the limits of the "young" group (19 to 39 years old) from a similar study which found an effect of set size on memory retrieval performance (Čepukaitytė et al., 2023). Specifically, as shown in Table 2.1, mean age was 25 (*SD* = 5) in Experiment 1, 22 in Exp. 2 (*SD* = 3), and 24 in Exp 3 (*SD* = 4), indicating that the majority of participants were on the younger end of the "young" group. Therefore, even if there were effects of set size on retrieval performance in my study, there would be little reason to assume that these effects would be related to age. Finally, subsequent work targeted at better understanding competition within and between memories at the behavioural and neural level is an important route towards better understanding memory impairments related to aging, or the onset of AD, and may aid with therapeutic targets such as the development of cognitive training exercises (Coughlan et al., 2019; Coutrot et al., 2019).

In the introduction to this thesis, I outlined the importance of scene semantics to associative learning and memory processes and covered some of the consequences of semantic congruency versus incongruency. Notably, in the experiments of this Chapter, each of the unique object-scene pairs was semantically incongruent, meaning that objects neither matched the scenes nor occurred in predictable locations. This design choice likely impacted participants' ability to learn the object-scene pairings as they could not use semantic guidance to initially find the objects, increasing their reliance on memory during learning (Võ & Wolfe, 2013). Also, a lack of semantic guidance likely made location recall more difficult (Draschkow et al., 2014; Spotorno et al., 2015), as rather than objects occurring in predictable

locations, they could have occurred anywhere within the scenes. The experiments were designed in this way to increase participants' reliance on memory during both the learning and memory retrieval tasks. Otherwise, if scenes and objects were semantically congruent during the memory retrieval task, it is possible that participants would have responded with locations where they expected objects might naturally occur (i.e., semantic memory guidance), as opposed to attempting to recollect where the objects actually occurred. Using semantic guidance would therefore have bypassed the use of memory, negating any potential effects of set size during retrieval.

Additional considerations that reinforced this design choice included the need for clearly differentiable scenes and objects. There were up to 90 separate scenes in the learning task, with up to 450 unique objects (Experiment 2) spread throughout the different scenes. Utilizing this sheer number of object-scene combinations while maintaining uniqueness would have been impossible if semantically congruence was enforced. Alternatively, if I sacrificed uniqueness, the degree of between-scene similarity would have increased. This may have contributed to a stronger effect of set-size on retrieval performance, as in Fukuda & Vogel, where the contextual backgrounds were identical between trials (2017). However, my primary goal was to explore the relationship between the objects and the scenes as opposed to the relationship between the scenes themselves, which would likely have been altered if the scenes were more similar. The downside to using semantically incongruent scenes and objects is that the ecological validity of my experiments was drastically reduced. This lack of ecological validity should be taken into account when interpreting these results. For example, it would be difficult to find a real-world environment with such a diversity of objects, that do not occur in similar locations, and that may take up a large swath of the space (up to 4.5% of the scene in the 7 objects condition). Subsequent research could systematically manipulate the diversity of objects and contexts to determine if in fact increased diversity may increase

our ability to recognize objects and remember their locations of occurrence. It would also be interesting to consider the reverse possibility: that decreased diversity may induce greater effects of set size on memory retrieval performance due to a reduced ability to pattern separate object-scene associations.

Another possible limitation to interpreting the results from the studies contained in this chapter is evidence showing that there was a lack of statistical power to detect certain effects. For example, for several measures (e.g., Experiment 2, response time), the main effect of set size was significant, but many or all of the pairwise comparisons between levels of the factors did not come out significant. Though it is possible that some of the effects themselves were weaker due to experimental manipulations, e.g., response time for the first clicked object gains less benefit from increases at higher (i.e., 3-7) versus lower set sizes (i.e., 1-3), it is also likely that Experiments 2 and 3 were underpowered to detect this effect. Future experiments that may wish to replicate or extend my results should therefore consider that, in particular, the latter studies of this chapter appeared to lack statistical power and alter their designs accordingly.

Finally, the tasks developed here provided valuable experience and proof of concept for using online testing to assess the relationship between different learning conditions and subsequent measures of behaviour. Though its interpretation is limited by lack of replication, finding that performance was similar in my first experiment between online and in-lab groups provided evidence in favour of the continued use of online testing for my subsequent studies. This evidence is aligned with assertions that, despite potential higher drop-out rates, increased at-home distractions, and more variable response times, with careful design (e.g., pictorial instructions and practice trials) online data collection is a viable method for behavioural testing (Sauter et al., 2020). I also gained a wealth of experience by building an online experiment from scratch using Gorilla. This process involved many difficulties such as

the requirement for learning how to interact with the Gorilla GUI, needing to code condition tables in Matlab to be fed into Gorilla, and learning/interacting with Gorilla's programming language: TypeScript. These difficulties were a major motivating factor for moving my experiment building to Psychopy in the ensuing chapters in my thesis. I also gained additional experience in experiment design by designing the learning and recall tasks, as well as the instructions, which needed to be extremely clear because online participants cannot ask the experimenter questions. Together, this knowledge was instrumental in improving the design quality of the subsequent studies in this thesis.

Chapter 3. Comparing how Contextual and Probabilistic Learning Guide Attentional Orienting and Memory Recall.

Abstract

During visual search, we quickly learn to attend to an object's probable location. Research has shown that this process is facilitated when learning of target locations is based on spatial contextual associations or probabilistic regularities. Here, I tested how these different types of learning aid the utilisation of established memories. In three online experiments, participants learned contextual and probabilistic associations between targets and unique real-world scenes. Next, the consequences of this learning were evaluated on performance in attentional orienting and memory-retrieval tasks. Participants demonstrated facilitated orienting and recall performance in both contextual and probabilistic association trials, confirming these associations can serve different behavioural purposes. However, for memory retrieval specifically, enhanced performance was most evident when learned associations aligned well with subsequent task demands. Therefore, whereas attentional orienting was generally facilitated by both associative learning conditions, memory retrieval performance was influenced by the congruency between learned associations and subsequent behavioural tests. These different patterns of facilitation between contextual and probabilistic associations may suggest functional differences between how these types of learning facilitate attentional orienting versus memory recall.

3.1. Introduction

In Chapter 1, I reviewed how long-term memories supporting visual search come in different flavours and are supported by different brain systems (Goldfarb et al., 2016; Henke,

2010). We use these systems dynamically and adaptively in our daily lives. For example, when moving to a new town, we might slowly learn that most restaurants are on one side of the main road. Then, when seeking somewhere to eat, we might find ourselves orienting to that side as *probabilistic* associations guide our attention (Jiang, 2018; Salovich et al., 2018). These gradually forming, regularity-based, memories have been linked to striatal brain function (Delgado et al., 2005; M. J. Frank, 2005; Knowlton et al., 1996; Packard & McGaugh, 1996). Alternatively, the surrounding buildings and visual scenery may activate representations which guide our attention to a specific restaurant sign (Chun & Phelps, 1999; Goujon et al., 2015; Jiang & Chun, 2001). These fast-forming, spatial *contextual* memories are thought to be supported by the hippocampus and related medial temporal structures (Ferbinteanu, 2016; Moody et al., 2004). How such probabilistic and contextual representations are formed and subsequently used to support visual search, memory recall, and attentional orienting has primarily been studied separately.

In contextual-learning tasks, a specific context guides visual search. For example, participants learn that the location of a target is associated with a particular stimulus configuration or scene identity. This contextual information can guide visual search in simple stimulus arrays (Chun & Jiang, 1998; Goujon et al., 2015; Harris & Remington, 2017; Jiang & Sisk, 2019). In the standard version of these paradigms (Chun & Jiang), participants are instructed to search for a target (e.g., the letter 'T') within a configuration of visually similar distractors (e.g., the letter 'L'). Half the configurations are repeated across many blocks of trials, while the others are presented only once during the task (novel). A benefit to search times, termed contextual cueing, is typically observed in the repeated contexts compared to the novel contexts. The dominant interpretation is that this search benefit is driven by learning of associations between a specific spatial context and target locations, e.g., a specific configuration of L's will guide attention to the location of the T. Notably, across all trials, no

region of space is more likely to contain the search target (Goujon, 2015; Jiang, 2018). Other metrics have also been used to measure contextual cueing, such as the number of fixations to find the target in repeated displays. A reduction in the average number of fixations required to find the target has been used to argue that the primary factor behind contextual cueing is improved attentional guidance (Harris & Remington, 2017). Interestingly, there is also evidence that the contextual cueing effect is acquired faster in real-world scenes compared to the classic T/L arrays described above (Brockmole & Henderson, 2006; Chun & Jiang; Harris & Remington, 2017). Further, new evidence has supported that contextual cueing also facilitates search in immersive virtual and real environments (Beitner et al., 2021; Draschkow et al., 2022).

Extending findings from the contextual-cueing literature, many studies in recent years have investigated how contextually learned associations can proactively guide attentional orienting in the service of scene-based perception (Doallo et al., 2013; Patai et al., 2012; Rosen et al., 2016; Stokes et al., 2012; Summerfield et al., 2011). In their landmark study, Summerfield et al. (2006) employed a modified version of the contextual-cueing task in which participants learned contextual associations via searching through scenes (i.e., real world photographs) for a small key that occurred in repeating locations within given scenes. One day later, participants completed two orienting tasks in counterbalanced order. In the memory-orienting task they viewed scenes from the learning task, whereas in the visual-orienting task they viewed novel scenes. Their task was to detect the brief appearance of the key in predictable (valid) or unpredictable (neutral) locations. In memory-orienting trials, the target key could appear at the learned location (valid) or at an unlearned location in studied scenes that previously contained no target key (neutral). In visual-orienting trials, the target key could appear just after a peripheral visual cue (a white box) captured attention to its location (valid) or after a central visual cue that offered no spatial information (neutral).

Performance in these tasks was significantly enhanced by either memory or perceptual cues. This demonstrated that contextual learning proactively guides spatial attention orienting. Further, they showed that memory-guided spatial orienting engaged the parietal-frontal network as well as the hippocampus. Interestingly, when comparing valid to neutral trials, the hippocampus was more significantly activated in memory-guided compared to visually guided spatial orienting. Following this work's important contributions, further progress has been made toward understanding how contextual learning can facilitate memory retrieval of target identity and location in healthy (Draschkow et al., 2014; Guevara Pinto et al., 2020; Helbing et al., 2020; Josephs et al., 2016) and at-risk populations (Salvato, Patai, McCloud, et al., 2016; Zokaei, Čepukaitytė, et al., 2019).

Representations acquired through probabilistic learning can also guide visual search (Jiang, 2018; Seger, 2018). As in contextual cueing, T-among-L tasks are often used to elicit learning of probabilistic associations. In these tasks, again, participants must search for the T among an array of Ls. Participants initially show no locational preference, then become faster at locating the T in a high-probability region, whether it is a specific half (Geng & Behrmann, 2002), quadrant (Jiang et al., 2013; Salovich et al., 2018), or hotspot (Druker & Anderson, 2010) of the visual display. This generalisable probabilistic information can facilitate visual search as a "probability cueing" effect. Probability cueing has been characterised as "habitual". Habits are typically learned gradually and implicitly, with persistent effects on behaviour (Graybiel, 2008; Seger & Spiering, 2011). For example, in Jiang et al.'s study (2013), the target was initially more frequently located in the upper left quadrant for 192 trials. But, after switching the more frequent location to the lower right quadrant for the subsequent 192 trials, the attentional bias remained in the originally learned quadrant. Further, the now uninformative bias interfered with the learning of the new spatial bias, demonstrating the persistent and habitual nature of probabilistic learning. Alternatively, in

Salovich et al.'s study (2018), participants began with a typical T-among-L task. Then, after learning the target's preferred quadrant of appearance, the task switched to a naturalistic scene search task where participants searched for arrows that appeared in equal distribution between quadrants. In this new context, the attentional bias persisted, resulting in faster search times in the quadrant that formerly had high target probabilities in the T-among-L task. Importantly, whereas the T-among-L task requires discrimination among readily identifiable stimuli against a plain background, scene search places high demands on perceptually segmenting the target from the background. Even so, probabilistic learning transferred to novel naturalistic settings (Salovich et al.), resulting in a persistent attentional bias. Only recently has research directly addressed whether attentional learning is habitual, most commonly through the simple probabilistic learning designs described above (Seger). Therefore, unlike in contextual learning, there is a paucity of literature on the consequences of probabilistic learning for subsequent memory-guided attention tasks (Goldfarb et al., 2016; Jiang, 2018).

Contextual and probabilistic learning have been associated with the hippocampus and striatum, respectively, using a variety of experimental tasks and methodologies (for review see Henke, 2010; Packard & Goodman, 2013; Voss et al., 2020). For example, animal models have employed plus-maze navigation tasks, where rewards can be received for effective use of striatal stimulus-response learning (reviewed in the introduction) or hippocampal contextual (place) learning (Ferbinteanu, 2016; Packard and McGaugh, 1996; Poldrack & Packard, 2003). In humans, most studies have investigated non-attentional or non-spatial factors such as probabilistic classification (Knowlton et al., 1996; Moody et al., 2005), object-face associations (Wang and Voss, 2014), or feedback reliability (Mattfeld & Stark, 2015, 2010). For example, in their study, Mattfeld and Stark (2015) demonstrated that whereas striatal activity scales with the strength of memory association under probabilistic

(incompletely reliable) feedback conditions, hippocampal activity does so under deterministic (completely reliable) conditions. However, the general principles and specifics of how these two systems fit together seamlessly and flexibly to guide learning, memory, attention and perception in the complex natural world remain poorly understood (Ferbinteanu 2016, 2018; Packard & Goodman, 2013; Nobre, 2019). Further, due to differences in methodologies used to study probabilistic and contextual associations, direct comparisons of their behavioural consequences and neural correlates are rare.

Noting this gap in research, Goldfarb et al. (2016) investigated how different types of memory cues guide attention, hypothesising that changing the type of cue can change the memory system that guides attention. Specifically, they measured visual search performance for targets abiding by either probabilistic or contextual regularities. In their task, contextual trials placed the T in a specific location amongst a configuration of Ls, whereas in probabilistic trials the colour of the stimulus array cued the quadrant containing the target and the required button press with 80% validity (20% of the time the button press and quadrant were invalid). Results demonstrated a learning benefit by both types of association as measured by decreasing response times over the course of the learning task in comparison to neutral trials that had no mnemonic cue. Additionally, brain imaging suggested the effects were supported by distinct neural systems. Trial-evoked blood oxygenation level dependant (BOLD) responses in the hippocampus predicted response time on subsequent exposure to contextual trials, while BOLD in the striatum predicted response time in probabilistic trials. This important study elucidated that probabilistic and contextual regularities guide visual search through dissociable neural systems and opened several additional interesting questions. Do similar patterns of search benefits generalise to visual search within natural scenes? Further, will these established learning benefits facilitate subsequent perception and

memory? In other words, what are the consequences of learned contextual and probabilistic regularities for attentional orienting and memory retrieval?

Over three experiments, I compared and contrasted how contextual and probabilistic memories guide learning in visual search, subsequent memory retrieval, and attentional orienting in service of perception. To this end, specific scenes within different scene categories were associated with a specific target location (contextual), a probable target hemifield (probabilistic), or were drawn randomly (random) over multiple learning blocks. Participants were blind to the types of associations embedded within the different categories of scenes in which they searched for a target item. Individual scenes from the three categories – contextual, probabilistic, and random – were randomly intermixed within each learning block, enabling the comparison of different types of learning benefits in a single task. To approximate natural search behaviour, participants searched through real-world scenes (Brockmole & Henderson, 2006b; Kristjánsson & Draschkow, 2021; Võ et al., 2019; Võ & Wolfe, 2015).

I hypothesised that the time course of learning – measured by improvements to search performance over repetitions – would be steeper for items bound to specific contexts than a probable region. Further, I predicted that contextual and probabilistic learning would facilitate learning in comparison to trials with no consistent associations (i.e., random; Goldfarb et al., 2016; Salovich et al., 2018; Spaak & de Lange, 2020; Yin & Knowlton, 2006). Next, I investigated the consequences of learning on subsequent behaviour. After completing the visual-search task, participants performed a surprise memory retrieval task in Experiment 4, a memory-guided attention task in Experiment 5, and consecutive tasks measuring attention and then retrieval abilities in Experiment 6. Overall, I aimed to determine if and how contextual compared with probabilistic memories guide perception and retrieval.

3.2. Experiment 4a and 5a: Comparing Learning of Different Kinds of Associations

Both Experiments 4 and 5 began with identical learning segments in which participants learned different types of associations between object locations and scenes. Specifically, participants learned contextual associations (trials in which object locations were associated with a specific context) and probabilistic associations (where the target hemifield remained constant though the exact location of the targets did not). I was interested in investigating the rate at which these associations were learned in comparison to one another, and to the baseline or random associations (no consistent association between context and target location). The random association condition served as a useful metric for measuring participants' general familiarity with the task and their ability to find targets when not assisted by underlying rules governing locations. As the learning tasks were identical between Experiments 4 and 5, results for the separate sets of participants in each experiment were combined and included in this section (3.2.). After the learning segment, participants went on to complete an explicit cued recall task (Experiment 4; section 3.3.) or a memory-guided attentional orienting task (Experiment 4; section 3.4.). Results from these tasks are split into separate experiments to delineate the separate hypothesis that guided the design and conduct of the experiments.

In all experiments in this chapter, participants completed surprise tests of memory, whether memory was to be recalled (Experiment 4), guide attention (Experiment 5), or both (Experiment 6, in separate tasks). In all cases, learning during the learning tasks was implicit. Participants were never explicitly told they had to remember target locations for subsequent tests and were kept blinded to the underlying nature of the associations being formed during the learning process. More discussion of this can be found in Intro section 1.2.4. as well as Chapter 3 section 3.3.1.2.1.. Also note that from this point forward whenever I say "Recall" I am referring to explicit cued recall of associations that were learned implicitly.

3.2.1. Methods

3.2.1.1. Participants. The study was approved by the Central University Research Ethics Committee of the University of Oxford code: R63062/RE001. Participants (age range = 18-40) were recruited online using Prolific, an online crowdsourcing platform (www.prolific.co). Participants were fluent in English and reported having no cognitive impairment, dementia, or history of mental health conditions. They were compensated £7 per hour. All participants had normal or corrected to normal vision.

An initial a-priori power analysis in G*Power (Faul et al., 2007) targeted on the detection of medium effects in the recall task ($d = 0.5$, $\alpha = 0.05$, $1-\beta = 0.95$) estimated a sample size of $n = 54$ per experiment. To yield 108 participants with usable data, 137 participants were initially recruited. Participants in all experiments who performed at near-chance level (in any of the tasks) were excluded as a precaution to avoid using data from online participants who were inattentive or could not/would not perform at a baseline that was expected based on prior lab-based experiments (Sauter et al., 2020). In Experiment 4, eleven participants were excluded from the analysis due to near-chance level performance (9 due to the learning phase and 2 due to the recall phase) and 3 due to technical malfunction (incorrectly assigned learning associations), meaning that 68 datasets were collected in total prior to exclusion. In Experiment 5, 14 participants were excluded from the analysis due to near-guessing level performance (9 due to the learning phase and 5 due to the orienting phase) and 1 due to technical malfunction (incorrectly assigned learning associations), for 69 total datasets prior to exclusions.

3.2.1.2. Stimuli. The experimental task was programmed using Psychopy (Peirce et al., 2019) and hosted on the online platform Pavlovia (https://pavlovia.org/). Participants

completed the experiment on their own personal computer. They were instructed to sit one arm's length away from their computer screen and to adjust the screen brightness to ensure good visibility. The same stimuli were used in Experiments 5 and 6.

One hundred and sixty-eight natural scenes were used in both experiments. All scenes were obtained from the publicly accessible Scene Stimuli image set compiled by UCSD Vision and Memory lab (Konkle et al., 2010). Scenes were drawn from six different categories in equal numbers (28 from bathroom, beach, desert, forest, gym, and kitchen scenes). Of these, 84 scenes (14 from each scene category) were randomly chosen to be included in the experiment for each participant. Four additional scenes that were not from any of these categories were used for the practice trials. The size of each scene was 768 x 768 pixels. Scenes were displayed centrally with a grey background filling the rest of the internet browser window. Semi-transparent, multi-coloured images of a bell and a dog were used as target stimuli. These two images were chosen as targets based on ease of visual discrimination (i.e., two objects that are not easily confusable). Participants searched for either of these two stimuli embedded within each scene. Target location was determined according to three conditions of memory association (contextual, probabilistic, or random). The target image was 23.04 x 23.04 pixels and appeared randomly rotated on each trial.

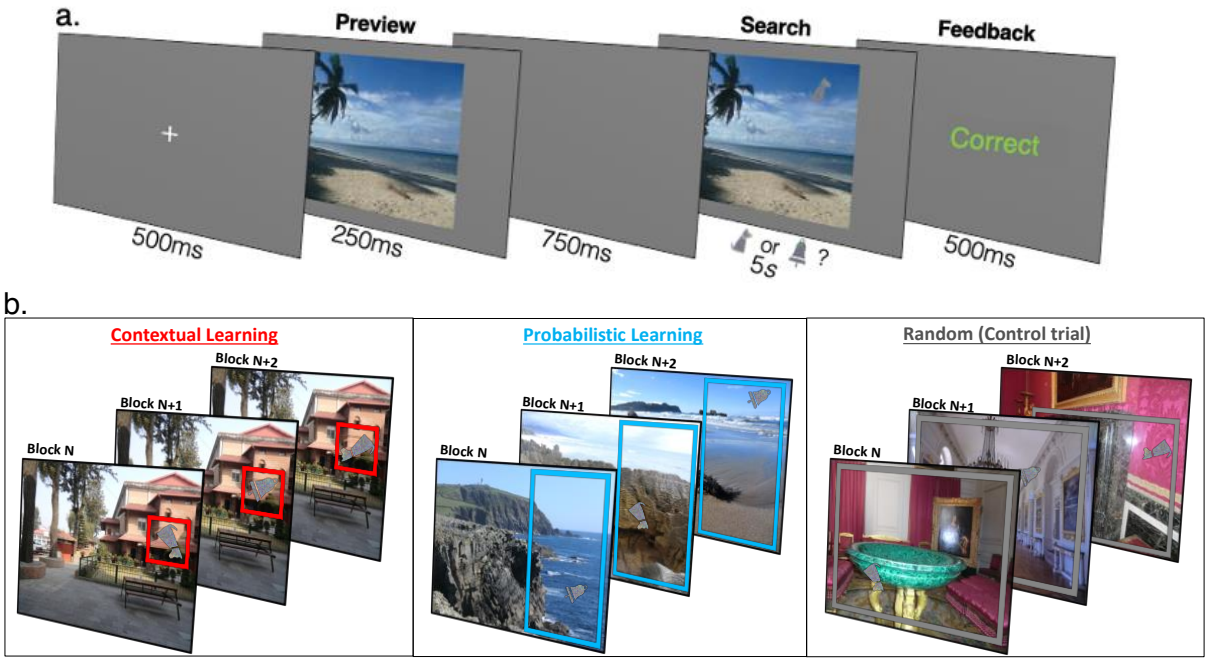
3.2.1.3. Procedure. Participants were provided with a link by Prolific (www.prolific.co), which rerouted them to the experiment on Pavlovia (pavlovia.org). After reading through a description of the study, participants provided informed consent. Before beginning the main learning task, they completed a set of 4 practice trials to become accustomed to the procedure.

3.2.1.3.1. Learning Task. During learning, participants searched through each of 84 unique scenes for the target (bell or dog) and made a speeded response as soon as they found the target (Figure 3.1). Target identity was randomised, and participants made a two-alternative forced choice to indicate if the target was the bell or the dog. They completed five blocks of searching through the 84 scenes, for 420 total trials. The specific scenes used in Block 1 were repeated in subsequent blocks, but the order of the scenes was randomised per block. After each block, participants had the opportunity to take a short break and to continue when they felt ready.

Figure 3.1a shows the experimental procedure for a given learning trial. First, a grey screen with a white fixation cross appeared for 500 ms. This was followed by a brief (250 ms) preview of the scene alone, with no embedded target. This served as a cue for the upcoming scene with the embedded target. After a 750-ms interval with a grey background, the scene was presented again, this time with an embedded target. Participants had up to 7 seconds to search for the target in the first block and respond with the correct keystroke corresponding either to the dog or bell. For the remaining blocks, search time was reduced to 5 seconds. If participants responded before the allotted time elapsed, the search window closed. After responding, participants received centrally presented feedback for 500 ms indicating if their response was ‘Correct’ or ‘Incorrect’. If the participant was not able to find the target within the allotted search time, ‘Incorrect’ was presented as feedback. Trials were separated by an inter-trial interval (ITI) of 200 ms.

Figure 3.1

Learning Task Design.



Note. (a) A schematic of the learning task. (b) A diagram of the learning associations. The left panel shows learning the Contextual associations, the middle panel shows learning the Probabilistic associations, and the right panel shows the Random associations. The coloured rectangles represent the possible range of coordinates in which targets could occur in the different conditions. Three example blocks are shown of the five blocks total in the learning task. Each unique scene was repeated once per condition per block.

Target locations during the learning phase (Figure 3.1a) were determined according to three experimental conditions: contextual, probabilistic, or random. The six categories were split evenly into these 3 conditions (Figure 3.1b), with 2 scene categories per condition, and 14 unique scenes in each category (3 conditions x 2 scene categories x 14 unique scenes = 84

total scenes). For the two scene categories with contextual associations, the location of the target remained the same for a given scene across all five blocks. In other words, there was an exact match between a scene and the target location within it. For example, if the target appeared on the window of a house in a scene in block one, the target always appeared in the same location on the window in that scene in the subsequent four blocks (see Figure 3.1b). Independent of scene category, for half the scenes this exact target location was on the left hemifield and for the other half it was on the right hemifield. For the two scene categories with probabilistic associations, the target consistently appeared in the same hemifield across the five blocks, but the exact location in that hemifield varied randomly. For example, for one participant, targets would always appear on the left for gym scenes and on the right for beach scenes. Finally, for the two scene categories with random associations, the target location varied randomly. The assignment of conditions to scene categories was counterbalanced across participants. Target locations could only occur within a specific region of pixel space defined within Psychopy. On the x-axis, possible locations were in the central 50% of the right or left hemifield (.25 to .75, if 0 is the middle and 1 is the edge of the scene). On the y-axis, possible locations ranged from the midpoint to 75% of the possible space in the upper or lower hemifield (0 to .75). The same boundaries for target placement were used for all experimental conditions. For scenes in the contextual condition, the initial location was drawn randomly, and this specific location was preserved for each subsequent learning block. For scenes in the random condition, a new draw would determine the target location in each block. For probabilistic associations, coordinates in each block were drawn randomly from values within the hemifield tied to the scene category.

The rationale behind the use of the term ‘probabilistic’ in this task is worth spelling out, as strictly speaking the locations where objects occurred in this condition were deterministic rather than probability driven. In the probabilistic condition, the scene category

dictated which side of the screen targets occurred on (e.g., in all beach scenes 100% of targets occurred on the right side and 0 on the left). Therefore, in this study, the side of the screen where the target occurred was deterministic (i.e., completely reliable), whereas in other studies the side of target occurrence was more probabilistic (e.g., 80% of trials target occurred on the left and 20% on the right; Geng & Behrmann, 2002, 2005; Smith, 2010). Nevertheless, the 'probabilistic' condition in my study fulfils the conditions laid out in literature for there to be a 'probability cueing' effect. During probability cueing, participants extract environmental statistics and use this information to guide attention. For example, frequently finding a visual search target in one region of space induces an attentional bias toward those locations (Jiang & Sisk, 2019; Salovich et al., 2018). Note that this type of learning is not context-specific like contextual cueing (e.g., learning the specific location of the road sign by your house), but more category-general (e.g., in most roads, road signs occur in predictable locations). As in the probabilistic condition of my study, this attentional habit is learned implicitly, acquired gradually (multiple blocks of learning), and is fixed (e.g., ocean scene always means that targets are more likely on the right; Salovich et al.,). Therefore, though the rule determining the location where targets occurred in the probabilistic condition is more deterministic than 'probabilistic', I chose to use the term 'probabilistic' to align with literature that describes the type of learning or behaviour that is occurring in this condition as probability learning.

In the probabilistic condition, I designed the task such that targets occur on one side of the screen with 100% probability because of proposals that humans may act as statistically optimized observers, i.e., performance is proportion to probability (Druker & Anderson, 2010). For example, in one study, with every 10% increase in the probability of a target occurring, the reaction benefits grew for targets that occurred in high vs low probability locations (Zhang et al., 2022). Indeed, in Goldfarb et al., (2016), when the 80:20 ratio of

target occurrence in the high probability versus low probability quadrants was used, participants needed many more exposures to targets in the probabilistic learning condition to gain the same attentional benefits as the contextual learning condition (this study is reviewed in Section 3.1). In my study, I wanted exposure frequency to the learned associations to be more equated, as participants would subsequently complete memory tests for the learned scenes and locations. Additional exposures to learning trials in the probabilistic than the contextual condition could influence retrieval performance, potentially confounding any performance differences related to the different learned associations. Therefore, I increased the probability ratio with the aim that, with the same number of trials for both the probabilistic and contextual conditions, participants would demonstrate adequate learning in both conditions (i.e., significantly better performance than the random condition). Finally, though no literature I have reviewed has specified that there are different mechanisms involved in probabilistic learning under more deterministic (100:0) versus more probabilistic (80:20) conditions, this possibility should be considered when evaluating the results of this study and planning follow-ups.

Finally, there notable differences were included from the learning task in Chapter 2. A longer interval was used between the scene preview and the target occurrence (750 ms) compared to the learning task in Chapter 1 (where 250 ms was used). In the learning task in Chapter 2, participants could either hold object identities in working memory and use these to guide the search for matching targets and/or try to remember the object locations from LTM. This was suited for testing object identity and location in subsequent memory retrieval tests. Alternatively, in this Chapter, participants did not learn or get tested on object identities. Therefore, in the learning task, participants could only use locations retrieved from LTM to guide search (i.e., not also object identities). Due to the additional time required to retrieve object locations from LTM compared to using the target identities already held in working

memory to guide search (Čepukaitytė et al., 2023; Staresina & Wimber, 2018), I opted to give participants more time. The timing choice (750 ms) was in line with past studies that have tested attentional guidance by LTM (Stokes et al., 2012). Also, because participants were not cued with the target identity and the targets were small and semi-transparent, it was important to provide participants with feedback so that they could be sure that they had correctly found and responded to the target identity correctly. Indeed, feedback that a target was missed can help participants adapt their search strategies (Chun & Wolfe, 1996). Finally, the overall allotted search time was reduced compared to Chapter 1 because there was only 1 target object.

3.2.1.4. Data Analysis. Parametric analyses were applied, transforming the data when necessary to conform to the required assumptions. In cases where the main effects were significant, planned paired samples t-tests were applied to compare levels of the experimental variables (i.e., between different learned associations). One notable difference in analysis compared to Chapter 2 is that, in this Chapter (and in the remainder of this thesis), paired-sample t-tests are used rather than Tukey HSD tests as Tukey tests are more suited to analysis involving between-subjects factors. The studies in this chapter primarily involve within-subjects factors, therefore, paired-samples t-tests were more appropriate. The Greenhouse-Geisser correction was applied when the sphericity assumption was violated. Throughout the experiment, to account for within-participant comparisons (i.e., between association conditions), procedures from Morey were followed (2008).

All analyses were conducted using RStudio (Version 1.1.463) by the R core team (2022). Descriptive statistics and paired sample t-tests were conducted using the “stats” package in (R core team, 2018). Within-participant ANOVAs were conducted using the “e” package when necessary to aggregate data (Version 4.4-0; Lawrence, 2016). Post-hoc, linear contrasts were conducted using the “emmean” in combination with the “emtrend” package

(Version 1.6.1; Lenth, 2021). All graphs were produced using the "ggplot" package (Villanueva & Chen, 2019).

3.2.1.4.1. Learning Task. To analyse performance on the learning task, target identification accuracy (% of correctly identified targets) and response time were tracked over the 5 blocks. The independent variables of interest were memory association (contextual, probabilistic, random) and block (1-5). Response times were analysed only for trials in which participants correctly identified the target. Response time outliers (beyond 2 standard deviations from the mean) were removed from the analysis (3.27% of the trials for all participants combined). The Box-Cox procedure (Box & Cox, 1964) was used to test the distribution and residuals of reaction-time values. Based on this, I applied an inverse square-root transformation to response times on both days of learning to approximate the normal distribution and to meet ANOVA assumptions.

In addition to accuracy and mean response time, the Balanced Integration Score (BIS) was calculated for each memory association and block (Liesefeld & Janczyk, 2019). When completing behavioural tasks, participants sometimes focus more on doing the task right (response accuracy) or doing it fast (response speed) resulting in a "speed-accuracy trade-off" or SAT that exists on a continuum (Heitz, 2014; Sanders & Sanders, 2013). SAT can vary unpredictably between or across participants and might even change systematically between conditions (Dutilh et al., 2012; Reuss et al., 2015). This trade-off can hinder the goals of a study by introducing confounds, for example, shorter RTs and fewer correct responses might indicate that the observed effects could partially be due to SATs rather than "real effects" (Liesefeld & Janczyk, 2019). In other words, participants might sacrifice accuracy to respond faster, potentially limiting the effectiveness of measuring experimental manipulations such as differences in accuracy between conditions. To address this issue, several measures have

been designed to combine response times and response accuracy with the goal of attenuating the effects of SATs while preserving “real effects” (Kristjánsson, 2016; Kunde et al., 2012). In their paper, Liesefeld & Janczyk analysed how effectively a number of these measures have achieved this goal and found that BIS was the most effective (2019).

BIS is a composite measure that gives equal weight to accuracy and response time. It is calculated by first subtracting the mean accuracy and mean response time from their respective data sets to centre the data. Next, the output values are divided by the standard deviation of accuracies and response times respectively. Finally, the standardised score for response time is subtracted from the standardised score for accuracy. Higher scores indicate either higher accuracy, faster response time, or both. Specifically, individual values reflect whether performance was below (BIS < 0) or above (BIS > 0) the average performance (across all participants and conditions) for the respective participant in the respective condition. In this learning task of this Experiment, for the sake of comparison, accuracy and response times have been included as well as BIS score. However, for the reasons included here, in the subsequent Experiments, BIS will act as the primary response variable of choice in my analysis. For measures where BIS is not reported, such as localization error, this is because performance is based on participants' precision of response (i.e., localization error as an x/y distance), rather than their accuracy (i.e., proportion of correct responses) or response times. BIS is specifically designed for the combination of accuracy and response times rather than other combinations of metrics.

For each of the measures (accuracy, response time, and BIS), pairwise linear contrasts were run between each of the association conditions. Contrast analysis is a type of paired comparison method (such as Tukey tests) that can be used to carry out comparisons in wider contexts, such as to compare treatment level groups or trends (Searle et al., 1980). A linear contrast is a linear combination of the treatment means such that their numerical coefficients

add to zero. They can be used to make comparisons among groups of treatment means. In this Chapter's analysis, they will be used to compare, for example, identification accuracy for each association condition in the different learning blocks. To do this analysis (again using accuracy as an example), the data is aggregated based on per-subject, per-block, and per-condition means. This data is then centred around 0 (so that the first block is -2 and the last is 2). An ANOVA is run with association condition as a within-subjects variable and block as a covariate. This ANOVA model is then used to calculate the linear contrasts. The linear contrast is run pairwise between each level of the association conditions (e.g., contextual – probabilistic, probabilistic – random). The contrast works by computing and comparing the slopes of the Block trend line over the levels of the predictor variables (e.g., mean accuracies in the contextual and probabilistic condition) and returns if these estimated mean values are significantly different (Version 1.6.1; Lenth, 2021). This analysis is ideal for my data because the model involves a numerical predictor (Block) interacting with another predictor that is a factor (association condition). In short, the model specifies that Block has a different trend depending on Association Condition, it then estimates and compares those trends and determines if they are significantly different.

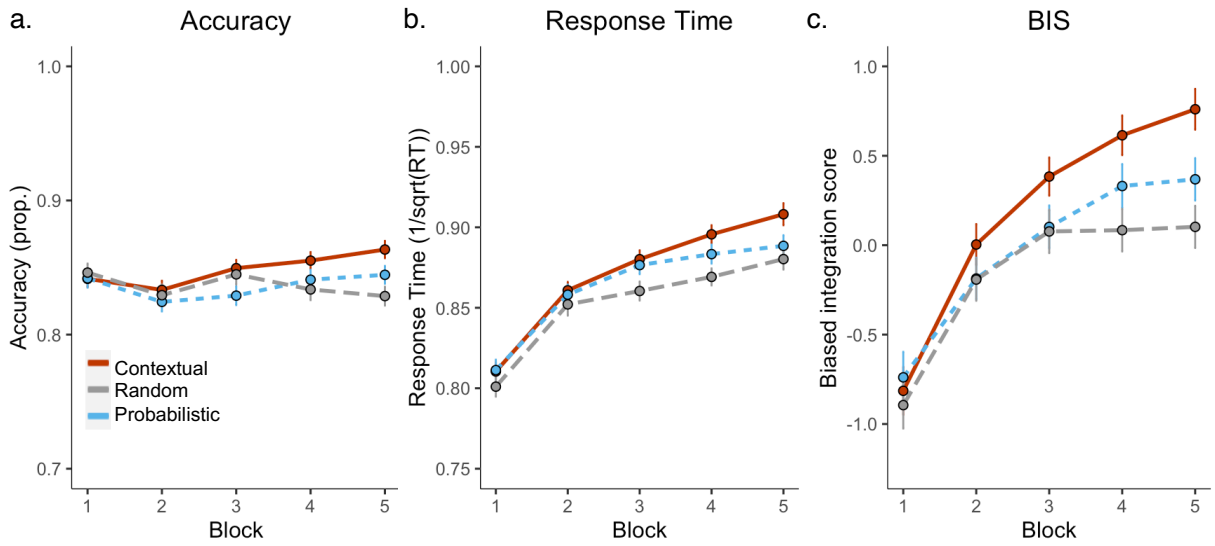
3.2.2. Results

3.2.2.1. Target Identification Accuracy. A two-way ANOVA with association and block as within-participant factors demonstrated an overall improvement in accuracy over time. There was a main effect of block on learning accuracy ($F(4,428) = 3.31$, $p < .05$, $\eta 2 = 0.01$, Figure 3.2a) and an interaction between Association and Block ($F(8, 856) = 2.26$, $p < .05$, $\eta 2 = 0.01$). Mean accuracy was 85% (SD = 8%) in the Contextual condition, 84% in the Probabilistic condition (SD = 8%), and 84% (SD = 9%) in the Random condition. The main effect of Association was not significant ($F(2,214) = 2.014$, $p = .14$, $\eta 2 = 0.01$). To compare

the rate of learning over time, linear contrasts of Block were run between each of the Associations conditions. As Block increased, accuracy for the Contextual Associations increased more than accuracy for the random associations ($t(1293) = 3.57$, $p < .001$). However, the slopes of the linear contrast between the Contextual and Probabilistic associations ($t(1293) = 1.62$, $p = .11$) and between the Probabilistic and Random associations ($t(1293) = 1.95$, $p = .051$) did not differ significantly. Therefore, during the learning task, target identification accuracy increased significantly only in Contextual associations compared to baseline, Random condition.

Figure 3.2

Learning Performance Plots



Note. (a) Accuracy at identifying the target over the 5 learning blocks. (b) Response Time at responding to target identity (1/sqrt(Response Time)). Participants were significantly faster at finding the target in the Contextual compared to both and Probabilistic and Random association trials. (c) BIS score representing equally weighted change to response time and accuracy over the 5 learning blocks. Again, BIS score was higher in the Contextual association compared to trials in both of the other association conditions. Error bars were calculated using the "summarySEwithin" function (Version 1.5.1), which normalizes data to remove between-participant variability and then calculates the variance from this normalized data.

3.2.2.2. Target Identification Response Time. A two-way ANOVA with association and block as within-participant factors and a subsequent linear contrast analysis demonstrated that participants were fastest at identifying targets in the contextual condition. There was a significant main effect of Association ($F(2,214) = 3.20$, $p < .05$, $\eta 2 = 0.01$; Figure 3.2b) and

Block ($F(3.17, 338.12) = 96.78$, $p < .001$, $\eta 2 = 0.14$) on target-identification response time. Mean negative square root of response times were 0.87 in the Contextual condition (SD = .22), .87 in the Probabilistic condition (SD = .21) and .85 in the Random condition (SD = .21). Planned paired-samples t-tests showed that participants were significantly faster at finding the target for Contextual compared to Random associations ($t(107) = 2.65$, $p < .01$, Cohen's $d = 0.31$) but not compared to Probabilistic associations ($t(107) = 1.00$, $p = .159$, Cohen's $d = 0.13$). There was no significant response time difference between Probabilistic and Random associations ($t(107) = 1.59$, $p = .058$, Cohen's $d = 0.20$). Here again, there was a significant interaction between Association and Block ($F(7.04, 753.28) = 2.06$, $p < .05$, $\eta 2 < .01$). Comparing the linear contrast of Block between associations revealed that response time increased more over blocks in Contextual associations than in the Random ($t(1293) = 2.61$, $p < .01$) and Probabilistic associations ($t(1293) = 2.42$, $p < .05$). The changes in response time over blocks did not differ significantly between the Probabilistic and Random associations ($t(1293) = 0.19$, $p = .85$). Therefore, over the course of the learning task, overall target identification response time was faster than Random in only Contextual associations. In addition, the rate at which response time increased was fastest in the Contextual associations compared to both the Probabilistic and Random associations.

3.2.2.3. Biased Integration Score. The Biased Integration Score (BIS) provided a composite measure for comparing performance based on both accuracy and response time to a similar degree, with higher BIS scores corresponding to higher accuracy and/or lower response time (Liesefeld & Janczyk, 2019). A two-way ANOVA with Block and Association as within-participant factors showed overall improvement in task performance with time. There was a significant main effect of Block on BIS ($F(3.14, 335.55) = 84.13$, $p < .001$, $\eta 2 = 0.09$; Figure 3.2c) and an interaction between Block and Association ($F(6.96, 744.72) = 2.65$,

$p < .01$, $\eta 2 < .01$). The main effect of Association was not significant ($F(6.96, 744.72) = 2.72$, $p = .068$, $\eta 2 = 0.01$). Mean BIS was 0.19 ($SD = 1.57$) in the Contextual Condition, -0.02 ($SD = 1.52$) in the Probabilistic Condition, and -.16 ($SD = 1.55$) in the Random condition. To compare the rate of learning over time as measured by BIS, linear contrasts of Block compared for the Association conditions. Performance improved more steeply in the Contextual than in the Random ($t(1293) = 3.82$, $p < .001$) and Probabilistic associations ($t(1293) = 2.64$, $p < .01$). Performance increases between the Probabilistic and Random associations did not differ significantly ($t(1293) = 1.19$, $p = .17$). Therefore, over the course of the learning task, participants' accuracy and response time for finding targets improved most in Contextual associations compared to both the Probabilistic and Random associations.

3.2.3. Conclusion

Combined learning results for Experiments 4 and 5 supported the hypothesis that the learning rate would be fastest for Contextual associations compared to the other two conditions. This finding is in line with results from past studies showing significant learning benefits from contextually consistent, implicitly learned associations (Chun & Jiang, 1998; Goldfarb et al., 2016; Spaak & de Lange, 2020). However, the case for Probabilistic learning was weaker, with no significant difference between Probabilistic and Random association learning as measured by response time, accuracy, and BIS. It is possible that this was an issue of power, as differences between the Probabilistic association learning and Random approached significance for accuracy ($p = .051$) and response time ($p = .058$). However, the large sample size in the combined learning analysis for Experiments 4 and 5 (e.g., double the estimated N for a medium effect size, or $N = 108$) makes this proposal unlikely. Alternatively, due to the gradual nature of probabilistic learning (Frank, 2005; Knowlton et al., 1996; Yin & Knowlton, 2006), it is possible additional learning blocks or overnight

memory consolidation might have been necessary for a learning effect to emerge (e.g., as in Goldfarb et al., 2016). This is a possibility I explore in Experiment 6. Overall, the results from the learning segments in the first two experiments supported participants' ability to reliably acquire specific associations between context and target location in an online experiment.

3.3. Experiment 4b: Comparing Memory Retrieval of Different Kinds of Associations

In the test segment that followed learning in Experiment 4, I investigated whether the learned contextual or probabilistic regularities facilitated memory recall. After completing 5 learning blocks, participants were informed about a subsequent surprise memory recall task (Figure 3.3). In this task, participants were presented with scenes and asked to 1) recall what hemifield the target had been present during the learning task indicate whether the scene was old or new, 3) and then click the exact location in which the target had appeared in the scene during the learning phase. I hypothesised that learning would facilitate tests of recall that closely resembled the learned associations. For example, learning target-hemifield associations in the probabilistic learning condition would facilitate recall for the target's hemifield in the subsequent recall test. Further, learning of specific, target-location associations in the contextual learning condition would facilitate participants' ability to remember and click that target location in the recall task.

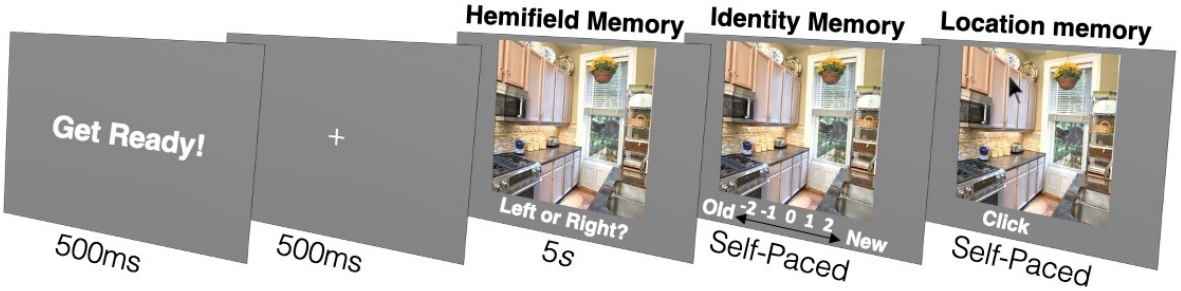
3.3.1. Methods

3.3.1.1. Participants. Procedures for participant recruitment are described in Section 2.2.1.1.. Individuals who completed the learning phase of Experiment 4 went on to complete the recall phase. Data from 54 participants were fully analysed.

3.3.1.2. Procedure. After completing the learning phase, participants were directed to the recall task within Pavlovia. Prior to beginning the recall task, they completed a set of 4 practice trials to become accustomed to the procedure.

Figure 3.3

Memory Retrieval Task



Note. A schematic of the recall task. The task began with a 'Get Ready' screen. After a short fixation, participants were tested on their memory for which side of the screen the learning target had appeared on in a speeded hemifield memory test. Next, they were asked to report if the scene was repeated from the learning ('Old') or never seen before ('New'). Finally, participants clicked the exact location where they remembered the object occurring or where they would predict it to occur if the scene was 'New'.

3.3.1.2.1. Retrieval Task. In the surprise memory retrieval test (Figure 3.3), participants were tested on their memory for target hemifield, scene identity, and target location. They viewed 84 'old' scenes from the learning phase, and 84 'novel' scenes drawn equally from the same scene categories. Participants made three successive judgements. First, they made a forced-choice response on whether the target location studied in a scene had been on the left ('A' key) or right ('K' key) hemifield within a 5-second recall window. If participants were unsure, they were asked to make their "best guess". For this response, I encouraged participants to make a "quick decision" as I wished participants to use their implicit learning to respond quickly based on the scene category. This design was based on my prediction that hemifield memory would be facilitated by probabilistic learning, where participants learned an association between a scene category and a specific hemifield. Therefore, I wanted to encourage participants to use their implicit learning to respond quickly rather than slowly registering whether the scene was old or new, and/or attempting to retrieve a specific object location. Then, after their hemifield response, participants had the opportunity to indicate whether they remembered the scene from the Learning phase by choosing one of the following options: "Definitely not", "Probably not", "I do not know", "Probably yes", and "Definitely yes". A confidence scale was included to account for possible different levels of recollection strength (Wixted, 2007; Wixted et al., 2010). Finally, participants completed a 'Location' memory phase, where they had to recall the precise location where they remembered seeing the target by clicking its location in the scene. The assessment of scene and recollection memory came after the speeded hemifield response so that participants could take their time to retrieve how well they recollected the scene and where precisely the target occurred within it. If the scene was new, participants were told to

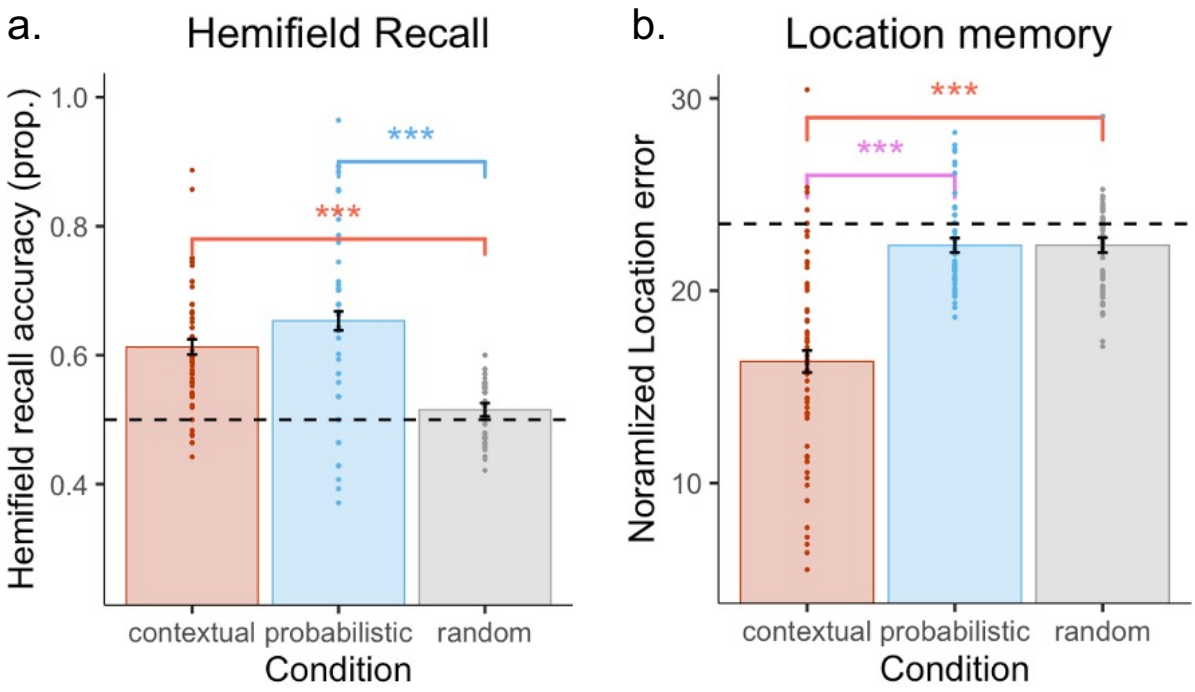
respond with their “best guess“ during the hemifield judgment, identify that the scene was new, then report the location where they would deem it most likely to find the target.
For the Probabilistic and Random association scenes participants were not given specific instructions on which of the five learned target locations to recall as I wished to keep them blinded to the association conditions underlying the experiment. If participants were told that, for example, in some scenes the targets appeared in specific locations whereas in other scenes the targets appeared in numerous locations during the learning, this may have divulged the different rules governing the target locations and potentially have altered their behaviour. In essence, my goal was to study how participants could use implicit learning of different types of associations for memory retrieval tasks, rather than measuring explicit learning of the rules underlying the experiment.

3.3.1.3. Data analysis. As for the learning task, parametric analyses were applied to data in the explicit recall task. The Greenhouse-Geisser correction was applied when the sphericity assumption was violated. To assess performance on the surprise memory-recall test in Experiment 4, I calculated participants’ accuracy, response time, and BIS at recalling the target’s hemifield, their sensitivity to identify the scene as old or new (d-prime), and their memory precision for the target’s specific location. Response time and BIS were calculated only for the hemifield response as accuracy and speed were emphasized in the instructions and participants had a limited time to respond. Hemifield memory accuracy was assessed by determining the proportion of trials in which participants correctly identified the hemifield in which the target occurred during the learning phase (Figure 3.4a). Scene identity memory was assessed by calculating d-prime (hit rate – false alarm rate, or the probability of responding old given the scene was old minus the probability of responding old given the scene was new).

Location recall error was calculated as the distance error to obtain a continuous measure of participants' memory for target locations. I calculated the distance in two-dimensional space between the centre of the target locations in each of the 5 learning blocks and the participants' responses during the location recall phase. To simplify error values from the raw Psychopy output coordinates, error values were divided by the maximum possible localisation error, which gave me normalised percentage error out of 100. Maximum possible localisation error was calculated as the maximum distance between a possible target and a possible response, i.e., the Euclidian distance from the limit of possible target appearance in the top left to the bottom right of the visual display – the most distant possible response. For this calculation, the actual size of the screen for any individual participant was immaterial, as the original Psychopy coordinates are standardized to be consistent regardless of screen size. The localisation error analysis was run only for the scenes from the learning (old) in which participants correctly identified the target's hemifield and correctly identified the scene as old. The 5 individual localisation error values relative to each of the learning locations were averaged to generate the location memory value reported in Figure 3.4b. I calculated chance-level location memory error for learned scenes (old) where participants correctly identified the target hemifield. This was done by shuffling response locations for every trial such that participants' localisation responses did not match the locations of the target. The new distance (localisation error) between target locations and shuffled response locations represented a realistic chance error generated using real locations and real participant response data. This new chance-level localisation error was then averaged across all trials. This procedure was repeated over 1000 permutations for each individual participant to reduce random variability. The resulting values from the 1000 iterations were then averaged across participants, generating a single chance value.

Figure 3.4

Recall Performance Plots for Experiment 4



Note. Recall performance is shown for trials where participants correctly identified the scene as old. (a.) Hemifield memory recall accuracy results. Recall performance was significant higher in the probabilistic and the contextual associations compared to the random association. Recall performance was also higher in the probabilistic association compared to the contextual association. (b.) Location memory recall results. Normed distance error from target is shown. Location memory error was significantly lower in the Contextual association compared with the Probabilistic and Random associations. Error bars specify normalized mean standard error.

3.3.2. Results.

3.3.2.1. Hemifield Recall. Hemifield recall ability was analysed only for scenes that participants had previously learned (old). A one-way ANOVA with Association as the within-participants factor demonstrated that participants were more accurate at identifying the learned target's hemifield in the Contextual and Probabilistic association conditions compared to Random. There was a significant main effect of Association ($F(1.7, 90.1) = 32.26$, $p < .001$, $\eta 2 = 0.25$, Figure 3.4a). Mean hemifield recall accuracy was 62% (SD = 9%) in the contextual condition, 65% (SD = 11%) in the Probabilistic condition, and 52 % (SD = 8%) in the Random condition. Subsequently, planned paired samples t-tests demonstrated that hemifield recall performance was significantly higher for Probabilistic associations than Random associations ($t(53) = 7.47$, $p < .001$, Cohen's $d = 1.33$). Hemifield recall performance was also significantly higher in Contextual compared to Random associations ($t(53) = 7.17$, $p < .001$, Cohen's $d = 1.28$). Next, though hemifield recall performance was numerically higher in Probabilistic versus Contextual associations, this difference did not reach significance ($t(53) = 2.0$, $p = .051$, Cohen's $d = 0.34$).

Participants' BIS was also higher for the Contextual and Probabilistic association conditions compared to Random. There was a significant main effect of Association ($F(2, 106) = 24.76$, $p < .001$, $\eta 2 = 0.17$). Means were 0.31 (SD = 1.0) in the Contextual condition, 0.46 (SD = 1.0), and -.077 (SD = 0.88) in the Random condition. Subsequently, planned paired samples t-tests demonstrated that hemifield recall performance was significantly higher for Probabilistic associations than Random associations ($t(53) = 6.85$, $p < .001$, Cohen's $d = .91$). Hemifield recall performance was also significantly higher in Contextual compared to Random associations ($t(53) = 5.93$, $p < .001$, Cohen's $d = 1.04$). There was no significant difference in BIS between the Contextual and Probabilistic conditions ($t(53) = -.75$, $p = .45$, Cohen's $d = -.13$). Finally, for response time, there was no main effect of Association ($F(2,$

106) = .59, p = .56, η2 < .01). Means (in seconds) were 3.15 (*SD* = .78) in the Contextual condition, 3.29 (*SD* = 0.58) in the Probabilistic Condition, and 3.34 (*SD* = .77) in the Random condition.

3.3.2.2. Scene Identity Memory. In a one-way ANOVA with Association as the within-participants factor, I analysed participants' ability to discriminate scenes as old or new (d prime). There was no main effect of Association (F(2, 106) = 0.65, p = .52, η2 < .01), on participants' scene identity memory performance. *D'* was 0.83 (*SD* = .56) on average in the Contextual condition, 0.86 (*SD* = .51) in the Probabilistic condition, and .93 (*SD* = .60) in the Random condition. Further, participants' bias (*C*) I towards reporting scenes as old or new was measured for the different learned associations. There was also no main effect of Association for participants' bias towards reporting scenes as old or new (F(2, 106) = 0.11, p = .90, η2 < .01). *C* means were .01 in the Contextual condition (*SD* = .30), -.02 in the Probabilistic condition (*SD* = .31), and -.01 in the Random condition (*SD* = .32).

3.3.2.3. Location Memory. Location memory showed a significant main effect of Association (F(1.5, 79.5) = 58.18, p <. 001, η2 = .25, Figure 3.4b). Mean normalized localization error was 16.30 (SD = 4.20) in the Contextual condition, 22.4 (SD = 2.76) in the Probabilistic condition, and 22.40 (SD = 2.90) in the Random condition. Planned paired-samples t-tests showed that location recall was significantly more precise for Contextual associations compared to both Probabilistic (t(269) = 14.99, p < .001, Cohen's d = 1.20) and Random associations (t(269) = 15.10, p < .001, Cohen's d = 1.20). Finally, paired t-tests showed that location recall for Probabilistic (t(269) = 3.90, p < .001, Cohen's d = 0.31) and Random (t(269) = 3.97, p < .001, Cohen's d = 0.30) associations were better than chance performance (the dotted black line in Figure 3.4b). Therefore, participants were significantly

more precise at recalling the target's location after contextual learning compared to the other associations.

3.3.3. Conclusion

After learning target-location associations following contextual, probabilistic, or random regularities, participants were tested on their memory for the target's hemifield and specific location. As hypothesized, recall performance was facilitated when there was congruency between the learning condition and the type of recall test. Probabilistic learning conferred significant improvements to accuracy and BIS during hemifield recall. There was, however, no impact of learning probabilistic or contextual associations on response times during hemifield recall, indicating that the effects of learning on BIS were primarily driven by accuracy rather than reaction time benefits. The facilitation of recall occurred for the probabilistic association condition despite the lack of a clear significant learning effect during the preceding visual-search phase of the study. This demonstrates that some form of learning did occur for probabilistic regularities. Past studies have shown that learned attentional habits can transfer to related tasks (e.g., simple stimulus-based visual search to natural visual search; Salovich et al., 2018). The results of this study extend those findings, showing that habitual attentional learning can facilitate hemifield recall accuracy but not response times for the associations that were the basis of the habitual learning, i.e., the hemifield where the target was most likely to occur in a given scene category. Though nearly significantly different ($p = .051$), participants were not more accurate at hemifield memory for probabilistic compared to contextual associations. Contextual associations also facilitated hemifield recall accuracy and BIS, but not response times, indicating that specific object-scene associations can also benefit hemifield memory recall.

Next, in line with past results (Summerfield et al., 2006, 2011; Stokes et al., 2012), learning that targets are associated with a particular location in a certain context facilitated participants' ability to recall this target location when presented with that specific context. Therefore, contextual learning was flexible in facilitating both hemifield and specific location memory. On the other hand, probabilistic learning did not facilitate specific location recall. This is likely because localization error was calculated as the average distance error between the recalled location and the actual target locations. This method of scoring location memory favoured recall in cases where all the learned target locations were identical or close together (as in the contextual condition). For example, if target locations were spread out (as in the probabilistic and random conditions), even if one of these locations was correctly recalled, localization error from the other non-identical points would increase the overall localization error average. Ultimately, it would have been difficult to choose a scoring method for location memory that was suited to probabilistic associations because the method of learning did not align with the instructions for participants to recall a single location. Therefore, when considering my argument that congruency between learning and recall demands is linked to performance, it should be noted that probabilistic learning was suited for hemifield recall, but contextual learning was uniquely suited for location recall. Together, these results extended past work on the uses of different types of memory on subsequent tests (Rosen et al., 2018) by comparing the relative consequences of probabilistic and contextual learning on different memory retrieval tasks.

3.4. Experiment 5b: Comparing Contextual and Probabilistic Associations in Memory-Guided Attentional Orienting

After observing that probabilistic and contextual associations could facilitate subsequent memory recall compared to random associations, I investigated whether the same

types of learned associations could also facilitate memory-guided attention. Further, I examined whether different measures of memory-guided attention would show differences in performance between contextual and probabilistic learning.

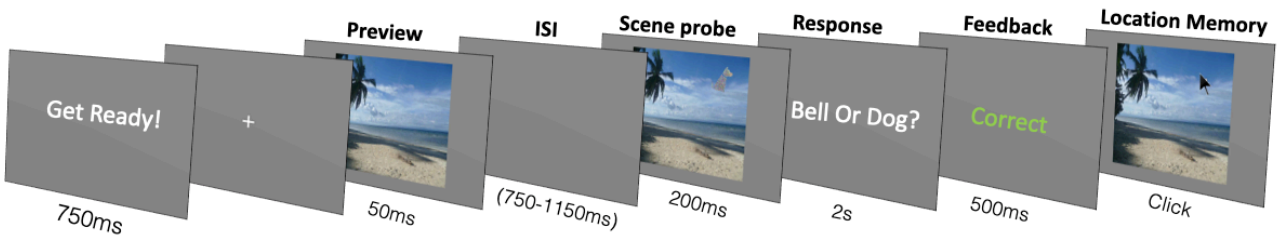
3.4.1. Methods

3.4.1.1. Participants. As in Experiment 4, participants were recruited using Prolific, and data from 54 participants were analysed (age range = 18-40). Participants were fluent in English and reported having no cognitive impairment, dementia, or history of mental health conditions. They were compensated £7 per hour. The study was approved by the Central University Research Ethics Committee of the University of Oxford. All participants had normal or corrected to normal vision.

3.4.1.2. Procedure. The procedure consisted of two phases - the learning phase and a subsequent memory-guided attention task. The learning task was identical to that of Experiment 4, and its procedures and results are described in section 2.2.

Figure 3.5

Memory-Guided Attention and Recall Task



Note. A schematic of the Memory-Guided Attention Task. The task began with a "Get Ready" screen, then after a brief fixation, a learned scene would flash briefly (preview). Following a jittered inter-stimulus interval (ISI), the same scene would flash again (scene probe), this time containing a target. Participants had 2s to respond whether the flashed target was a bell or dog. Finally, after a feedback screen, participants clicked the location in the screen where the target had flashed (location memory).

3.4.1.2.1. Memory-Guided Attention Task. In Experiment 5, after the learning phase, participants completed a surprise memory-guided attention task (Figure 3.5). In this task, a scene from the learning phase flashed for 50 ms, acting as a memory cue to initiate retrieval of the learned target-scene association (Summerfield et al., 2006). After a blank inter-stimulus interval jittered between 750 and 1150 ms, the scene flashed again for 200 ms, this time containing the target. The target identity ('Bell' or 'Dog') was randomized. A jitter was used so that participants would not use temporal predictability to learn when the target would occur (Coull & Nobre, 1998), which would potentially have confounded their response behaviour. After the target and scene flash, a grey background then appeared with the

question “Bell or Dog?” in white. Participants had 2 s to respond indicating the identity of the target on the corresponding flashed scene. This response disclosed participants’ target identification ability – our primary measure of memory-guided attention. After responding, they received feedback indicating whether their response was “Correct” or “Incorrect”. Because the target flashed very briefly, it was helpful to give participants feedback so they had a sense of whether they were responding correctly or not and could adapt accordingly (Chun & Wolfe, 1996). Finally, participants were asked to click the location of the target in the flashed scene. The location of the target in the flashed scene matched the rules from the learning. In each Contextual trial during learning, the target appeared in the exact same location as the matching scene; in Probabilistic trials, the target appeared in the same hemifield as in the learning; and in Random trials, the location was random.

3.4.1.3. Data Analysis.

3.4.1.3.1. Memory-Guided Attention Task. I assessed memory-guided attention by examining target identification accuracy, response time, BIS, and location memory. Response time averages were calculated only for trials in which participants correctly identified the target in the orienting task. The Boxcox procedure (Box & Cox, 1964) was used to test the distribution and residuals of response time values. Based on this, a log transformation was applied to response time values to ensure the data were normally distributed to meet the ANOVA assumptions.

Orienting location memory was calculated for all trials by taking the Euclidian distance between participants’ responses and the target locations. As in Experiment 4, this value was calculated by dividing trial-specific localisation error by the maximum possible localisation error to generate a normalised value. Following the inspection of the

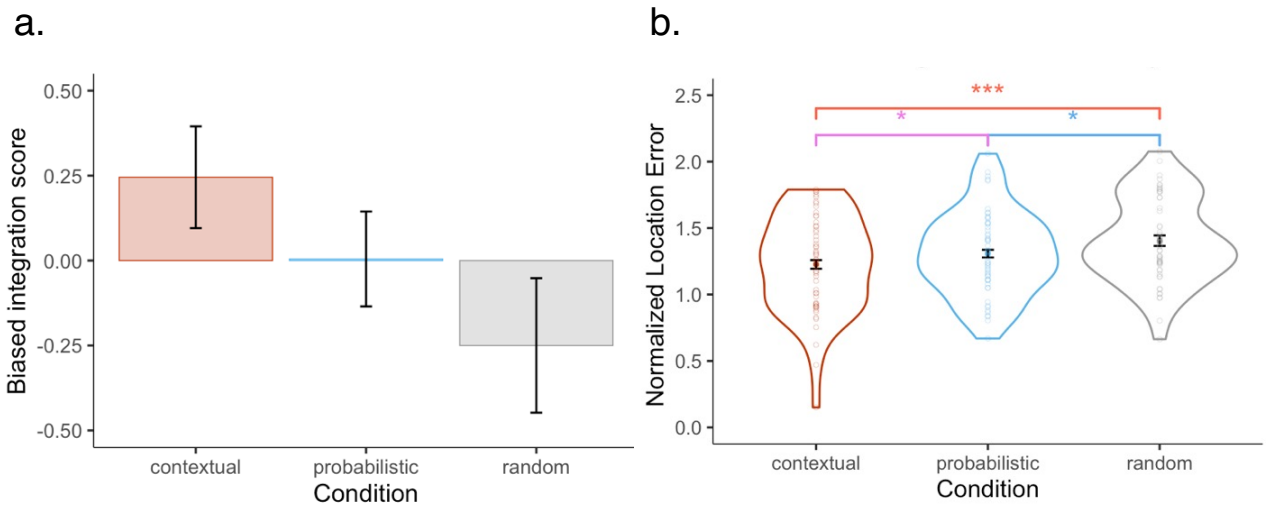
distribution/residuals and the power coefficient output of the Box-Cox procedure, location memory values were log-transformed.

3.4.2. Results

3.4.2.1. Target Identification. I predicted that target identification would be enhanced by contextual associations. Means for target identification BIS were .25 (*SD* = 1.10) in the Contextual condition, 0.0 (*SD* = 1.0) in the probabilistic condition, and -.25 (*SD* = 1.45) in the Random condition. However, a one-way ANOVA with association as a within-participant factor, demonstrated no effect of Association on target-identification accuracy ($F(2,106) = 1.56$, $p = .21$, $\eta 2 = 0.01$, Figure 3.6a). Also, there was no effect of Association for target-identification response time ($F(2,106) = 1.71$, $p = .19$, $\eta 2 < .01$). Finally, there was no effect of Association for BIS ($F(2,106) = 2.16$, $p = .121$, $\eta 2 = 0.01$). Therefore, overall, there was no significant facilitation of participants' accuracy or response time when identifying targets between the association conditions.

Figure 3.6

Memory-Guided Attention Results in Experiment 5



Note. (a) BIS for target identification. There was no significant main effect of association for BIS. (b) Log of normalized location memory error. Location memory error was significantly lower in the Contextual and Probabilistic associations than in the Random associations. Location memory results are shown for all trials. Each dot in the violin plot corresponds to the condition-specific performance of a single participant. Error bars specify normalized mean standard error.

3.4.2.2. Target location memory. Analyses were run on participants' location memory responses for all trials, i.e., regardless of whether participants accurately identified the target. The analysis was run in this manner to ensure that trials in which participants saw the target (i.e., covertly detected it), but did not identify it (i.e., overtly fixated on it), were included in analysis. "Zoom lens" theories of attention support that, as the size of the attentional field (locations where targets have occurred) grows, the density of processing

resources decreases (Eriksen & James, 1988). In other words, because in contextual learning the target occurred in a single location this would allow for a 'zoomed-in' attentional field, facilitating high detail fixation and subsequent target identification. However, in probabilistic learning the target locations were distributed throughout a hemifield; I hypothesized that this would cause a 'zoom-out' of the attentional field, making it possible to detect targets but harder to identify them (Druker & Anderson, 2010; Miller, 1988). By including trials where participants both did and did not identify the target in the location memory analysis, I aimed to allow for the facilitation of location recall by both types of attentional fields (i.e., zoomed-in and zoomed-out).

Indeed, both Probabilistic and Contextual association learning facilitated location memory compared to Random. In a one-way ANOVA with Association as the within-participant factor, there was a significant main effect of Association ($F(1.76, 93.28) = 7.01$, $p < .01$, $\eta 2 = 0.05$, Figure 3.6b). Means for log of localization error were 1.22 ($SD = 0.24$) in the contextual condition, 1.31 ($SD = .21$) in the probabilistic condition, and 1.41 ($SD = 0.29$) in the Random condition. Subsequent planned paired-samples t-tests showed that participants' location reports were more precise in the Contextual ($t(53) = -3.31$, $p < .001$, Cohen's $d = -0.53$) and Probabilistic ($t(53) = -1.96$, $p < .05$, Cohen's $d = -0.31$) associations compared to Random. Participants were also more precise in the Contextual compared to the Probabilistic association ($t(53) = -2.12$, $p < .05$, Cohen's $d = -0.24$).

3.4.3. Conclusion

In my second experiment, participants used their learning of the different types of associations to guide subsequent attentional orienting. However, neither contextual nor probabilistic learning yielded significant facilitation of attentional orienting as measured by BIS. Interestingly though, participants' ability to subsequently report the target locations was

facilitated by both contextual and probabilistic association learning. Specifically, location report was facilitated when all trials were included in analysis (i.e., both trials where participants correctly identified and did not identify the orienting target). Relatedly, it is possible that participants developed different attentional fields during the learning task: a 'zoomed-in' field from contextual learning and a 'zoomed-out' field from probabilistic learning (Druker & Anderson, 2010; Miller, 1988). In particular, I hypothesized that a 'zoomed-out' field would help participants to detect targets, and a 'zoomed-in' field would help them to identify targets. But, despite participants' improved performance at recalling orienting target locations in both association conditions, they were not significantly better than random at identifying them. This result raises the possibility that participants saw the orienting target, but did not have time to identify it in both association conditions, effectively increasing their location memory but not their target identification performance. Therefore, I reasoned that it was not that contextual and probabilistic learning could not facilitate subsequent attentional orienting, instead, that the parameters of the task itself required alteration.

3.5. Experiment 6: Impact of Learning Contextual and Probabilistic Associations over Multiple Days on Subsequent Memory-Guided Attentional Orienting and Memory Recall

Experiment 5 provided some evidence that contextual and probabilistic association learning could facilitate memory-guided attention as measured by location memory, but I found no significant facilitation of the primary measure of memory guided-attention: target

identification performance as measured by BIS. I reasoned that this lack of effect could be attributed to two potential causes: inter-stimulus interval and strength of learning.

Studies examining the time course of retrieval suggest that hippocampal-based memories operate on longer timescales in comparison to striatal-based memories (Staresina & Wimber, 2019; Vogel et al., 2017). For example, Staresina & Wimber support that sensory cues interact with the medial temporal lobe within the first 500 ms of stimulus onset. It is then from 500 – 1500 ms after cue onset that hippocampal processes such as pattern completion and cortical memory reinstatement occur. Also, in their study, Vogel et al. had human participants complete a spatial memory task based on the Morris water maze (Morris et al., 1982). The virtual task was designed to distinguish between striatal stimulus-response learning and hippocampal spatial map-based learning. To complete the task, participants could navigate using salient landmarks in the environment (landmark-base navigation, e.g., a traffic cone) or based on flexible spatial representations in the surrounding environment (boundary-based navigation, e.g., mountains and the position of the sun). The hippocampus is typically involved in boundary-based navigation due to its flexible spatial characteristics, whereas inflexible and landmark-based navigation is striatal-linked (Doeller & Burgess, 2008). Importantly, in Vogel et al., reaction times for object location recall were generally shorter for landmark-based objects than boundary-based objects, supporting that retrieval of striatal-based memories may act on a faster time scale than hippocampal-based memories.

Based on evidence that probabilistic learning is striatal-linked and contextual learning is linked to the hippocampus (Henke, 2010; Packard & Goodman, 2013; Voss et al., 2020), I hypothesized that retrieval timings may work similarly in my task, i.e., that retrieval of probabilistic associations from memory may occur faster than contextual associations. Specifically, I hypothesized that keeping the interval between the memory cue and the target identity response (inter-stimulus interval or ISI) shorter than 500 ms would preclude retrieval

from contextual associations from working as effectively (Staresina & Wimber, 2019), facilitating the use of probabilistic associations instead. Alternatively, in line with other work (Summerfield et al., 2006), using an ISI longer than 500 ms would facilitate contextual retrieval. Therefore, in the memory retrieval task for Experiment 6, I updated the intervals between the memory cues and the discrimination array (ISI) to include a fast (150 ms) and slow (750 ms) condition to align the orienting task with the hypothesized timescales of the striatal and hippocampal systems, respectively.

In the first two experiments of this chapter, though there was clear evidence of a contextual learning effect, evidence for learning in the probabilistic condition was comparatively weaker. Research supports that contextual learning is acquired quickly (Spaak & de Lange, 2020), whereas probabilistic learning is more gradual (Salovich et al., 2018; Schmitzer-Torbert, 2007; Yin & Knowlton, 2006). For example, in a related experiment, participants took additional learning trials to reach the same performance level on probabilistic association trials as contextual association trials (Goldfarb et al., 2016). Therefore, in Experiment 6, participants were able to strengthen their associative learning over the course of two days. I hypothesized that, with an additional day of learning, the added learning blocks and opportunities to consolidate memories overnight would strengthen learning performance in the probabilistic condition. Once participants completed these two days of learning, on a third day, they were tested on their memory-guided attention and retrieval abilities. Additionally, on this third day, I separated the memory-guided attention and recall tasks by a delay to separately assess participants' performance on these different measures. This was an improvement on the design in Experiment 5 where participants were tested on their location memory immediately after completing the orienting trial. Due to this back-to-back testing, it was likely that performance on the two tasks was heavily correlated,

making it difficult to dissociate the impact of participants' learning on their attentional orienting abilities vs. their retrieval performance.

3.5.1. Methods

3.5.1.1 Participants. Participants were recruited online using Prolific (www.prolific.co). Participants were fluent in English, aged 18-40, and reported having no cognitive impairment, dementia, or history of mental health conditions. Participants were chosen only if they had successfully completed more than 10 studies previously on Prolific and had an approval rating of over 90%. They were compensated £7.50 per hour for their participation. All participants had normal or corrected to normal vision.

The full study included three sessions over three separate days (see below). Progressing to the next day required a minimum level of performance (accuracy above 60% on Blocks 4 and 5 of Day 1 learning, and accuracy above 60% on every Block of Day 2 learning). Once again, a sample size of n= 54 was targeted. To achieve this final number of participants, the initial sample recruited consisted of 105 individuals. After day 1, 18 participants were excluded (14 based on performance and 4 based on technical malfunction). Eighty-seven participants were invited to the session on day 2. Of these, 13 did not complete the task and an additional 6 were excluded (5 based on performance and 1 based on technical malfunction). The remaining 68 participants were invited to the final session on day 3. Seven did not complete the task and 7 were excluded from the analyses (6 based on performance and 1 based on technical malfunction). Technical malfunctions entailed failure of the online experiment hosting platform (Pavlovia) to save the data after study completion or to re-route participants correctly between segments of the study on day 3. The final sample consisted of 54 participants who completed all sessions to a satisfactory level (age range: 22 to 40 years;

mean age: 30 years; 32 females, 47 right-handed). Demographic information was only collected for participants who made it to the final day of Experiment 6.

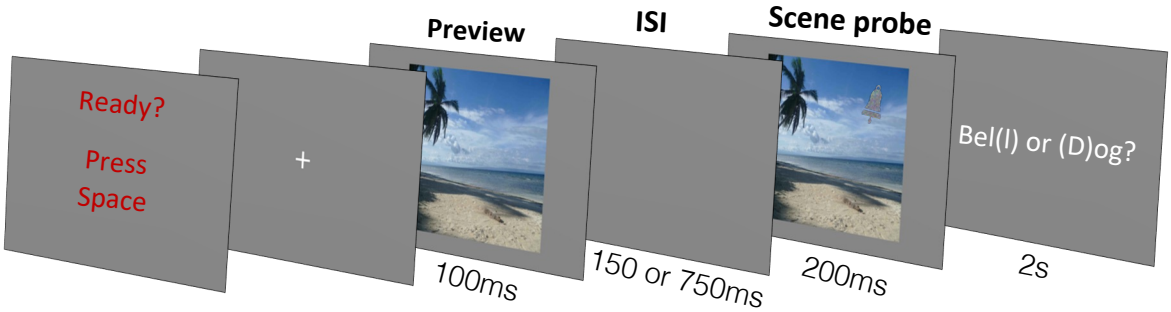
3.5.1.2. Procedure. The experiment consisted of three sessions. The first two sessions made up the learning phase. On the third day, participants completed a surprise memory-guided attention-orienting task and, after a pause, a surprise memory recall task.

3.5.1.2.1. Learning. In each learning session (day 1, day 2), participants completed five blocks of searching through the 84 scenes. Apart from being repeated two days in a row, the learning task was identical to that in Experiments 1 and 2.

3.5.1.2.2. Memory-Guided Attention. On day 3, participants completed a surprise memory-guided attention-orienting task (Figure 3.7). The same scenes were used as in the learning phase, but they were presented much more quickly. The order of the scenes was randomised. The participants' task was to discriminate whether the bell or dog target appeared embedded in the briefly presented scenes.

Figure 3.7

Memory-guided Attentional Orienting Task.



Note. A schematic of the Memory-guided Attentional Orienting Task. The task began with a 'Ready' screen. Next, after a brief fixation, a learned scene flashed (preview). Then, a blank ISI occurred that was either 150 or 750 ms in length. After this interval, the same learned scene flashed, this time containing a target. Subsequently, participants had 2s to report if the target in the scene was a bell or dog.

So that participants could prepare for the quick pace of the ensuing trial, each trial began with a screen that stated "Ready? Press space." After a subsequent fixation cross (750 ms), one of the scenes flashed for 100 ms with no embedded target. After a short (150 ms) or long (750 ms) blank inter-stimulus interval, the scene flashed again for 200 ms, this time containing the target. A grey background then appeared with the question "Bell or Dog?" in white font. Participants had 2s to identify the target using the 'D' key for dog and the 'L' key for bell. After participants responded to the target identity or ran out of time, the next trial immediately began. Target location matched the rules from learning. In each Contextual trial, the target appeared in the exact same location as in the learning phase, in Probabilistic trials

the target appeared in the same hemifield as in the learning phase, and in Random trials the location was random.

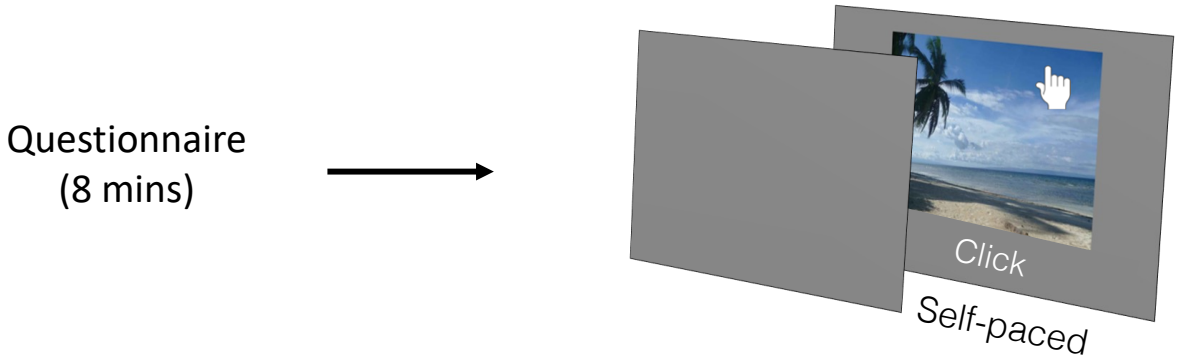
Two further changes are worth noting compared to the attentional orienting task in Experiment 5. First, when evaluating the lack of a significant attentional orienting effect in Experiment 5, I thought it was possible that the scene cue was too quick, resulting in participants not having enough time to register the scene such that it could effectively cue the related memory. I revisited literature on memory-guided attentional orienting and decided to increase the duration of the scene cue from 50 ms to 100 ms to match the procedure from Stokes et al., (2012). Second, I decided to re-evaluate the usefulness of including feedback in the design of Experiment 5. It is true that it was helpful to give participants a sense of how they were doing as the experiment proceeded, but it was also possible that the feedback screen interrupted the flow of the experiment (Bailey & Konstan, 2006). It was important in this experiment for participants to be in a focused attentional state as otherwise it could be difficult to detect the rapidly flashing objects. For example, interrupting this state with feedback or other longer pauses could make it more likely for them to get distracted, particularly in an online experiment where external distractors couldn't be controlled (Sauter et al., 2020). Therefore, in Experiment 6 I opted to remove feedback.

3.5.1.2.3. Memory-Recall. On day 3, after completing the memory-guided attention task, participants completed a demographics questionnaire (i.e., age, handedness, average screen time etc.), which lasted 8.2 minutes on average. This was followed by a surprise memory-recall task (Figure 3.8). Participants were tested on the location memory for the target-scene associations they had learned throughout the experiment. Specifically, they were instructed to "Click the exact location you remember seeing the target during the previous two days of the study". They were not given specific instructions on which of the learned

locations to recall on Probabilistic and Random trials to keep them blinded to the associations underlying the task and to allow them to respond naturally. Therefore, if they remembered more than one location from the Probabilistic or Random trials, it was up to the participant to choose which of these specific locations they wished to recall (more Discussion of the ramifications of this for analysis in Section ***3.5.1.3.3.)***. Finally, in each trial, participants viewed each of the scenes at their own pace and used the mouse to click the location where they remembered seeing the target. Trials were presented in random order. After responding, an inter-trial interval of 750 ms occurred until the next scene appeared.

Figure 3.8

Memory Recall Task



Note. A schematic of the Memory Recall Task. After the learning task, participants spent on average 8 minutes completing a demographics questionnaire. Then, they completed the memory recall task shown above. Each trial began with a blank screen then a scene from the learning would appear. Participants could take as long as they needed to report the location where they remembered the target occurring in this scene.

3.5.1.3. Data analysis.

3.5.1.3.1. Learning. To analyse performance on the learning task, I tracked target identification accuracy (% of correctly identified targets) and response time over the 5 blocks for each day (Appendix Section A). For the reasons already outlined in *Section 3.2.1.4.1*. the main measure of interest in the analysis of learning was BIS combined over both days of learning (Figure 3.9, Table 3.1). The independent variables of interest were memory Association (Contextual, Probabilistic, Random), Day (1 or 2), and Block (1-5). Only response times for trials in which participants correctly identified the target were examined. Reaction-time outliers (above 2 standard deviations from the individual mean across trials of all conditions) were removed from analysis (this came to 3% of all trials across participants on day 1 and 2% on day 2). The Box-Cox procedure (Box & Cox, 1964) was used to test the distribution and residuals of reaction-time values. Based on this, a log transformation was applied to response times on both days of learning to approximate the normal distribution and meet ANOVA assumptions.

3.5.1.3.2. Memory-Guided Attention. I assessed memory-guided attention by examining target identification accuracy (% of correctly identified targets), response time, and BIS. BIS was the main measure of interest (Figure 3.10a), therefore analysis for accuracy and response times are reported in Appendix Section B. The independent variables of interest were memory association (Contextual, Probabilistic, Random) and ISI (short or long). The Box-Cox procedure (Box & Cox, 1964) recommended log transformation for the reaction-time values. These same log-transformed reaction-time values were used to calculate BIS. Individual BIS scores are not shown on plot 3.10a because these scores have a great deal of variance, therefore, including them would have required the plot to be much more zoomed out. Zooming out the plot would have resulted in it being difficult to see the extent to which

the group-level means and error bars were similar or different. Instead, to visualize the results on a participant-specific level, a BIS difference score was calculated between each of the Association condition pairs as follows: contextual – random, probabilistic – random, and contextual – probabilistic BIS (Figure 3.10b). This violin plot figure allows for visualization of the results for each individual participant (each dot), which is helpful to determine the extent to which the group-level effects were consistent across participants.

3.5.1.3.3. Memory Recall. To assess performance on the surprise memory-recall test, I calculated participants' accuracy at locating the target in the correct hemifield (Figure 3.11a) as well as their precision in placing the target at a learned location (Figure 3.11b). The independent variable of interest was memory Association (Contextual, Probabilistic, Random).

In this analysis, I chose to measure participants' memory recall performance compared to the orienting target rather than the learning target locations for a few reasons. First, though we instructed participants to respond with the locations they learned during the "previous days", there were no significant differences in average localization error when comparing their memory recall responses to the orienting target (Euclidian distance) versus the learning locations (averaged Euclidian distance errors from learned target locations) in any of the learning conditions. For example, memory recall precision was at chance in the random condition regardless of whether the learning targets or orienting target were the comparison point. Second, one of the important metrics we analysed was memory recall accuracy (Figure 3.11a). This result examined the proportion of memory recall trials where participants placed the target in the same hemifield as it had occurred during the orienting task. This calculation could only be made using the orienting target location, as random association locations during the learning task varied between hemifields, meaning that there

was no intuitive hemifield to use to calculate hemifield recall accuracy. Alternatively, the single hemifield where the random target occurred during the orienting task made a natural comparison point. Therefore, given that it did not impact the overall results and it allowed for calculation of memory recall accuracy, it made strong logical sense to use orienting target location for calculation of memory retrieval performance.

Memory-recall performance was only calculated for trials in which participants had correctly identified the orienting target. I focused on these trials to increase the likelihood that participants had seen the target for which they were reporting the location (though overall correct identification did not impact the memory recall results). For these trials, location report accuracy was assessed by determining the proportion of trials in which participants correctly localised within the hemifield in which the target occurred during the orienting task. In other words, during the orienting task, the target flashed once for any given scene, regardless of learned association. During memory recall, if participants clicked in the hemifield where this target occurred during the orienting task, I determined that they responded accurately (Figure 3.11a). Then, for these correct trials only, location precision was calculated by measuring the distance in two-dimensional space between the centre of the target location in the orienting task and the participants' response during the memory-recall task (Figure 3.11b). I focused on these accurate response trials to demonstrate that, beyond responding in the correct hemifield, precision in the probabilistic and random conditions was at chance (Figure 3.11b). Whereas in the contextual associations condition, participants were able to localize near the orienting target's location. To simplify error values from the raw Psychopy output coordinates, error values were divided by the maximum localisation error, which generated a normalised percentage error out of 100.

A specific hemifield memory chance error value was calculated for each individual participant, for correct identification report trials only (this was used in Figure 3.11a).

Response locations in the left hemifield and in the right hemifield for the corresponding scenes were shuffled with responses to other scenes with left and right response locations (e.g., left hemifield target locations shuffled with other left hemifield target locations). The localisation error was then recalculated using these shuffled values for each participant over 1000 iterations. These new localisation error values were then averaged to generate the chance-performance value.

Finally, for the first 13 participants who finished the experiment, half of their memory-recall scenes were novel (did not occur during the learning), whereas the other half were scenes that had occurred in the learning. For these participants, memory-recall performance was only assessed on the half of the scenes that were repeated from the learning. Therefore, in the memory-recall data shown, 13 of the participants are missing half of their data (the other half of the scenes were repeated from the learning). However, for the other participants in the dataset, all their memory-recall scenes were repeated from the learning, so their full data set could be used for analysis. I ran an analysis (see results section ***3.5.2.)*** comparing recall performance between the group missing half their data and the full dataset group and found no significant differences. Therefore, I concluded that the missing data did not significantly impact results for participants' performance on memory recall, and I chose to include these participants in the larger data set.

3.5.2. Results

In an online experiment conducted over 3 consecutive days, I investigated how object-scene associations based on contextual vs. probabilistic learning guided visual-search performance, attentional orienting, and memory recall. Because BIS was the primary dependent variable of choice, I did not investigate the main effects and interactions for accuracy or response times during the learning and memory-guided attention tasks. However,

descriptive statistics and ANOVA results can be found in Appendix Sections A and B for the learning and memory-guided attention tasks respectively.

3.5.2.1. Biased Integration Score. I analysed BIS across both days of learning using a three-way ANOVA with Association, Day, and Block as within-participant factors. The ANOVA showed overall improvement in task performance with time, as well as significant learning benefits from both Contextual and Probabilistic associations relative to the Random condition (see Table 3.1 for summary of results and Figure 3.9). Main effects occurred for the Day and Block factors, showing that BIS improved over days and over blocks. These two factors also interacted. Effects involving association appeared as interactions with Day and with Block. The three-way interaction was not significant, and Association did not exert a main effect in isolation.

Table 3.1

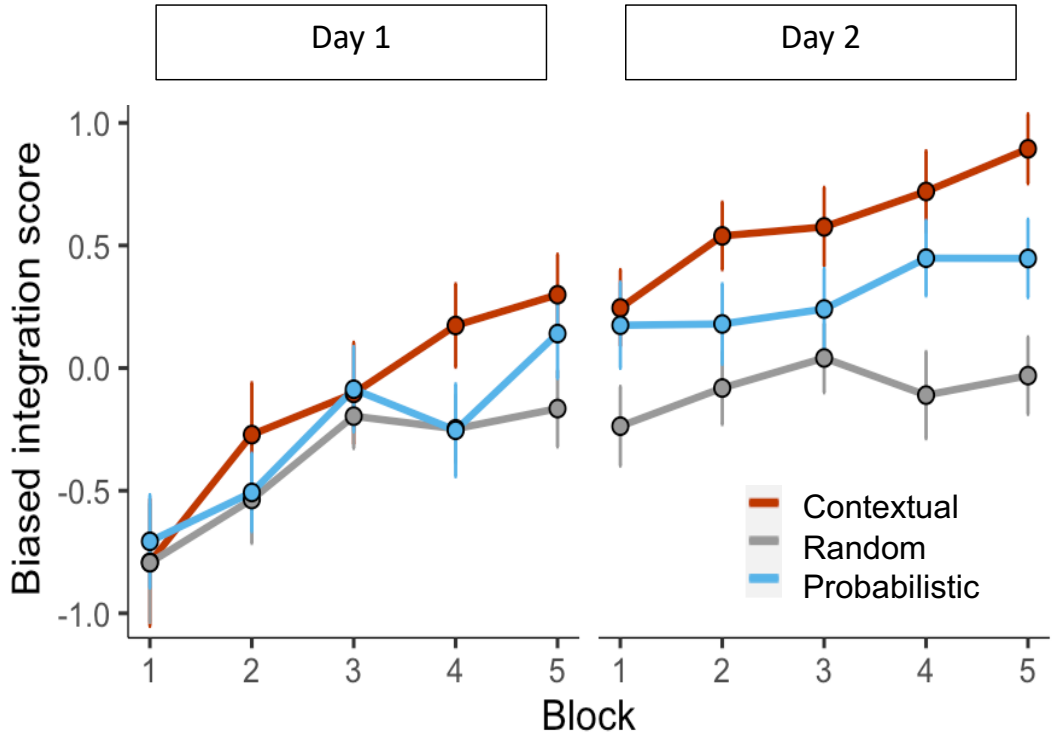
Analysis of BIS score for Days 1 and 2 of Learning

Effect	***DFn***	***DFd***	***F***	***p***	***η2***
Association	2	106	2.31	0.1	0.02
Day*	1	53	36	< .001	0.03
Block*	2.23	118.45	17.6	< .001	0.02
Association x Day*	1.76	93.30	8.86	< .001	< .01
Association x Block*	8	424	2.3	0.02	< .001
Day x Block*	2.56	135.77	2.96	0.042	< .001
Association x Day x Block	8	424	0.65	0.74	< .001

Note. There were significant main effects of Block and Day. Interactions occurred between Association and Day, Association and Block, and Day and Block. An asterisk (*) signifies a p-value below .05.

Figure 3.9

BIS Scores over Both Days of Learning



Note. On the second day of learning BIS was significantly higher in the Contextual and Probabilistic condition than in the Random condition. Overall, learning relative to the Random condition was steeper in the Contextual than in the Probabilistic condition. Error bars specify normalized mean standard error.

Planned paired samples t-tests explored the nature of effects involving association. To test for performance improvement over days in each association condition, BIS was compared for each of the Association conditions between Days 1 and 2. On Day 1, Mean BIS was -0.14 (*SD* = 1.78) in the Contextual condition, -0.28 (*SD* = 1.53) in the Probabilistic condition, and -0.39 (*SD* = 1.60) in the Random Condition (Figure 3.9). On Day 2, Mean BIS

was 0.59 (*SD* = 1.41) in the Contextual condition, 0.30 (*SD* = 1.37) in the Probabilistic condition, and -0.08 (*SD* = 1.47) in the Random Condition. In all cases, performance was better on Day 2 compared with Day 1 (Contextual associations: $t(53) = -5.60$, $p < .001$, Cohen's $d = -0.50$; Probabilistic associations ($t(53) = -5.99$, $p < .001$, Cohen's $d = -0.48$, and Random associations ($t(53) = -3.31$, $p < .01$, Cohen's $d = -0.23$). To test for learning-specific benefits brought by different types of associations in each day, we compared BIS between Association conditions within Days 1 and 2. Learning effects were not significant on day 1 (Contextual x Random: ($t(53) = 1.00$, $p = .16$, Cohen's $d = 0.17$; Probabilistic x Random: ($t(53) = 0.55$, $p = .71$, Cohen's $d = 0.08$; Contextual x Probabilistic: $t(53) = 0.53$, $p = .60$, Cohen's $d = 0.10$). Significant and equivalent learning effects emerged on day 2 for both Contextual and Probabilistic associations relative to the Random condition (Contextual x Random: $t(53) = 3.30$, $p < .001$, Cohen's $d = 0.52$; Probabilistic x Random: ($t(53) = -2.15$, $p < .05$, Cohen's $d = 0.31$; Contextual x Probabilistic: ($t(53) = 1.33$, $p = .19$, Cohen's $d = 0.24$). The three-way interaction (Association x Day x Block) was not significant, suggesting a similar pattern of improvements over blocks for the two days.

To examine the rate of learning over time, learning blocks from both days were concatenated to compare learning benefits using linear contrast across Blocks 1-10. Linear contrasts revealed an interaction between Association and Block ($F(1.93, 1039.18) = 5.43$, $p < .01$, $\eta 2 = 0.01$; Figure 3.9), and main effects of Association ($F(1.93, 1039.18) = 16.80$, $p < .001$, $\eta 2 = .015$) and Block ($F(1, 538) = 53.16$, $p < .001$, $\eta 2 = .05$). To investigate the interaction between Association and Block, t-tests were run between levels of association. This analysis revealed a steeper learning rate for Contextual associations relative to Probabilistic associations (Contextual x Probabilistic: $t(1455) = 2.08$, $p < .05$, Cohen's $d = 0.37$). Learning of each type of association relative to the Random condition was also

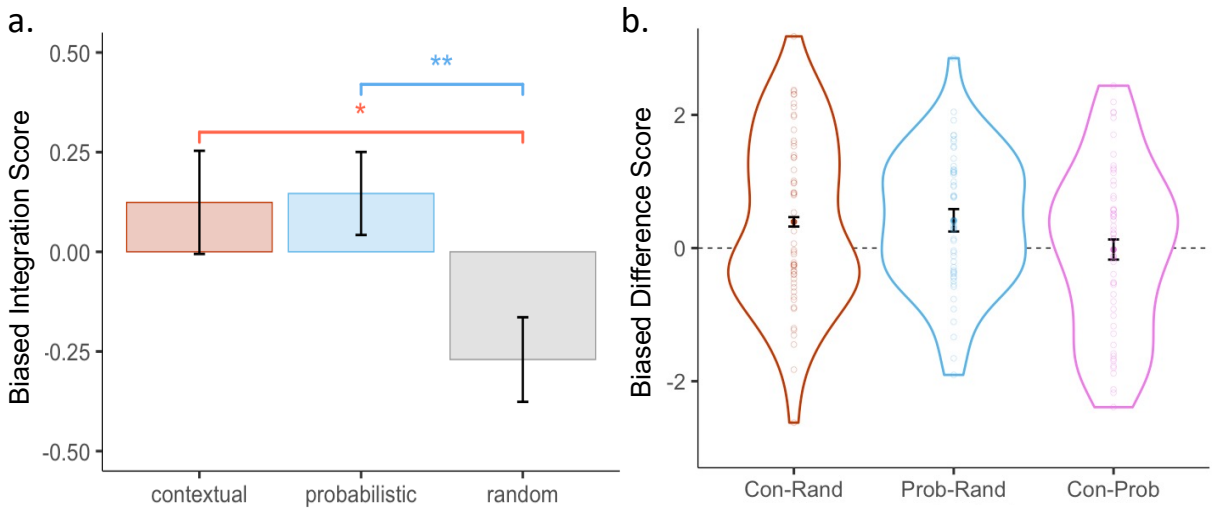
confirmed (Contextual x Random: $t(1455) = 4.82$, $p < .001$, Cohen's $d = 1.03$ and Probabilistic x Random: $t(1455) = 2.74$, $p < .01$, Cohen's $d = 0.66$).

3.5.2.2. Memory-guided Attention. On the 3rd experimental day, participants completed a memory-guided attentional orienting task to investigate whether learned contextual and probabilistic associations would guide attentional orienting (Figure 3.7). To examine whether the time course of using these associations to guide attention was dissociable, different inter-stimulus intervals (ISI) were included between the cue and response phases of the task.

3.5.2.2.2 Biased Integration Score. BIS was used as the dependent variable of interest in a two-way ANOVA assessing the effects of the two within-participants factors: Association (Contextual, Probabilistic, Random) and ISI (Short or Long). There was a significant main effect of Association on BIS ($F(2, 106) = 4.24$, $p < .05$, $\eta 2 = 0.02$, Figure 3.10a) but no main effect or interaction with ISI (main effect: $F(1, 53) = 0.03$, $p = .86$, $\eta 2 < .01$; interaction: $F(2, 106) = 1.91$, $p = .15$, $\eta 2 = 0.05$).

Figure 3.10

Memory-guided Attentional-Orienting Results



Note. (a) Biased Integration Score (BIS) was higher for both Contextual and Probabilistic associations than in Random associations. (b) Within each participant, BIS was compared between conditions to generate a difference score. Each dot corresponds to the Difference Score of a single participant in a given comparison of association conditions. Error bars show the normalized mean standard error.

Planned paired-samples t-tests showed that both types of association guided attentional orienting to a similar extent. Mean BIS was .13 (SD = .69) in the Contextual condition, .12 (SD = .62) in the Probabilistic condition, and -.19 (SD = .63) in the Random condition. Performance for identifying the target was superior for Contextual ($t(53) = 2.27$, $p < .05$, Cohen's $d = 0.28$) and Probabilistic ($t(53) = 3.08$, $p < .01$, Cohen's $d = 0.30$) conditions relative to the Random condition. There was no significant difference in identification

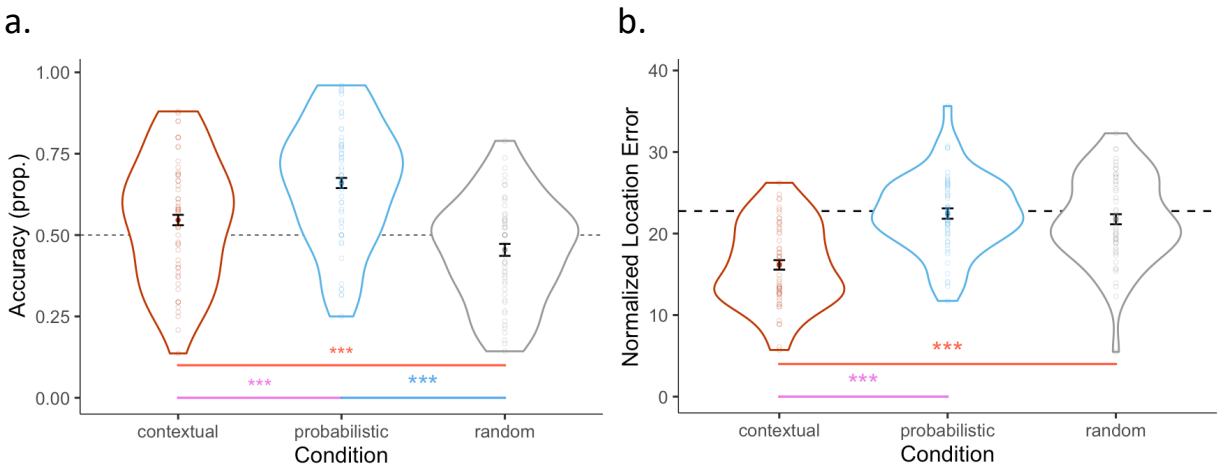
performance between Contextual and Probabilistic conditions ($t(53) = 0.13$, $p = .9$, Cohen's $d = 0.02$).

One sample t-tests on BIS difference scores reinforced the finding of memory-based guidance of attention by Contextual and Probabilistic associations compared to Random associations on a participant-specific level. The mean difference between the Contextual and Random conditions ($t(107) = 2.54$, $p < .01$, Cohen's $d = 0.24$, Figure 3.10b) and the Probabilistic and Random conditions ($t(107) = 3.22$, $p < .001$, Cohen's $d = 0.21$) differed significantly from 0. The mean difference between the Contextual and Probabilistic conditions did not differ significantly from 0 ($t(107) = 0.15$, $p = .56$, Cohen's $d = 0.01$).

3.5.2.3. Memory Recall. The final phase of the experiment was an explicit recall task in which participants were tested on their memory for the locations of the targets learned throughout the experimental days. In this final phase of the experiment, I investigated how learned contextual and probabilistic associations would differentially facilitate explicit recall accuracy and localisation precision (See Figure 3.8). Both of the metrics used to measure memory recall (location accuracy and precision), were calculated in comparison to the orienting target location. However, I also calculated these metrics in comparison to the average learning location (mean across the 10 learning blocks), and there was no difference in performance.

Figure 3.11

Memory-Recall Performance Plots



Note. Memory recall performance for trials in which participants correctly identified the orienting target. If participants recalled (clicked) in the same hemifield as the orienting target, this counted as a correct location accuracy report for the proportion in (a). The distance between where participants recalled the target to occur and the orienting target's actual location represented their location report precision (b). (a) Location report accuracy for localizing the target in its correct hemifield. Location report accuracy was significantly higher in the Probabilistic and Contextual associations than in the Random associations, and significantly higher in the Probabilistic than in the Contextual condition. (b) Location report precision results. Only trials in which participants localized in the correct hemifield of the target are shown. Location-memory error was significantly lower in the Contextual than in the Probabilistic and Random associations. Error bars represent normalized mean standard error. Dotted lines represent chance value.

3.5.2.3.1. Target Location Accuracy. As a proxy for memory accuracy, I calculated the proportion of trials in which participants correctly identified (clicked) the target hemifield from the orienting task. I did this by taking their memory recall response and determining whether it was placed in the same hemifield as the orienting target, if it was that would count as a correct response (Figure 3.8). This metric was largely independent of the precision of their location memory. Rather, it simply measured whether they could make a left-right judgement about the target location. Given that targets were associated with a specific hemifield of the scene in probabilistic learning trials, I predicted that probabilistic learning would specifically benefit this memory accuracy measure.

A one-way ANOVA with Association as the within-participants factor demonstrated a significant main effect of Association ($F(2, 106) = 38.04$, $p < .001$, $\eta 2 = 0.19$, Figure 3.11a) on location report accuracy. Mean accuracy was 54% (SD = 12%) in the Contextual Condition, 66% (SD = 11%) in the Probabilistic condition, and 46% (SD = 14%) in the Random condition. Planned paired-samples t-tests showed that participants' location report accuracy was higher in the Contextual ($t(53) = 3.67$, $p < .001$, Cohen's $d = 0.53$) and Probabilistic ($t(53) = 8.34$, $p < .001$, Cohen's $d = 1.2$) associations compared to Random. Furthermore, participants were more accurate in the Probabilistic compared to the Contextual association trials ($t(53) = 5.43$, $p < .001$, Cohen's $d = 0.61$).

3.5.2.3.2. Target Location Precision. Next, I measured localisation precision as the Euclidian distance between the participants' localisation response and the location of the target in the orienting task. Only trials in which participants localised within the correct hemifield of the target were examined to measure memory precision beyond simple identification of the target hemifield. Given that in contextual learning trials targets were

associated with a specific location of the scene, I predicted that contextual learning would particularly benefit this memory precision metric.

A one-way ANOVA with association as the within-participants factor demonstrated a main of effect of Association ($F(2, 106) = 31.80$, $p < .001$, $\eta 2 = 0.25$; Figure 3.11b) on location report precision. Mean of normalized location error was 16.02 ($SD = 6.63$) in the Contextual Condition, 22.38 ($SD = 6.10$) in the Probabilistic condition, and 22.24 ($SD = 8.11$) in the Random condition. Planned paired-samples t-tests indicated that participants' location report was more precise for Contextual associations compared with both Random ($t(53) = -6.74$, $p < .001$, Cohen's $d = -1.10$) and Probabilistic ($t(53) = -7.31$, $p < .001$, Cohen's $-d = 1.31$) associations. There was no difference in location report precision between the Probabilistic and Random association trials ($t(53) = 0.77$, $p = .78$, Cohen's $d = 0.14$).

Location precision was compared between the group missing half their recall data and the full dataset group (N = 41) via a two-way ANOVA with Group (missing data or full dataset) as a between-participants variable and Association as a within-participants variable. No significant main effect of the Group variable was found ($F(1, 52) = 1.99$, $p = .16$, $\eta 2 = 0.02$), nor an interaction between Group and Association ($F(2, 104) = .24$, $p = .79$, $\eta 2 < .01$). The main effect of Association remained significant ($F(2, 104) = 31.35$, $p < .001$, $\eta 2 = 0.25$).

3.5.3. Conclusion

In Experiment 6, participants completed two days of learning the locations of targets in scenes according to contextual or probabilistic associations. On the third day, they were tested on memory-guided attentional orienting and memory recall. In this final experiment of the chapter, both contextual and probabilistic learning facilitated attentional orienting and improved memory recall performance. Therefore, despite differences in the types of associations learned, contextual and probabilistic learning effectively guided the attentional

selection of briefly flashed targets. Alternatively, as in Experiment 4, memory-recall benefits were more sensitively captured when response requirements best matched the type of association. Specifically, hemifield-report accuracy revealed stronger effects of probabilistic learning at the hemifield level, whereas precise localisation reports were better for unique and precise contextual associations.

These differences in recall performance may point to underlying differences in the probabilistic and contextual types of learning. In probabilistic associative learning, participants learned associations between a scene category and a hemifield. Subsequently, participants were effective in applying the learned attentional habit (e.g., desert scene = target on the right side) to place the target location in the correct hemifield (3.11a). But, the actual location in the hemifield where participants placed the target was no closer to the orienting target location than chance (3.11b). Therefore, as in past studies (Geng & Behrmann, 2002; Jiang & Sisk, 2019; Salovich et al., 2018; Seger et al., 2018), probabilistic learning was unspecific and relatively inflexible in that it facilitated retrieval of the learned association between category and hemifield. But, probabilistic associations were not influenced by individual object-scene associations such as the orienting target location, resulting in chance-level location report precision. Alternatively, in contextual learning, participants learned associations between a specific scene and a specific location where targets occurred. Interestingly, compared to probabilistic associative learning, contextual learning was less suited to hemifield memory recall (though performance was still better than the random condition). However, for the hemifields that participants did respond correctly to, the location where they placed the target was the most precise in the contextual condition. This finding aligns well with the literature arguing that contextual associative learning is spatially specific but still relatively flexible, in that was still effective at hemifield report, but was best suited

for recall of specific target locations (Doeller & Burgess, 2008; Summerfield et al., 2006; Stokes et al., 2012).

3.6. Discussion

By manipulating the types of regularities about the location of targets according to scene categories, significant learning benefits were demonstrated for both contextual and probabilistic associations during repeated blocks of visual search. Both contextual and probabilistic learning subsequently guided spatial orienting of attention, whereas performance on explicit spatial memory recall measures varied according to the type of memory report. These findings demonstrate the usefulness of experimental tasks that tap into learning and utilisation of different types of memory associations within a common framework. They also extend previous reports (Goldfarb et al., 2016; Rosen et al., 2018) by using natural scene stimuli to approximate everyday behaviour.

Over this set of experiments, I developed a task that promoted learning of two different types of associations within a common setting. Utilizing a single, incidental learning task enabled equating stimulus materials, response requirements, and state variables between participants. In other words, participants never had to mentally state switch between blocks of searching for probabilistic targets versus contextual targets or to change the way they responded based on the learning condition or scene category. Participants simply searched for embedded targets in scenes and responded to their identities, unaware of the implicit associative learning occurring. This design allowed for learning to be as equated as possible in the different conditions and for emergent differences to be due to the benefits of the learned associations themselves rather than other factors. Additionally, including a random-association condition captured effects related to overall familiarity with the task and provide a continuous comparison point from

which behavioural benefits in the other associations could be measured. Lessons from Experiments 4 and 5 were incorporated to design a more sensitive task that included more extended learning over two successive days and then tests for attentional orienting and recall ability on a subsequent day. The timings of stimulus presentation were also adjusted to test for different utilising contextual and probabilistic associations in guiding spatial attention.

Despite the online nature of the task – participants showed good performance. Improvements occurred for all three conditions, but significant learning benefits occurred for both the contextual and probabilistic associations only when participants were able to learn over two days of testing (Experiment 6). The prediction that contextual associations would lead to faster learning compared to both other association conditions was partially supported. Though learning performance for both association types was equivalently better compared to random associations on day 2, a linear contrast analysis showed the overall learning slope (over days 1 and 2) to be steeper for the contextual condition. As in many search tasks (Goldfarb et al., 2016; Salovich et al., 2017), performance also increased gradually in the random condition, without any spatial regularity for target locations. Therefore, it is possible that participants learned to optimise search trajectories according to the overall stimulus parameters. Additionally, the probabilistic learning manipulation differed from some previous approaches (e.g., Goldfarb et al., 2016) by separating response mapping from associative learning. In my experiments, the scene category only cued the target's hemifield but not the required response. Thus, it was easier to rule out performance benefits resulting merely from response-related associations. In Experiments 4-6, participants could only use probabilistic associations to find the target rather than as a heuristic to respond (e.g., the category is beach = so the response is left). The probabilistic learning manipulation differed from past

approaches by dictating object locations more deterministically (e.g., in beach scenes, the target always occurs on the right) rather than probabilistically (e.g., in beach, scenes the target occurs on the right 80% of the time and 20% on the left). This deterministic rule achieved its intended purpose, as participants learned probabilistic associations adequately in Experiment 6, i.e., significant learning was achieved in the probabilistic condition without requiring additional trials compared to the contextual condition (e.g., Goldfarb et al., 2016). However, subsequent work should explore if different mechanisms are involved in probability cueing under the more deterministic conditions used here versus the typical probabilistic conditions used prior (e.g., Geng & Behrmann, 2002, 2006; Smith et al., 2010). Overall, the robust learning in this phase of the task provided a solid basis for exploring the consequences of different types of associations on different behaviours in subsequent tasks.

Separating learning from subsequent measures of perception provided some important advantages. It is common practice to study memory-guided attention within visual search tasks as a function of repeated array configurations (contextual; Chun & Jiang, 1998) or more likely target location within a region of the display (probabilistic; Goldfarb et al., 2016; Geng & Behrmann, 2002). However, within search, many factors are at play when responding to one display, such as learning, finding the target, overcoming distraction, and preparing a response. Accordingly, it is difficult to isolate the step of orienting attention. Including a separate task tuned for investigating spatial orienting after learning has stabilised and lessens the impact of some of these other variables (Nobre et al., 2019). Similar arguments have been made in past memory-guided attention studies that have manipulated spatial-contextual associations (Doallo et al., 2013; Patai et al., 2012; Rosen et al., 2016; Stokes et al., 2012; Summerfield et al., 2006, 2011).

Both contextual and probabilistic learning conferred significant and similar benefits to perception through memory-guided spatial orienting. Interestingly, these effects were only significant in the third experiment, potentially supporting a role for reliably learned associations and/or memory consolidation in facilitating subsequent memory-guided orienting performance. For example, in Experiment 5, learning effects were not robust. Further, subsequent tests of memory-guided attention were not separated from learning by much time, potentially contributing to the lack of a significant orienting effect. However, in Experiment 6, the learning effects were robust. This may have been because memory consolidation could occur between learning days 1 and 2, as well as between learning day 2 and the subsequent attention-orienting and memory-recall tasks on day 3 (Barsky et al., 2015; Geyer et al., 2013). Also, the overall number of learning blocks increased from 5 in Experiments 4 and 5, to 10 in Experiment 6. Therefore, as in past studies, it appears as though the benefits of memory consolidation and additional learning blocks outweighed the possible effects of memory decay that may have resulted from increasing time between learning and retrieval test (Hardt et al., 2013; Roediger & Karpicke, 2006; Thorndike, 1911). Future work can investigate the necessity or sufficiency of learning robustness compared to sleep-related memory consolidation for facilitating subsequent enhancement of memory-guided attention.

These results also provide a nice platform to investigate whether different neural systems that have been implicated in contextual or probabilistic learning can support similar magnitudes of perceptual benefits through different mechanisms. Brain-imaging and human neurophysiological studies will be useful for examining this fundamental question. By varying the stimulus parameters and demands in the orienting task it may also still be possible to disentangle differences in the psychological consequences of

contextual and probabilistic memories for guiding attention. For example, the tasks employed here stressed both perceptual sensitivity (i.e., target identification) and response times and used two different intervals between the memory cue and the target array (ISI). Though significant effects of intervals were not found in this study, more can be done to explore whether short and long intervals can modulate behavioural performance in related tasks by tapping into the fast (Spaak & de Lange, 2020) and slow (Salovich et al., 2018; Yin & Knowlton, 2006) systems for learning and memory. For example, it would be interesting to determine if behavioural performance would differ, or be more sensitive to ISI intervals, if perceptual sensitivity was measured with classical signal detection manipulations such as having participants discriminate if a target is present or absent in learned scenes (Patai et al., 2012; Stokes et al., 2012).

My findings extend those from prior investigations of memory-guided spatial attention using contextual and probabilistic associations. Specifically, prior research has demonstrated that learning of scenes that cue the memory of specific target locations has resulted in higher perceptual sensitivity and faster response times to detect targets (Doallo et al., 2013; Patai et al., 2012; Summerfield et al., 2006). Here, contextual association learning enhanced perception as measured by a combined metric for accuracy and response time (BIS), and this operated on a participant-specific level (BIS difference score). Further, my results added a new angle to established contextual-learning research by demonstrating that probabilistic learning can similarly guide attention. Thus far, studies on probability associations have focused on the enhancement of visual search and discrimination by varying the distribution of targets in space (Druker & Anderson, 2010; Ferrante et al., 2018; Geng & Behrmann, 2002, 2005) but not on their future utility. Here, I have shown that learning probabilistic associations can bring benefits to subsequent attentional orienting.

The explicit memory tasks (in Experiments 4 and 6) revealed how the two types of learned associations were expressed differently during recall. Probabilistic associations led to the strongest accuracy in placing targets in their matching hemifield, as measured by hemifield recall in Experiment 4 and location report accuracy in Experiment 6, suggesting that the probabilistic rule was well learned and expressed. Specifically, in the probabilistic association trials, rather than needing to remember individual target locations, participants were able to reduce memory load by remembering only the association between a scene category and a hemifield (e.g., beach scene = target located on the left). The benefit conferred by this generalizability of target location may partially explain participants' enhanced hemifield recall and location memory accuracy performance in comparison to both the contextual and random association conditions (Delgado et al., 2005; Geng & Behrmann, 2002; Jiang & Sisk, 2019; Salovich et al., 2018; Seger et al., 2018). On the other hand, contextual associations uniquely improved memory recall of specific target locations (Experiment 4: location memory, Experiment 6: location report precision). These results were unsurprising given that there was no correct, consistent target location for the probabilistic condition. Learning of contextual associations may have resulted in a 'zoomed-in' attentional field that contributed to improved performance during visual search task and that also may have subsequently aided recall performance (Eriksen & James, 1988). For example, it has been found that participants are more likely to remember attended information when hippocampal activity patterns strongly match the relevant attentional field (Aly & Turk-brown, 2016).

Overall, the experimental tasks developed here appear highly promising for studying how different types of memories are learned and utilised. These robust behavioural measures provide a strong base for subsequent neuroscientific studies that could investigate how different memory systems support behaviour and selectively break down in

different neurodegenerative conditions. With potential, for example, to measure disorders affecting the hippocampus (Chun & Phelps, 1999; Chun, 2000; Manns & Squire, 2001; Negash et al., 2015) or the striatum (Foerde and Shohamy, 2011; Shohamy, Myers, Grossman, et al., 2004; Knowlton et al., 1996) in a single task. The approach also provides a great platform for investigating how different memory systems either can work together to support cognition or compete (Dickerson et al., 2011; K. Duncan et al., 2018; Foerde & Shohamy, 2011). For example, MRI and EEG studies could tease apart how these systems interact on different time scales and elaborate on whether they work independently, together, or compete while supporting these different behavioural outcomes. These follow-ups will be important to verify my predictions of synergistic interactions: contextual associations are supported by the hippocampus and probabilistic associations by the striatum. Also, to refute accounts of competition between systems, which assert that the time spent learning (e.g., more learning blocks result in the transition from hippocampal-dependent to striatal-dependent learning) could be more important for determining the neural correlates than the learned association itself (Packard & Goodman, 2013; Wang & Voss, 2014). Finally, though my results supported behavioural differences in recall facilitation between association conditions, backing this up with neural evidence would significantly strengthen this framework (e.g., increased striatal BOLD during hemifield recall for probabilistic trials while hippocampus BOLD increases during localisation recall for contextual trials).

Important lessons were learned from this set of experiments. First, online testing brought advantages and limitations. Advantages included the broader and more diverse participant pool and the speed of data collection compared to in-lab testing. Disadvantages included the lack of control over the stimulus display and response equipment (e.g., screen size, distance from eyes to the screen, quality of mouse and keyboard, etc.), variability in timing responses (e.g., computer lag, network quality,

etc.), and possible distractions during the task. However, decreased attention to online tasks compared to in-lab is not necessarily always found (Clifford & Jerit, 2014; Hauser & Schwarz, 2016). Also, as in Experiment 1 of my thesis, online data quality is often comparable to in-lab studies (Casler et al., 2013; Dandurand et al., 2008). Nevertheless, to account for possible distracted participants, strict exclusion criteria had to be implemented to ensure a certain standard of performance on the learning task for inclusion in analysis. It is possible that due to the online nature of the study, an increased number of participants were excluded from analysis compared to if this study had been run in-lab. The attrition rate for the multi-day study was particularly high. Further, online testing limited the range of possible behavioural measures. For example, recording eye movements would provide rich additional information such as how many and which different locations were attentionally selected during memory recall prior to response, and whether eyes moved in anticipation of target appearance during the memory-guided orienting task (Summerfield et al., 2006; Stokes et al., 2012). Taking these factors into account, future studies should replicate this work in the lab as well as try hybrid approaches. For example, a combination of learning occurring online and the final testing occurring in the lab should ensure strong learning followed by high levels of experimental control during the critical assessments. A study such as this would help to verify whether the attrition rate would in fact be lower in person and if learning effects would be similar with fewer participant exclusions.

Finally, though a significant strength of this study was exploring how different types of learned associations facilitate future behaviour, some of the measures we used may have been biased toward benefitting more from some associations over others. For example, the location report precision metric, as it measured memory for a focal point in space, was best suited to benefit from contextual learning. Whereas the more dispersed locations in

probabilistic association learning would be less likely to facilitate participants' ability to precisely remember the target's location, which would have occurred on a point they never learned on days 1 and 2. Ultimately, this was part of the nature of the task, and it would be difficult to have a single metric that was equally suited to both learning types. Therefore, it was even more interesting to reveal similar benefits of memory-guided attention, despite learning associations via different methods.

Chapter 4. How Fixed and Variable Associations guide Memory Retrieval and Attentional Orienting.

Abstract

During visual search, ignoring distractors can be just as important as learning where to find targets. Research has shown that predictable (fixed) target and distractor locations can facilitate visual search. Here, I tested how learned regularities about target and distractor locations impact subsequent memory retrieval and attentional orienting. In two online experiments, participants learned to identify unique targets in real-world scenes, while simultaneously ignoring distractors. A factorial design manipulated whether each item acted as the target or distractor and occurred consistently in the same or variable position. The consequences of this learning were tested on performance in memory-retrieval (Experiment 7) and attentional-orienting (Experiment 8) tasks. In Experiment 7, participants' object identification and scene recognition were better overall for learned targets than distractors, with no performance differences based on association type (fixed or variable). But, for speed of scene recognition specifically, participants were faster at responding correctly when scenes had contained a variable-location target during learning. In Experiment 8, participants demonstrated better attentional-orienting performance for learned targets than distractors, with performance benefits demonstrated for fixed compared to variable targets, but not for fixed vs. variable distractors. Overall, the spatial regularity of object-scene associations had important implications on the effective use of these memories, with differences emerging between how fixed vs variable associations facilitate memory retrieval compared to attentional orienting. This supports the view that the functional utility of associative regularities during learning may relate to their subsequent application, such as in memory retrieval or attentional orienting.

4.1. Introduction.

We update our predictions and expectations about the sensory world continuously, based on consistent and variable interactions with our surroundings. We can think of consistent experiences as stable over time, meaning that we can use past experiences to guide expectations and subsequent behaviour (Aly & Turk-Browne, 2017; Nobre & Mesulam, 2014; Nobre & Stokes, 2019; Sherman et al., 2022). Whereas, during variable experiences, what will happen next is uncertain, making expectations more difficult to generate (Noonan et al., 2016). For example, if you have a fish tank containing two fish, a shy clownfish and an excitable blue tang, you might implicitly build expectations to help you find them amongst the coral. Knowing that the clownfish always hides in the sea anemone (a fixed location), you would quickly look for him there, without needing to search through the surrounding environment. Therefore, reliable or fixed predictions about the clownfish's location may speed search. In turn, this heightened predictability could signal that exploring and thus learning about the surrounding environment is not necessary, potentially reducing memory for it (Sherman et al., 2022). In contrast, the blue tang is harder to predict (her location is variable), so each time you search high and low for her, you learn the ins and outs of the coral and underwater castle in the fish tank. Therefore, though search speed may be slowed by variable target locations (Geng & Behrmann, 2002), this unpredictability could encourage exploration, potentially heightening memory for the surrounding environment (Greve et al., 2019). In these examples, there were potential complementary costs and benefits of the learned regularity of target (fish) locations to the resulting attention vs. memory functions stemming from the visual-search experience. However, distinctions between how regularity-derived expectations may help versus hurt memory and attention are not clear-cut and have not been compared directly to the best of my knowledge.

Attempts to understand how expectations have costs and benefits to learning and memory are long-running, with Bartlett (1933) observing that memory for new information that fits into our prior expectations is encoded better. More recent work has backed up this finding (Tse et al., 2007; Van Kesteren et al., 2012). For example, Kan et al., (2009) asked healthy controls and amnesic patients to study prices for everyday items. Both groups then performed a recognition test for the studied prices, which were either congruent (e.g., eggs at market price) or incongruent (e.g., eggs at 4x market price) with their prior knowledge. Healthy controls showed a congruency benefit to their retrieval performance, whereas retrieval benefits for the amnesics were related to the extent of their MTL lesions (Kan et al., 2009).

Interestingly, other researchers have argued for the opposite, proposing that events that are incongruent with our predictions are remembered better (e.g., Greve et al., 2017; Hunt & Worthen, 2006; Tulving & Kroll, 1995). For example, the "Isolation Effect" established by Von Restorff (1933), describes how an item that is distinct in a list is remembered better (for example, the one lowercase word is remembered better than the 5 uppercase words). Parsing out the situations in which events that are congruent or incongruent with our predictions result in better memory is thus an ongoing fundamental topic of inquiry (Frank & Kafkas, 2021).

One proposal is that contextually novel stimuli, e.g., an item that is unexpected in a given context, benefit memory performance as measured by recognition (Ranganath & Rainer, 2003) and retrieval tasks (Rajaram, 1998). An example of a typical contextual novelty task is the Oddball paradigm, where the context (e.g., a black background) is a property shared by the majority of the presented stimuli (e.g., yellow box), and participants are meant to detect and respond to the non-standard or target stimulus (e.g., yellow sphere; Malik & Amin, 2017). In this experimental set-up, participants implicitly form expectations from the

pattern of stimuli and required responses. Because most stimuli are non-targets that require no response, participants learn to predict that non-targets are likely and become biased toward not responding (Huettel & McCarthy, 2004). Importantly, the task of differentiating the oddball from similar non-targets leads to better memory for the contextually novel oddball items compared to the non-targets (Sakamoto & Love, 2006). Therefore, the unpredictable and rare oddballs are remembered better compared to the predictable and frequent non-targets. However, behaviour in this task may also be impacted by the possibility that the way in which expectations guide learning and memory for targets (e.g., the oddball) could differ from non-targets.

In a visual world that is rich with information, the ability to discriminate between the targets of our search and distracting non-targets is essential for effective contextual learning (Kafkas & Montaldi, 2015a). A range of factors can benefit the search for targets, such as contextual information (Chun & Jiang, 1998) or statistical regularities (e.g., Jiang et al., 2013), as discussed in detail in Chapter 3. Specifically, in contextual cueing, stable information about the location of targets in a specific context can increase the efficiency of search (Goujon et al., 2015). In probability cueing tasks, targets that appear in high-probability locations are found more quickly than those that appear in lower-probability locations (as in the probabilistic or random conditions of my Chapter 3 studies; Geng & Behrmann, 2002; Jiang et al., 2013; Salovich et al., 2018).

Importantly, consistent information about distractor locations can also increase the efficiency of search for targets. Recent work has shown that if distractors appear in a specific location with high frequency, this lowers their ability to distract from the target, increasing the rate at which participants find targets (Ferrante et al., 2018; Noonan et al., 2016; Reder et al., 2003). Alternatively, if the distractor appears in different locations, they interfere more with target search (Ferrante et al., 2018; Kelley & Yantis, 2009; Pascucci & Turatto, 2015).

For example, in Wang & Theeuwes (2018), participants searched for a target (circle) among seven distractors (diamonds) in a symmetrical circular array and responded with whether the line segment inside the circle was vertical or horizontal. One of the distractor shapes was uniquely coloured and varied in its probability of appearance, with one location having a probability of 65% and the other five locations having a combined probability of 35% of distractor occurrence. When the coloured distractor occurred in the high probability location, it had the least distracting impact on reporting the target (participants were faster at finding the target circle and more accurate in reporting the orientation of the line segment). Interestingly, participants performed worse if the distractor occurred further away from the high probability location, suggesting a spatial gradient in the effects of predictable distractors on target search, with the least effect of distraction at the peak of the probability distribution (Wang & Theeuwes, 2018).

The competition between target and distractor locations for attentional selection is illustrated well by Ferrante and colleagues' study (2018). Over a series of experiments, they manipulated the spatial probability of targets and distractor locations. In their task, participants were simultaneously shown four triangle pairs and had to detect the singleton with both triangles pointed in the same direction. They found an interdependence between target selection (finding the triangles pointed in the same direction) and distractor filtering (ignoring the triangles pointed in different directions). For example, there was a greater cost to search efficiency when distractors occurred at locations with a high target probability compared to a low target probability. However, the authors noted that this result had some asymmetry, reporting a consistent effect of manipulating target probability on distractor suppression whereas manipulating distractor probability did not consistently impact target selection. This finding ties into evidence suggesting some degree of functional dissociation between cognitive and neural mechanisms supporting target selection and distractor filtering

(Couperus & Mangun, 2010; Houghton & Tipper, 1996; Luck, 1995). For example, some have argued that distractor suppression is not as flexible as control mechanisms for target enhancement by showing that distractor suppression only benefits target selection when the distractor location is fixed over numerous trials (Noonan et al., 2016).

There are also neural differences between the systems involved in attentional guidance to targets and suppression of distractors. For example, in their EEG experiment, Noonan et al., (2016) found reduced P1 component during distractor suppression, whereas alpha-band activity was associated with target selection. Further, a number of functional imaging studies have shown separately that activity in different brain networks are correlated with the selection of target objects (frontoparietal circuits and visual cortex; Serences et al., 2004) and the filtering of distractors (right middle frontal gyrus and basal ganglia; Anderson et al., 2002; Marini et al., 2016; Ruff & Driver, 2006).

Interestingly, spatial attention regions involved in target selection are connected with those involved in expectation-driven novelty (Duszkiewicz et al., 2019; Kafkas & Montaldi, 2018; Kafkas & Montaldi, 2015b; Shohamy & Adcock, 2010a). Specifically, the hippocampus has an important role in novelty detection (Knight, 1996). For example, enhanced exploration of the unexpected information (as shown by increased fixations and pupil responses) and enhanced memory formation (higher d' recollection rates) has been linked to hippocampal activity and connectivity with the basal ganglia (Kafkas & Montaldi, 2015a). The hippocampus has also been shown to interact with frontoparietal regions involved in attentional selection (Summerfield et al., 2006; Stokes et al., 2012; Voss et al., 2011; Wang & Voss, 2014). For example, frontoparietal-hippocampal interactions can mediate memory-guided strategic exploration (Bridge et al., 2017). Overall, how the cognitive and neural mechanisms for target selection, distractor filtering, and novelty

detection work together to facilitate visual search is an ongoing topic of inquiry (Ferrante et al., 2018).

One important related question is: how are learned associations (i.e., between object and location of appearance) that abide by different degrees of spatial regularity (i.e., fixed or variable) used for subsequent memory retrieval and attentional orienting? Further, does the utility of these different types of learning for subsequent behaviour differ between targets and distractors? Evidence suggests that target memory can operate differently than distractor memory (Thomas & Williams, 2014; Williams, 2010a, 2010b). Though task-relevant objects in visual search are remembered better than those which are irrelevant, irrelevant items can also be reliably encoded (Castelhano & Henderson, 2005; Draschkow & Võ, 2016). However, there is less information on how different types of associations stored in long-term memory influence subsequent memory retrieval versus attentional orienting. For example, though memory can guide attention, there is debate about whether attentional selection from episodic memory involves similar or different neural networks as attentional selection during perception (Cabeza et al., 2008, 2011). Further, the neural basis of memory retrieval and attention have been shown to be more segregated than overlapping (Hutchinson et al., 2009a). A connected question is: does subsequent memory-guided attentional orienting follow similar mechanisms to those present during visual search? If so, we might predict that attentional orienting to a target in a high-priority location (e.g., fixed target location) would be facilitated, whereas attentional orienting to a low-priority location (e.g., variable distractor location) would be inhibited. Alternatively, as I have reviewed, fixed expectations may not always benefit memory retrieval (e.g., Greve et al., 2017; Hunt & Worthen, 2006; Tulving & Kroll, 1995). If expectations are variable, participants may have to engage with an environment more. Will this benefit memory for that environment and items within it? If so, this may result in different consequences of fixed and variable association learning on

memory retrieval compared to memory-guided attentional orienting. Parsing out these differences between the behavioural purposes of memory is the primary purpose of the set of studies outlined in this chapter. In other words, I intend to address the question: do the consequences of memory depend on what that memory is for?

In two experiments, I examined how learning of fixed vs variable associations can facilitate visual search, subsequent memory retrieval, and subsequent attentional orienting. In both experiments, participants first completed a learning task in which they searched for a target object in a scene that also contained a distractor object. In any given scene, the target and distractor objects always followed different associative rules. One object had a fixed association and always appeared in the same location in every learning block. The other object was variable and appeared in a different location in every learning block. In each scene, there were two possible pairings of target and distractor associations: fixed targets were always paired with variable distractors and variable targets with fixed distractors. Participants were blinded to the regularities underlying their visual search. With this task, I investigated how targets and distractors that appeared in fixed or variable locations influenced learning in visual search. I hypothesized that, over the course of learning, participants would find fixed targets faster and with higher accuracy than variable targets. After the learning task, participants completed either a memory retrieval (Experiment 7) or an attentional orienting (Experiment 8) task. In the retrieval task, participants made a two-alternative forced choice (2AFC) decision between a target and a visually similar foil (identification memory) and then chose the associated learned scene out of two possibilities (scene memory). I predicted that the increased time spent interacting with scenes to find the variable targets would result in better retrieval performance compared to fixed targets as measured by object identification and scene memory tests. In Experiment 8, participants completed an attentional orienting task in which they had to respond as quickly as possible to

targets or distractors that flashed briefly in learned locations. In contrast to the predicted consequences on retrieval in Experiment 7, I predicted that fixed targets would benefit attentional orienting compared to variable targets. Overall, I aimed to determine how spatial expectations resulting from learning are utilized adaptively for different types of subsequent behaviour.

4.2. Experiment 7a and 7b: Comparing Simultaneous Learning of Fixed and Variable Associations

In this experiment, I investigated the rate at which learning based on spatial regularities influenced visual-search performance. In each scene, there were two possible pairings: fixed targets always occurred with variable distractors, while variable targets always occurred with fixed distractors. Experiments 7 and 8 began with an identical training phase in which participants learned about fixed and variable associations during visual search. I hypothesised that fixed target associations (scenes for which target location was constant) would be learned faster than variable target associations (scenes for which target location varied). The learning task was followed by an explicit retrieval task in Experiment 7b (Section 4.3.) and an attentional orienting task in Experiment 8b (Section 4.4.) As the learning tasks were identical between both experiments, their results were combined and reported in this section.

4.2.1. Methods.

4.2.1.1. Participants. The study was approved by the Central University Research Ethics Committee of the University of Oxford code: R63062/RE001. Participants (age range = 18-40) were recruited online using Prolific (www.prolific.co), an online crowdsourcing platform. Participants were fluent in English and reported having no cognitive impairment,

dementia, or history of mental health conditions. Also, participants could only register for the study if they had successfully completed more than ten studies previously on the platform and had an approval rating of over 90%. They were compensated £8.00 per hour for their participation.

An initial a-priori power analysis in G*Power (Faul et al., 2007) targeting the detection of medium effects in the retrieval task ($d= 0.5$, $\alpha = 0.05$,$1-\beta = 0.95$) suggested a sample size of $n= 54$ for Experiment 7. This sample size was also supported by the effect sizes found in Chapter 2, where the same number of participants and a relatively similar design resulted in medium-large effect sizes in the retrieval tasks. For example, in Experiment 4, the main effect of Association had an effect size of $\eta2 = 0.25$, which is designated as a large effect for an ANOVA by Cohen (1988). For Experiment 8, the suggested sample size was doubled to 108 datasets because only previously learned target locations were used in the attentional orienting task for half the participants (N=54) and only learned distractor locations for the other half (see more details in Section 4.4).

To yield the final combined sample size of 162 participants with useable data (54 from Experiment 7 and 108 from Experiment 8), 185 participants were initially recruited. Participants who performed at near-chance level (in the learning task) were excluded as a precaution to avoid using data from online participants who were inattentive or could not/would not perform at a baseline that was expected based on prior lab-based experiments (Sauter et al., 2020). In Experiment 7, four participants were excluded from the analysis due to near-chance level performance, two due to technical malfunction (were not rerouted to the retrieval segment correctly), and three for not following the instructions (completed the retrieval segment hours later). Therefore, 63 datasets were collected in total prior to exclusion of 9 participants, leaving 54 participants who completed the experiment satisfactorily (age range: 21 to 40 years; mean age: 32.17 years; 22 females, 32 males; 49 right-handed). In

Experiment 8, seven participants were excluded from the analysis due to near-chance level performance, one for poor performance on the attentional orienting task and admitting having difficulty, four for timing out (not responding) on over 50% of attentional orienting trials, and two due to technical malfunction. Therefore, 122 datasets were collected in total prior to exclusion of 14 participants, leaving 108 participants who completed the experiment to a satisfactory level (age range: 21 to 40 years; mean age: 28.85 years; 47 females, 61 males; 97 right-handed).

4.2.1.2. Stimuli. The task was programmed using Psychopy (Peirce et al., 2019) and hosted on the online platform Pavlovia (https://pavlovia.org/). Participants completed the experiment on their own personal computers. They were instructed to sit one arm's length away from their computer screen and to adjust the screen brightness to ensure good visibility. The same stimuli were used in Experiments 1 and 2.

Forty-two natural scenes were used in both experiments. The size of each scene was 1200 x 900 pixels. All participants viewed the same set of scenes during the experiment. Four additional novel scenes (which did not occur during the main experiment) were used for the practice trials. Scenes were taken from an in-lab dataset created by a former lab member containing photographs of outdoor scenes taken in countries throughout the world (Roüast, 2021). All scenes were images of the outdoors and were chosen carefully to be as different as possible (e.g., only one photo of a mountain, a forest, a beach, etc). The scenes did not contain clearly distinguishable objects that could be mistaken for the target or distractor objects. Additionally, the scenes and objects were converted to grayscale to reduce the 'pop-out' of certain objects with bright colours against darker backgrounds (Draschkow et al., 2014). Scenes were displayed centrally, and a grey background filled the rest of the internet browser window.

Forty-two distinct toy and clothes images were used as either target or distractor stimuli (84 objects total). These 84 objects were chosen out of 168 total possible objects: 84 learning targets and 84 matching foils that were later used during the object identification segment of the retrieval task. The object sets were compiled by myself using freely available objects sourced from an online database (stickpng.com). Objects were chosen to be as unique as possible within their category (i.e., only one robot toy). Additionally, each object was chosen such that it was sufficiently different from its matching foil (e.g., the robot toy was white and blue, whereas its matching foil robot toy was grey and black and designed slightly differently). Each participant had a unique set of targets and foils. To achieve this, out of each target-foil pair, one was chosen randomly to be the learning target and the other to be the foil during retrieval. During the learning task, participants searched for one of the two categories (toys or clothes) of stimuli as their targets, while the other category served as the distractors. Target location was determined according to two conditions: fixed or variable. The target image was 70 x 70 pixels and appeared upright on each trial.

The placement of objects in the scenes ensured that one object always appeared at a fixed location while the other object appeared in different locations across the five learning blocks. To achieve this, scenes were divided into 6 pre-defined sextants of the screen and a potential location was identified within each of the sextants. During the first block of the experiment, the fixed object location was drawn randomly from these 6 possible locations for each individual participant. Next, the location for the variable object was drawn from one of the 5 remaining locations. In the ensuing blocks, the fixed location remained the same, while the variable location continued to be drawn randomly from the remaining unchosen locations until, at the end of the 5th block, each of the 5 possible variable locations had been sampled once. In addition, the fixed locations were counterbalanced across scenes so that, regardless

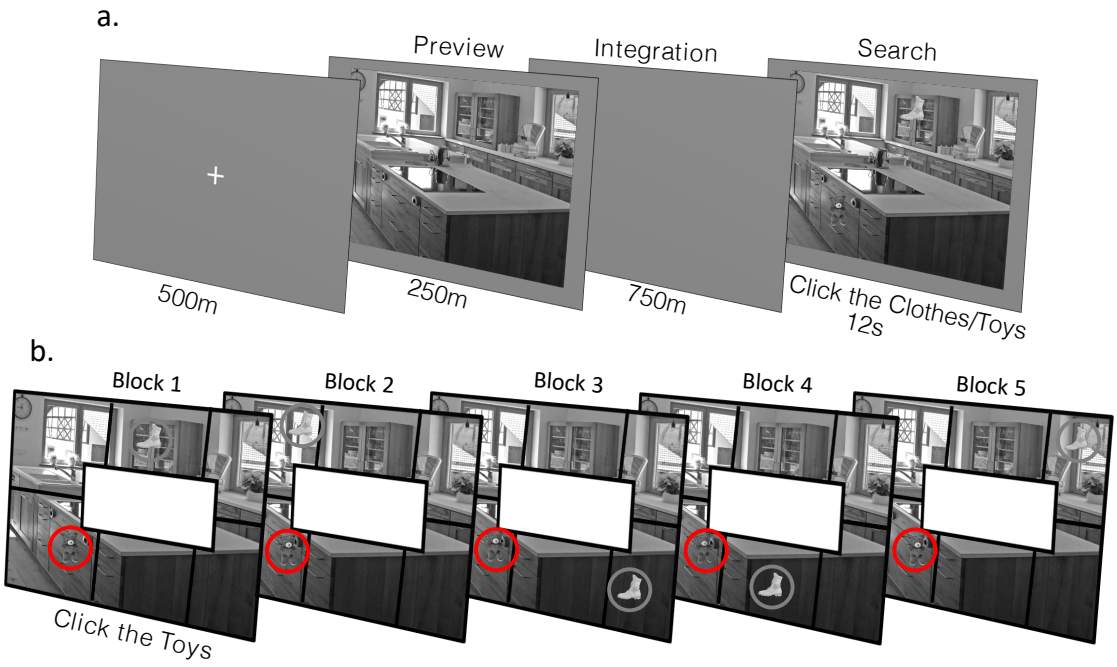
of if the objects occurred in fixed or variable locations, each of the 6 sextants was sampled approximately equally across the 42 scenes.

I chose possible object locations prior to data collection to ensure object locations fell within the sextants and were in non-obvious locations (Figure 4.1b). Pre-specifying possible locations rather than placing objects randomly helped to reduce 'pop-out' effects and encourage search (e.g., targets were not placed in the sky to avoid being too obvious against the uniform background). To identify target locations, I created a separate, utility task, in Psychopy that allowed me to view each of the scenes with lines delineating the usable sextants and a central rectangle (400 x 300 pixels) defining a 'no-go' zone. This zone precluded selecting locations in the centre region, encouraging participants to search for the targets as opposed to seeing them immediately with foveal vision. Having participants search for the target was beneficial as it would encourage memory for the scene itself, which would be tested later. I also was careful to choose locations that were not too close to the edge of the scene. The task ran through each of the scenes and allowed me to click 6 times per scene, once for each of the sextants, before continuing on to the next scene.

4.2.1.3. Procedure. Participants were provided with a link by Prolific which rerouted them to the experiment on Pavlovia. After reading through a description of the study, participants provided informed consent. Next, they completed a set of four practice trials to become accustomed to the learning task. After completing the learning task (Figure 4.1a), they were rerouted to Qualtrics to complete a demographics questionnaire (i.e., age, handedness, average screen time), which lasted 2.6 minutes on average. Finally, they were sent back to Pavlovia, where they completed an explicit retrieval task in Experiment 7 or an attentional orienting task in Experiment 8.

Figure 4.1

Learning Task Diagram



Note. (a) A schematic of the learning task. After a preview of the scene, participants had 12s to search and click their assigned target category (toys or clothes). (b) A diagram depicting an example learning scene across all five blocks of the task where the target is fixed and the distractor is variable. For visualisation purposes only, the figure has black lines to delineate the sextants, a white box to demonstrate the 'no-go' zone, and coloured circles on the target and distractor. The object highlighted by a grey circle is the distractor object, in this case, an article of clothing. This distractor object has a variable association with the scene, so its location varies randomly between each of five possible sextants during each block. The target, highlighted by the red circle, occurs in the remaining sixth sextant. In this case, the target is a toy, and it has a fixed association with this scene, so its location is stable throughout the learning blocks.

4.2.1.3.1. Learning task. During the learning task, participants searched and clicked on the target (toys or clothes) with their mouse for each of the 42 scenes. The target category was counterbalanced across the experiment. Therefore, 81 participants searched for toy targets while the remaining 81 participants searched for clothes targets. If participants were assigned toys as their target category, clothes would be their distractor category and vice versa. Participants were instructed to click the centre of the target when they found it to continue on to the next trial. They completed five blocks of learning, each containing all 42 scenes. The order of the scenes was randomised per block. After each block, participants had the opportunity to take a short break and continue when they felt ready.

Figure 4.1a shows the experimental procedure for a given learning trial. First, a blank grey screen with a white fixation cross appeared for 500 ms. This was followed by a brief (250 ms) preview of the scene alone, with no embedded target. This served as a cue for the upcoming scene with the embedded target. After a 750-ms interval with a grey background, the scene was presented again, but with an embedded target and distractor. Participants had 12 seconds to search for the target and click it. When they clicked an object, whether target or distractor, the next trial began immediately. If the participant was not able to find the target within the allotted search time, the experiment advanced automatically to the next trial.

A few specific differences from past experiments were introduced to facilitate the investigation of my initial hypothesis. The duration of the initial fixation (500 ms), scene preview (250 ms), and integration period (750 ms) matched procedures from the learning task in Chapter 2. But, participants had longer (12 s) to search for the target than the learning tasks in Chapter 1 (10 s) or Chapter 2 (5 s). Search duration was increased because half of the targets occurred in variable locations, and the scenes and objects were in greyscale, making it more difficult to find the target because its location was unpredictable, and it was relatively

well hidden within the scene compared to past studies. In this study, trials ended immediately after participants clicked the object because I was specifically interested in investigating the consequences of differences in search behaviour on subsequent applications of memory to retrieval or attentional orienting. Therefore, I designed the learning task to allow participants to take longer in certain trials if they needed additional time. For example, if in variable association trials, participants took longer to find the target and viewed more of the scene in the process, I was curious if this additional time spent would subsequently benefit their memory for the scene itself.

Object locations during the learning phase (Figure 4.1b) were fixed or variable. The targets and distractors were split evenly into these 2 conditions. Each participant learned 42 scenes with 2 objects in each, making for 42 targets and 42 distractors total. Of these, 21 targets appeared in fixed locations and the remaining 21 targets appeared in variable locations. These were accompanied by 21 distractors that appeared in variable locations and the remaining 21 distractors that appeared in fixed locations, respectively. Fixed-location targets or distractors would appear in the same location across the 5 blocks of learning. Variable target or distractor locations varied systematically across the other sextants in each of the 5 learning blocks.

In summary, between participants and within each object category (toys or clothes), which specific objects appeared as targets or distractors, in what scene they occurred in, and whether they were shown in fixed or variable locations was randomized (e.g., within the toy objects, which toy appeared as a target or distractor was randomized). For example, for two participants who had toys as their target category, they would both search for a teddy bear, but, for one participant that object might occur in a fixed location in a beach scene, whereas for the other participant it could occur in a variable location in a forest scene. Next, because during the memory-retrieval task participants had to choose between a target and a matching

foil, the identity of the objects during the learning task were randomly chosen from two possible matching objects. For example, in the prior example, one participant might have had to search for a teddy bear wearing a bow tie, whereas the other participant searched for a teddy bear wearing a cap.

4.2.1.4. Data Analysis.

4.2.1.4.1. Learning. The independent variables of interest were memory Association (Fixed or Variable) and Block (1-5). Target Identity (Toys or Clothes) was included in the analysis as a between-subjects variable to control for the possibility of category-wise differences in visual search, i.e., that participants' behaviour may differ when searching for Toys versus Clothes. To analyse performance on the learning task, I tracked target identification accuracy (% of correctly identified targets) and response time over the 5 blocks. Importantly, only the response times for trials in which participants correctly identified the learning target were examined. Response-time outliers (above 2 standard deviations from the individual mean across trials of all conditions) were removed from the analysis. This totalled 6% of all trials across participants in Experiment 7 and 6% in Experiment 8. The Box-Cox procedure (Box & Cox, 1964) was used to test the distribution and residuals of response-time values. Based on this, a log transformation was applied to response times to approximate the normal distribution and meet ANOVA assumptions. Also, pairwise linear contrasts were run to compare BIS across the learning blocks between the association conditions. The procedure and rationale for running this form of contrast analysis can be found in Chapter 3 Section 3.2.1.4.1..

The main measure of interest in the analysis of learning was BIS (Biased Integration Score) combined between both experiments (Figure 4.2, Table 4.1). Biased Integration Score (BIS) is a composite measure for comparing performance based on both accuracy and

response time to a similar degree, with higher BIS scores corresponding to higher accuracy and/or lower response time. As in Chapter 3, BIS was measured as the main dependent variable of interest because it combines response times and response accuracy with the goal of attenuating the effects of Speed-Accuracy Trade-Offs (SATs) while preserving "real effects" of experimental manipulations (Liesefeld & Janczyk, 2019). The rationale for this choice is explained in more detail in Chapter 3, Section 3.2.1.4.1.. BIS was calculated by subtracting the mean accuracies and response times from their respective data sets to centre the data, then dividing by their respective standard deviations, and finally, subtracting the standardised score for response time from the standardised score for accuracy. Individual values reflect whether learning performance was below (BIS < 0) or above (BIS > 0) the average performance (across all participants and conditions) for the respective participant and condition. Therefore, throughout the results section, means for the different levels of the factors included in BIS ANOVAs are centred around 0, with higher numbers in one level indicating better performance compared to the other level, and 0 indicating no difference in performance at the different levels of the factor.

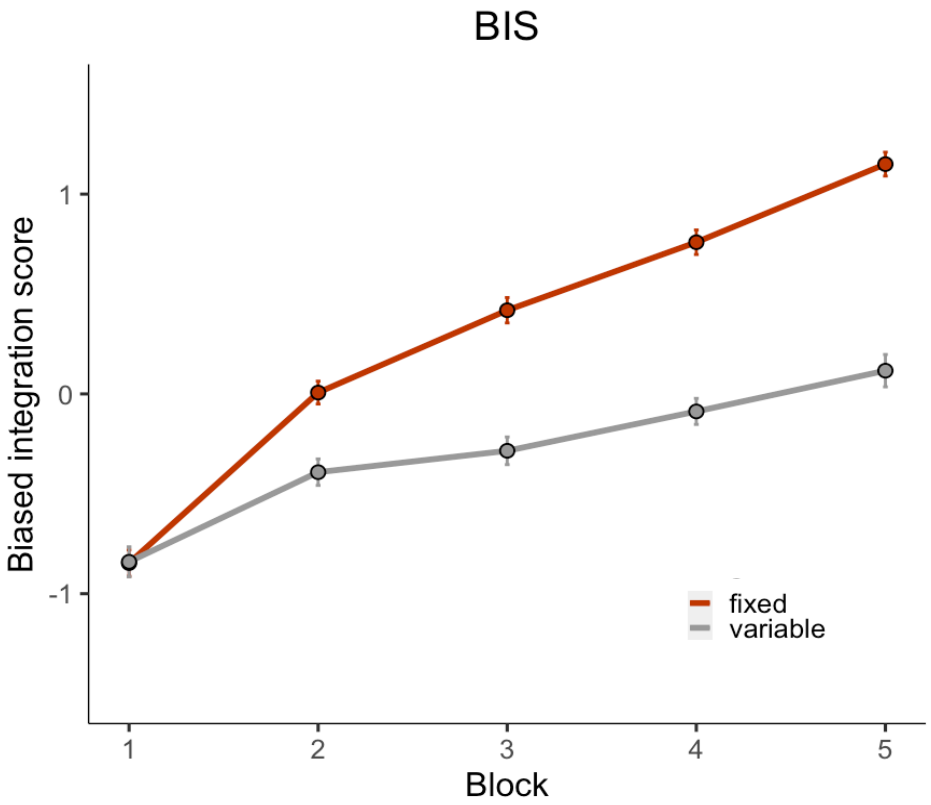
4.2.2. Results

4.2.2.1. Learning Accuracy and Response Time. I examined the effects of Target Association (Variable or Fixed), Block (1-5), and Target Identity (Toys or Clothes) on participants' response time and accuracy. Because BIS was the primary dependent variable of choice and the theoretical implications of the accuracy and response times analysis did not differ from that of BIS, I have included the descriptive statistics and analysis for accuracy and response time in Appendix C.

4.2.2.2. Biased Integration Scores during Learning. I analysed the combined learning BIS for both studies using a three-way mixed ANOVA with Association and Block as within-participant factors and Target Identity as a between-subjects factor (see Table 4.1 for a summary of results and Figure 4.2 for the plots).

Figure 4.2

Learning BIS Results



Note. Across the learning blocks, BIS was significantly higher and steeper in the Fixed target condition than in the Variable condition. Error bars specify normalized mean standard error.

Table 4.1

Analysis of BIS Combined for Experiments 1 and 2

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association*	1	160	80.9	< .001	0.04
Block*	3.56	569.23	149	< .001	0.11
Target Identity*	1	160	11.9	< .001	0.05
Association x Block*	4	640	27.7	< .001	0.02
Target Identity x Block	3.56	569.23	1.64	.17	< .01
Association x Target ID	1	160	< .01	.97	< .01
Association x Target ID x Block*	4	640	2.65	.003	< .01

Note. There were significant main effects of Association, Block, and Target Identity. Interactions occurred between Association and Block, and between Association, Target Identity, and Block. An asterisk (*) signifies a p-value below .05.

The main effect of Association showed that participants performed significantly better at identifying targets with Fixed (M = 0.30, SD = 1.66) compared to Variable associations (M = -.30, SD = 1.51). There was also a main effect of Block, and Block interacted with Association. Mean BIS during Block 5 was .63 (SD = 1.59) compared to -.83 (SD = 1.53) during Block 1, showing that participants' performance improved as learning blocks progressed (Figure 4.2). There was also a main effect of Target Identity. Mean BIS was higher for Toys 0.33 (SD = 1.69) compared to clothes at -0.33 (SD = 1.46), showing that participants who had Toys as targets performed significantly better than those in with the Clothes category. Finally, there was a three-way interaction between Association, Target Identity, and Block.

To investigate the interaction between Block and Association, linear contrasts of Block were run on each of the Association conditions. As Block increased, BIS for Fixed

targets increased more than BIS for Variable targets ($t(1294 = 9.25, p < .001$). Therefore, during the learning task, though participants' performance increased in both Association conditions, as the task went on, their rate of benefit was higher for Fixed compared to the Variable associations.

Finally, to delve into the three-way interaction between Association, Target Identity, and Block I focused on the most critical component of the 3-way interaction by comparing the linear contrasts between the different association conditions. Specifically, I ran linear contrasts between Fixed and Variable target trials for participants who had Clothes as their target. In this group, BIS for Fixed targets increased more than BIS for Variable targets ($t(646) = 7.71, p < .001$). Then, I ran separate linear contrasts between the Fixed and Variable target trials in participants who had Toys as their target. In this group, BIS for Fixed targets increased more than BIS for Variable targets ($t(646) = 5.19, p < .001$). Therefore, in both Target Identity groups (Toys and Clothes), participants performed significantly better across the learning blocks for Fixed than Variable targets.

4.2.3. Conclusion

The learning results supported my hypothesis that the learning rate, as reflected in the improvements in visual-search performance, would be fastest for targets with fixed associations compared to variable associations. There were, however, performance differences based on object category, with participants scoring high on BIS for toys than clothes. These differences may indicate that participants found it overall easier to search for toys than clothes as measured by BIS. However, despite my efforts to choose objects that were as similar in saliency as possible, some specific objects may have been easier to find than others, contributing to the category-level differences in search for toys versus clothes. Despite BIS differences between the toys and clothes categories, the results consistently

showed learning-related benefits for detecting targets appearing in fixed compared to variable locations. Therefore, performance differences based on target identity did not have significant implications for interpreting benefits of fixed or variable spatial expectations to visual search (these category-wise differences are discussed in more detail in the Discussion section). The results from the learning segments in these experiments reinforced our findings in Chapter 3 demonstrating participants' ability to reliably acquire specific associations between context and target location in an online experiment. Further, this effect persisted even when a variable distractor was simultaneously present during visual search.

4.3. Experiment 7b: Comparing Memory Retrieval of Different Kinds of Associations

In the test segment that followed learning in Experiment 7, I investigated whether fixed or variable associations during learning facilitated memory retrieval. I also examined whether memory for targets was facilitated in comparison to memory for distractors. After completing the 5 learning blocks, participants completed a short questionnaire and then were informed about a subsequent surprise memory retrieval task (Figure 4.3). In this task, participants were presented with an object from the learning task and a matching foil and asked 1) to retrieve which object was previously associated with the scene from the learning and 2) to choose which of two scenes previously contained the object. I hypothesised that the increased difficulty and time required to find variable targets, as measured by lower BIS scores in the learning task, would actually require participants to engage more with scenes containing variable targets (Greve et al., 2019; Hunt & Worthen, 2006; Tulving & Kroll, 1995). I predicted that this increased engagement would facilitate both object identification and scene memory retrieval for variable compared with fixed associations.

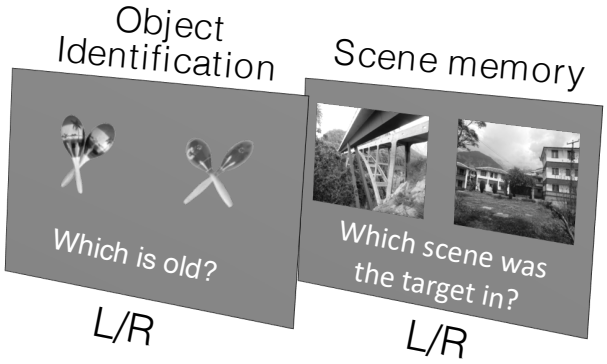
4.3.1. Methods

4.3.1.1. Participants. Procedures for participant recruitment are described in the Participants segment 4.2.1.1. Individuals who completed the learning phase of Experiment 7 went on to complete the retrieval phase. Data from 54 participants were fully analysed.

4.3.1.2. Procedure. After completing the learning phase on Pavlovia, participants were redirected to Qualtrics where they completed a demographics questionnaire. They then returned to Pavlovia to complete the retrieval task (Figure 4.3). Prior to beginning the retrieval task, they completed a set of 4 practice trials to become accustomed to the procedure.

Figure 4.3

Memory Retrieval Task



Note. A schematic depicting the memory retrieval task. First participants responded to which object was "old", or previously encountered during the learning task. Next, they responded to which scene that object had occurred in during the learning task. Both responses were self-paced.

4.3.1.2.1. Explicit Retrieval Task. Participants completed 84 trials during the retrieval task, 2 for each of the 42 learning scenes. They were tested twice on each learning scene because memory performance was assessed separately for the targets and distractors. Therefore, every object from the learning, whether target or distractor, appeared once during the explicit retrieval task. First, two objects appeared side by side. One object was from the learning session and the other was a matching foil. Participants had 10 s to complete a 2AFC response with their keyboard to indicate which object was "old", the object on the left or the object on the right. Next, regardless of whether their response was correct or not, they were shown two scenes. One scene had contained the probed object during the learning task and the other was a scene from another learning trial. Therefore, both scenes were 'old', but only one was previously associated with the target object. Participants had 10 s to respond with their keyboard to indicate which scene was "old", left or right, before the task progressed to the next trial. The location of the 'old' object and scene on the left or right side of the screen were counterbalanced. Also, as discussed during the learning session, which objects occurred as targets or foils during the retrieval task were randomized for each participant.

The decision to test recognition memory using a two-alternative forced choice procedure (2AFC) was based on piloting and other results in literature. Prior to running this study, a pilot study was run with a similar design. The main difference in design was that the retrieval task was an individual object report (i.e., participants report if a single centrally presented object is Old or New). This object could have been a learned target/distractor or a novel foil. In past studies, participants have generally performed better in 2AFC tasks compared to Old/New reports because, given the same underlying memory strength, it is easier to pick the maximum likelihood of two things (i.e., choosing which object is familiar rather than recollecting if a single object has been seen before; Macmillan & Creelman, 2004). Indeed, in my initial pilot study, participants' recognition memory accuracy was

relatively low. In particular, memory for learned distractors was poor, with participants' accuracy well below 50%. This was problematic because with lower accuracy there is a risk of floor effects, which can detract from the ability to detect real differences between experimental conditions (Liu & Wang, 2021). In addition, the learning task of this pilot study had a problem with randomization where for each scene the fixed location was identical across participants, i.e., out of six possible locations the fixed location could have appeared in a given scene, the same location was chosen for each of the participants. For example, in any scene, the fixed location was chosen randomly, but then that location would occur for all participants. Therefore, there was a risk that fixed location performance was better equated between conditions and target categories across participants because of this randomization flaw. Because these limitations may have greatly impacted the results such that the theoretical implications were altered artificially (i.e., by design flaws, not real effects), this study was not reported in my thesis. To address these limitations of the pilot study, in the study reported here, the randomization in the learning task was fixed such that the locations of the fixed target were different between participants. Also, I switched to having participants make a 2AFC judgement, which was effective in improving their recognition memory accuracy for both targets and distractors.

4.3.1.3. Data analysis. As in the learning task, parametric analyses were applied, transforming the data when necessary to conform to the required assumptions. In cases where interactions of main effects were significant, planned paired samples t-tests were applied to compare levels of the experimental variables. The Greenhouse-Geisser correction was applied when the sphericity assumption was violated. Throughout the experiment, to account for within-subject comparisons (i.e., between association conditions), procedures from Morey were followed (2008).

The main independent variables of interest were Association (Fixed or variable) and Category (Target or Distractor). However, it is important to reiterate that Fixed targets occurred in the same scenes as Variable distractors and Variable targets with Fixed distractors. Therefore, though memory for Fixed targets and Variable distractors were assessed on separate explicit retrieval trials, their reported data are not unrelated due to their association with the same scene during the learning task (Figure 4.1b). Object Identity (Toys or Clothes) was included as a between-subjects variable in all analyses to control for potential differences between how the different object identities were recalled. However, its inclusion in the ANOVAs did not impact the theoretical implications of the results via main effect or interactions, therefore it has not been included in tables or plots for the sake of simplicity. To assess performance on the surprise memory-retrieval test in Experiment 7, I calculated participants' accuracy at recalling the Object Identity as well as their Scene memory. Both were assessed by determining the proportion of trials in which participants correctly identified the target that occurred during the learning phase and the accompanying scene. Response time values were only included in analysis if participants had responded correctly to the target. As in the learning, only the response times for trials in which participants correctly identified the target were examined. As in the learning session, accuracy and response time values were combined to create the BIS metric.

4.3.2. Results

4.3.2.1. Object Identification Accuracy and Response Time. I examined the effects of Category (Target or Distractor) and Association (Variable or Fixed) on participants' accuracy and response time. As BIS was the primary dependent variable of choice, and effects were matched between BIS, response time, and accuracy, tables for analysis of learning and response times can be found in Appendix D. RT data were log-transformed to

approximate the normal distribution and meet ANOVA assumptions. RT data were only analysed for trials in which participants correctly identified the object.

4.3.2.2. Object Identification Biased Integration Score. I analysed BIS for target identification using a three-way mixed ANOVA with Category (Target or Distractor) and Association (Fixed or Variable) as within-participant factors (see Table 4.2 for a summary of results and Figure 4.4a). There was a main effect of Category, with participants showing better retrieval for Targets (M = 0.73, SD = 1.17) compared to Distractors (M = -0.73, SD = 1.31). However, there was no significant difference in target identification performance based on Association type.

Table 4.2

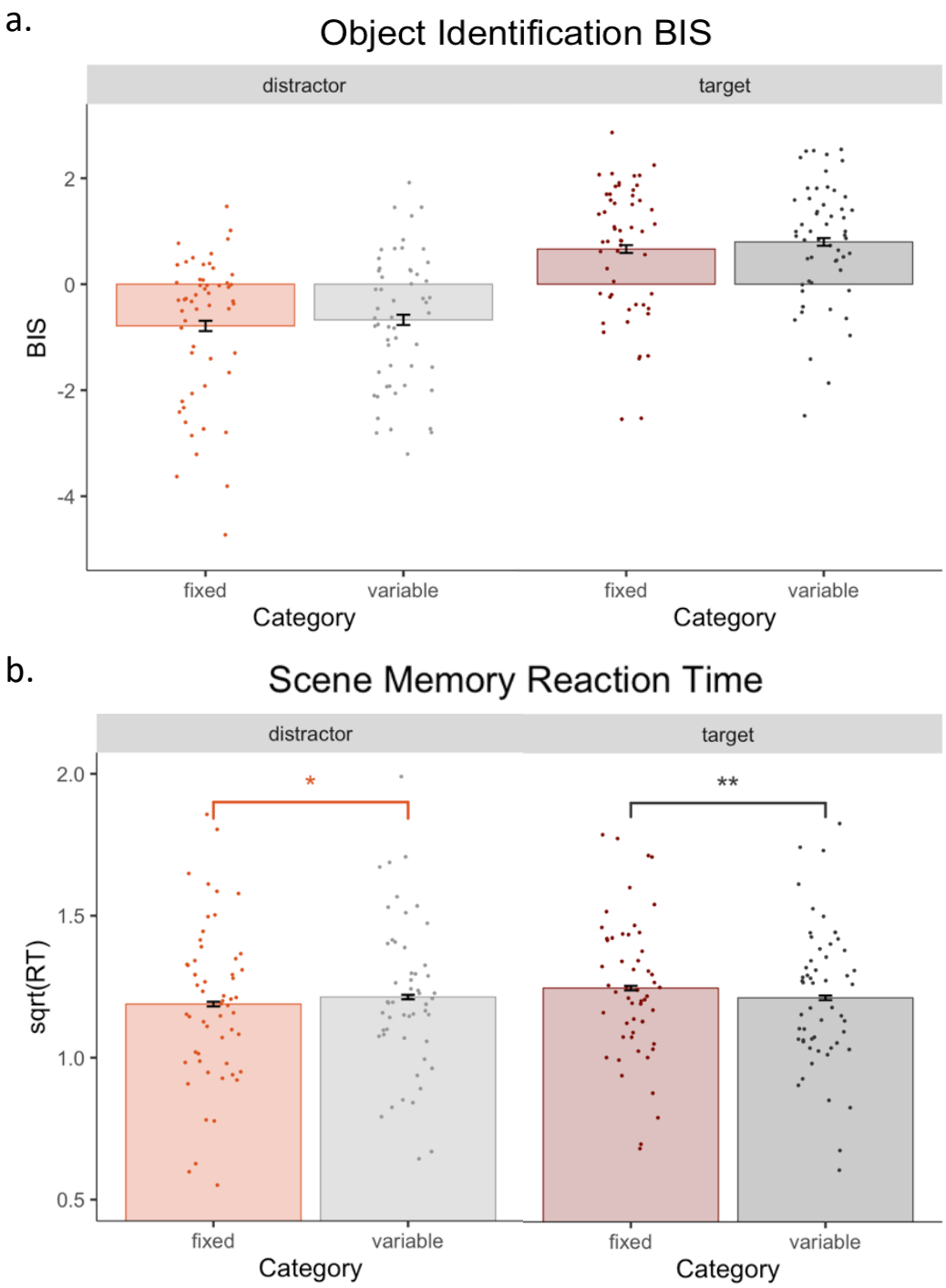
Object Identification BIS

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	52	146.71	< .001	0.26
Association	1	52	0.95	.34	< .01
Category:Association	1	52	0.02	.90	< .01

Note. There was a significant main effect of Category on Object Identification BIS. An asterisk (*) signifies a p-value below .05.

Figure 4.4

Memory Retrieval Task and Performance Plots



Note. (a) Object Identification BIS. Participants performed significantly better for targets than distractors. However, there was no significant difference in Association type with participants performing similarly regardless of whether targets or distractors were fixed or variable. (b)

Scene Memory Response Time. Results are shown only for correct scene memory trials. Participants were significantly faster at correctly recalling scenes for fixed distractors compared to variable distractors and for variable targets compared to fixed targets. Variable targets and fixed distractors shared the same learning scene as did fixed targets and variable distractors. Dots are scattered on the x-axis so individual participants' performance and the overall distribution can be visualized. Error bars specify normalized mean standard error.

4.3.2.3. Scene Memory Accuracy and Response Time. I examined the effects of Category (Target or Distractor) and Association (Variable or Fixed) participants' scene memory accuracy and response times. RT data were transformed using square root to approximate the normal distribution and meet ANOVA assumptions. I have elaborated on the results for scene memory accuracy (Table 4.3) and RT (Table 4.4) because BIS results (Table 4.5) did not mirror the accuracy and RT data. Specifically, the BIS measure missed an important interaction in the RT data that deserved further discussion.

For scene memory accuracy, there was a main effect of Category with participants performing better for scenes linked to Targets (M = 74%, SD = 10%) than Distractors (M = 59%, SD = 10%; Table 4.3). Means for accuracy were 75% for fixed targets (SD = 11%), 74% for variable distractors (SD = 11%), 58% for fixed distractors (SD = 11%), and 61% for variable distractors. Contrary to my hypothesis, there was no significant difference in scene memory performance based on Association type. There was also no interaction between Category and Association.

Table 4.3

Scene Memory Accuracy

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	52	68.57	< .001	0.21
Association	1	52	0.22	.64	< .01
Category:Association	1	52	1.75	.19	< .01

Note. There was a significant main effect of Category on Scene memory Accuracy. An asterisk (*) signifies a p-value below .05.

For scene response time, there no was no main effect of Category or of Association type. However, there was a significant interaction between Category and Association. Planned paired samples t-tests explored the nature of interaction involving Category and Association. They demonstrated that participants were significantly faster at correctly linking scenes to a Variable target compared to a Fixed target ($t(53) = 2.49$, $p = < .01$, Cohen's $d = .14$; Figure 4.4b; Table 4.4). Participants also performed better for scenes linked to a Fixed distractor compared to a Variable distractor ($t(53) = -1.77$, $p < .05$, Cohen's $d = 0.09$). Also, participants performed better for scenes linked to a Fixed distractor compared to a Fixed target ($t(53) = -2.71$, $p < .001$, Cohen's $d = -0.22$). There was no difference in performance between scenes linked to Variable targets compared to Variable distractors ($t(53) = -0.01$, $p = .99$, Cohen's $d < .001$).

Table 4.4

Scene Memory Response Time

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category	1	52	1.97	0.17	< .01
Association	1	52	0.24	0.63	< .01
Category:Association*	1	52	8.75	< .001	< .01

Note. There was a significant interaction between Category and Association. An asterisk (*) signifies a p-value below .05.

4.3.2.4. Scene Memory Biased Integration Score. I analysed BIS for scene memory using a three-way mixed ANOVA with Category (Target or Distractor) and Association (Fixed or Variable) as within-participant factors. There was a main effect of Category with participants performing better for linking scenes to Targets (M = .40, SD = 1.35; Table 4.5) than Distractors (M = -.40, SD = 1.12). Contrary to my hypothesis, there was no significant difference in scene memory performance based on Association type.

Table 4.5

Scene Memory BIS

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	52	31.90	< .001	0.10
Association	1	52	0.46	.50	< .01
Category:Association	1	52	< .01	1.00	< .01

Note. There was a significant main effect of Category. An asterisk (*) signifies a p-value below .05.

4.3.3. Conclusion.

The memory retrieval results partially supported my hypothesis that associations learned under variable conditions would facilitate both object identification and scene memory. Contrary to my hypothesis, participants did not perform better at object identification memory for variable compared to fixed targets or distractors. However, considering that participants performed better on fixed than variable targets during the learning tasks, a lack of performance differences between association types for object identification memory suggests that learning occurred in both association conditions. Next, for scene memory, there was again no significant difference between variable and fixed targets or distractors as measured by accuracy or BIS. However, variable targets and fixed distractors improved participants' speed at identifying scenes correctly compared to fixed targets and variable distractors, partially supporting my hypothesis that variable target associations would benefit scene memory. Importantly, variable targets and fixed distractors were associated with the same scenes. Therefore, it is possible that faster scene memory in this condition resulted from either or both the presence of variable targets or fixed distractors.

4.4. Experiment 8b: Comparing Memory-Guided Attention for Fixed and Variable Associations

In the test segment that followed learning in Experiment 8, I investigated whether fixed or variable associations facilitated memory-guided attentional orienting. Further, I investigated whether attentional orienting for targets was facilitated in comparison to distractors. After completing the 5 learning blocks, participants completed a short questionnaire and then were informed about a subsequent surprise attentional-orienting task (Figure 4.5). Participants were split into two groups during the orienting task: targets or distractors. If they were in the Target group, during the task they would see a scene from the

learning flash briefly containing either a target, or nothing, and had to detect whether the object was present or absent. If they were in the Distractor group, the flashed scene would contain either a distractor from the learning task, or nothing, and again they reported whether the object was present or absent.

I hypothesised first that fixed target associations would facilitate memory-guided attentional orienting compared to variable targets, and second that participants would perform better on orienting to variable distractors than fixed distractors. My first hypothesis was based on past findings that learning contextually consistent target locations can facilitate attentional orienting (Summerfield et al., 2006; Stokes et al., 2012). My second hypothesis was based on results demonstrating that if distractors appear in a specific location with high frequency, this lowers their ability to distract from the target (Ferrante et al., 2018; Noonan et al., 2016; Reder et al., 2003). This evidence supports my argument that distractors that occur in fixed locations may be less likely to be chosen for attentional selection than distractors that occur in variable locations, which have been known to interfere more with target search (Ferrante et al., 2018; Kelley & Yantis, 2009; Pascucci & Turatto, 2015).

4.4.1. Methods

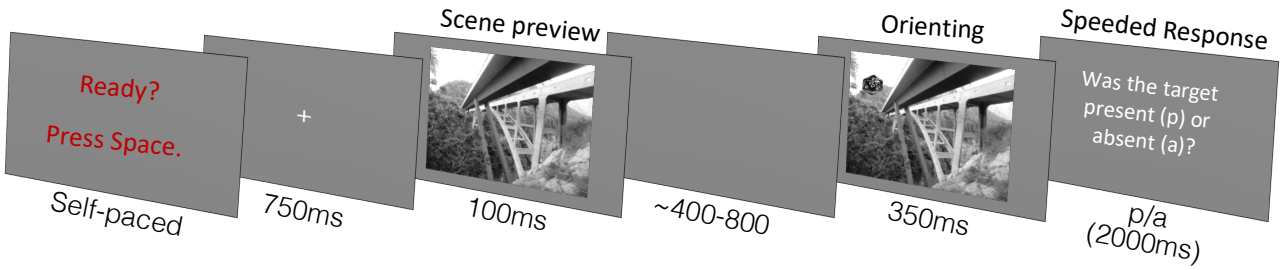
4.4.1.1. Participants. Procedures for participant recruitment are described in the Participants segment (Section 4.2.1.1.). Individuals who completed the learning phase of Experiment 8 went on to complete the attentional orienting task. Data from 108 participants were fully analysed.

4.4.1.2. Procedure. Participants were provided with a link by Prolific that sent them to the experiment on Pavlovia. After reading through a description of the study, participants provided informed consent. After completing the same learning task as in Experiment 7, they

were rerouted to Qualtrics where they completed a demographics questionnaire. Next, they were sent back to Pavlovia, where they read through instructions on the memory-guided attentional orienting task (Figure 4.5) and completed a set of 16 practice trials (4 rounds of 4 trials). During each trial, they received feedback on their performance to help them become acquainted with the task. Finally, they completed the main attentional-orienting task.

Figure 4.5

Memory-Guided Attentional Orienting Task



Note. A schematic of the Attentional Orienting task. The task began with "Ready?" screen. Followed by a 750 ms fixation period, then a 100 ms scene preview, a jittered 400-800 ms integration window, and then the orienting phase occurred for 350 ms. Depending on which group participants were in (target or distractor group), during this phase a learned scene would flash either containing a target or distractor from the learning phase. Or, in half the trials, the scene would flash containing no object. Subsequently, participants would respond if the attentional-orienting target had been present or absent (target detection).

4.4.1.2.1. Memory-Guided Attention Task. In this task, the same scenes and objects were used as in the learning phase. In each trial, participants had a very brief preview of a previously studied scene with no embedded object, and, after a short interval, the scene reappeared briefly with one of the objects embedded or without any object. Participants made a forced-choice judgement based on their detection of the Presence or Absence of an object. The scene preview thus served as a memory cue, which could prompt the anticipation of the Target or Distractor object in the orienting array containing the same scene. The order of the scenes was randomised. The objects were 1.5x larger than previously presented in the learning task to ensure object detectability was above chance levels during the brief exposure. Each trial began with a screen that stated "Ready? Press space." After a subsequent fixation cross (750 ms), one of the scenes from the learning task flashed for 100 ms with no embedded target. In 50% of the trials, after a jittered blank inter-stimulus interval (400-800 ms), the scene flashed again for 350 ms, this time either containing an object or without an object. A grey background then appeared with the question "Was the target present (p) or absent (a)?" in white font. Participants had 2.35 s to respond starting from the moment the scene appeared. They used the 'P' key to indicate that the object was present and the 'A' key for absent. After participants responded or ran out of time, the next trial immediately began. For participants in the Target group, their orienting targets would match the targets they had learned (e.g., Toys would be the learning and orienting target). For participants in the Distractor group, their orienting targets would be the objects from the category they did not click during the learning (e.g., if Toys were the learning target, Clothes would be the orienting target). Regardless of category, the orienting target, when present, occurred in the same location as in the final block of learning. Therefore, if the targets/distractors appeared in a Fixed or Variable location, the location where they occurred in Block 5 of learning would be used again as the orienting target location. The orienting target was Present in 50% of

trials and Absent in the remaining 50%. The trials in which the orienting target was Present or Absent were counterbalanced between the association types so that it was equally Present or Absent for both Fixed and Variable associations.

There were some notable differences in this attentional orienting task compared to the task used in Chapter 2, Experiment 6. The periods for the fixation cross (750 ms) and scene preview (100 ms) were identical. In Experiment 6, the inter-stimulus interval (ISI) was either short (150 ms) or long (750 ms), whereas in this Experiment it was jittered between 400-800 ms. In this experiment, the joint amount of time between the shortest ISI and the scene preview (100 ms + 400 ms) was equivalent to the minimum hypothesized amount of time necessary for hippocampal LTM retrieval (500 ms; Staresina & Wimber, 2018). Given the specific associations between scenes and target identities, it is likely that this task required hippocampal retrieval to guide attention (Aly & Turk-Browne, 2017), therefore it made sense to use in ISI of at least 500 ms. The jitter was included, as in past studies in my thesis, so that temporal predictability could not guide responses (Nobre & Coull, 1998). Next, the duration of the actual orienting phase (350 ms) was increased from Experiment 6, where it was 200ms, because of the increased difficulty of target detection with greyscale objects and backgrounds where there was less 'pop-out' (Draschkow et al., 2014). Finally, the response window matched the duration of Experiment 6 (2 s).

The decision to use a present/absent target detection design was primarily based on piloting. Initially, a pilot study was run with an identical learning task, but a slightly different memory-guided attention task that was based on the design in Summerfield et al., (2006). The significant difference was that the learned scene initially appeared without the target, but after a jittered interval (500-900 ms), the target flashed for 100 ms, and then participants had 1400-1000 ms response period where they had to respond as quickly as they could after the target appeared. 50% of the trials were 'catch' trials where a butterfly appeared rather than the

target and participants were instructed to withhold responding. In this initial task, participants' performance was extremely high (over 90% accurate) for both learned targets and distractors. Because performance was so high, it was possible that participants were performing at or near ceiling, making it more difficult to detect effects on performance related to the experimental conditions (Uttl, 2005). Additionally, participants performed relatively poorly during the catch trials (60% accuracy). Therefore, participants were often unsuccessful (40% of trials) in withholding their responses when the catch (butterfly) occurred and instead were responding as soon as they saw an object flash, potentially indicating that they defaulted to responding rather than attempting to identify the target. These limitations likely made it difficult to detect real effects if there were any, greatly limiting the theoretical potential of the results. Therefore, I chose not to report these results in full. Based on the limitations of this initial pilot study, the design for Experiment 8 was updated to be more in line with the attentional orienting task in Chapter 3, Experiment 6 and Stokes et al., (2012), where the target and scene flash at the same time during the orienting probe and participants respond whether the target is present or absent. I hypothesized that this task would be relatively more difficult because, unlike the initial design, an object is not always occurring so participants cannot default to responding. Indeed, the final design used in the study reported here proved to be comparatively more difficult (see means for accuracy in Appendix E), allowing for real effects of the experimental conditions to emerge.

4.4.1.3. Data Analysis.

4.4.1.3.1. Memory-Guided Attention Task. As in the retrieval task, parametric analyses were applied, transforming the data when necessary to conform to the required assumptions. When interactions of main effects were significant, planned paired samples t-tests were applied to compare levels of the experimental variables. When significant

interactions included between-subjects variables, unpaired Wilcox two-sample t-tests were applied. The Greenhouse-Geisser correction was applied when the sphericity assumption was violated. Throughout the experiment, to account for within-subject comparisons (i.e., between association conditions), procedures from Morey were followed (2008).

The main variables of interest were Association (Variable or fixed) and Object Presence (present or absent) as within-subjects variables, and Category (Target or Distractor) as a between-subjects variables. Object Identity (Toys or Clothes) was included as a between-subjects variable in all analysis to control for potential differences between how the different object identities were attended to. However, it's inclusion in the ANOVAs did not impact the theoretical implications of the results via main effect or interactions, therefore it has not been included in tables or plots for the sake of simplicity.

To assess performance on the surprise memory-guided attentional orienting task in Experiment 8, I calculated participants' target detection accuracy as the proportion of trials in which they correctly responded 'p' when the object was present or 'a' when the object was absent. Response-time values were only included in the analysis if participants had responded correctly to the target. Response-time outliers above 2 standard deviations from the individual mean across trials of all conditions were removed from the analysis (5.4% of all trials across participants). The Boxcox procedure (Box & Cox, 1964) was used to test the distribution and residuals of response-time values. Based on this, a log transformation was applied to ensure the data were normally distributed to meet the ANOVA assumptions. Mean accuracy was 70.20% with a standard deviation of .14 when assessing the proportion of trials in which participants correctly responded to the target being present or absent. The mean response time was 1.01 seconds with a standard deviation of .19.

The primary measures of interest were BIS and d'. Procedures for calculating BIS are described in the learning section (***4.2.1.4.1.).*** However, BIS is not as well suited to assessing

performance on present vs absent trials while taking response biases into account (i.e., tendency to respond present or absent) compared to a signal detection measure such as d' (Huang & Ferreira, 2020). Therefore, for BIS, I have only plotted results for trials where the target was present (Figure 4.6a). To consider both present and absent trials, I calculated d' (perceptual sensitivity) as the hit rate minus the false alarm rate, or the probability of responding present given the target was present minus the probability of responding present given the target was absent.

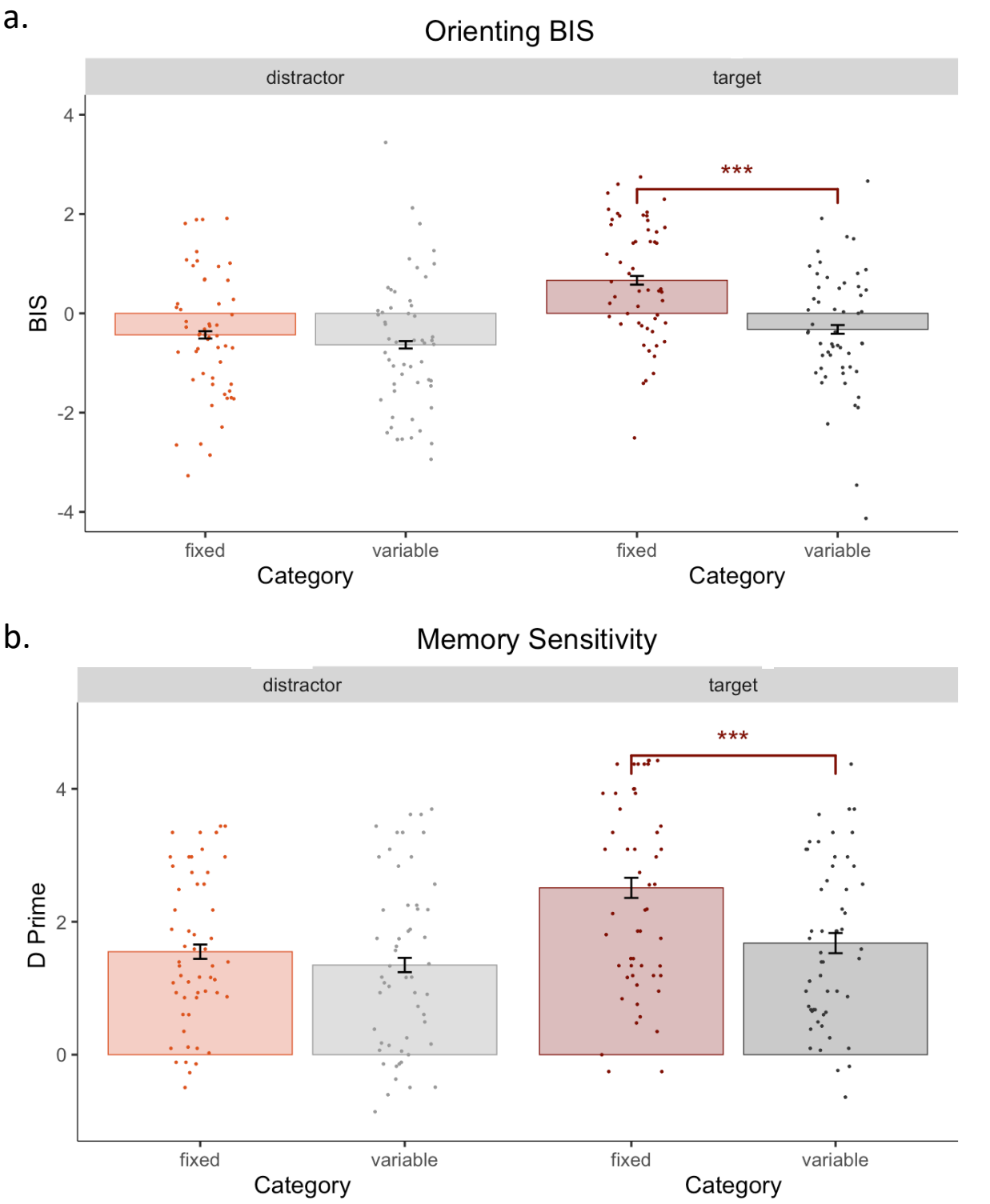
4.4.2. Results

4.4.2.1. Attentional-Orienting Accuracy and Response Time. Because BIS was the main dependent variable of choice, summary statistics for accuracy and response times are reported in Appendix E.

4.4.2.2. Attentional-Orienting Biased Integration Score. I analysed BIS for memory-guided attentional orienting using a three-way mixed ANOVA with Association (Fixed or Variable) and Object Presence (Present or Absent) as within-participant factors and Category (Target or Distractor) as a between-subjects factor (see Table 4.6). There was a main effect of Category, with participants performing better at detecting Targets (M = 0.17, SD = 1.32; Figure 4.6a) than Distractors (M = -0.17, SD = 1.70). A main effect of Association showed better performance for detecting objects previously studied with Fixed (M = 0.20, SD = 1.34) compared to Variable associations (M = -0.20, SD = 1.35). Finally, there was a main effect of Object Presence, with participants performing better when objects were Absent (M = 0.18, SD = 1.35) than when they were Present (M = -0.18, SD = 1.34).

Figure 4.6

Memory-Guided Attentional Orienting Results



Note. (a) Attentional orienting BIS for present object trials. Participants performed significantly better for targets than distractors. Further, participants performed significantly better for fixed than variable targets. There were no significant differences in performance between fixed and variable distractors. (b) D Prime (d'). Participants were more sensitive to targets than distractors. Also, their sensitivity to fixed targets was higher than variable targets, though there was again no significant difference between fixed and variable distractors. Error bars specify normalized mean standard error.

Table 4.6

Biased Integration Score for Attentional Orienting

Effect	DFn	DFd	F	p	η2
Category	1	104	3.33	.071	0.02
Association*	1	104	36.42	< .001	0.02
Object Presence*	1	104	6.84	.010	0.02
Category:Association*	1	104	9.70	.002	< .01
Category: Object presence*	1	104	6.93	.010	0.02
Association:Object Presence*	1	104	9.13	.003	0.01
Association:Category:Object Presence*	1	104	8.25	.004	< .01

Note. There were significant main effects Association and Object presence as well interactions between each combination of the variables. An asterisk (*) signifies a p-value below .05.

To understand the interactions among the experimental factors, I focused on breaking down the three-way interaction among Category, Association, and Object Presence using planned paired t-tests. Here, I will specifically highlight the comparisons in Table 4.7. that likely drove the overall interaction because the pattern of effects was not symmetrical. First, there was no significant difference in participants' performance at detecting Fixed or Variable

Targets that were Present compared to correctly responding that Fixed or Variable Targets were Absent. There was a different pattern for learned distractors: participants performed worse at detecting Fixed and Variable Distractors that were Present compared to correctly responding that Distractors were Absent. One possible explanation for these results is that participants found it more difficult to detect Distractors compared to Targets. Consequently, they were more likely to respond that the Distractors were absent, leading to worse performance when the Distractors were actually present. Next, the group that oriented to Fixed Targets that were Present performed better than the group that oriented to Fixed Distractors that were Present, but when the Fixed Target or Fixed Distractors were Absent there was no difference in performance between groups. Alternatively, there was no difference in performance between the Target and Distractors groups for detecting Variable Present or Variable Absent orienting targets. Overall, these results reinforce the assertion that Fixed Targets, especially when Present, facilitated attentional orienting performance.

Table 4.7

Three-way Interaction between Category, Association, and Object Presence

Effect	*df*	*t*	*p*	*d*
Present Targets (Fixed) vs. Present Targets (Variable)*	53	6.51	< .001	0.82
Present Distractors (Fixed) vs. Present Distractors (Variable)	53	1.56	.12	0.16
Absent Targets (Fixed) vs. Absent Targets (Variable)	53	1.82	.22	0.15
Absent Distractors (Fixed) vs. Absent Distractors (Variable)	53	1.38	.17	0.13
Fixed Targets (Present) vs. Fixed targets (Absent)	53	2.04	.11	0.31
Variable Targets (Present) vs. Variable Targets (Absent)	53	1.79	.079	0.31
Fixed Distractors (Present) vs. Fixed Distractors (Absent)*	53	3.09	< .001	0.55
Variable Distractors (Present) vs. Variable Distractors (Absent)*	53	3.30	< .001	0.55
Fixed Present (Target) vs. Fixed Present (Distractor)*	105.77	4.69	< .001	0.91
Fixed Absent (Target) vs. Fixed Absent (Distractor)	105.77	.061	.95	0.01
Variable Present (Target) vs. Variable Present (Distractor)	105.49	1.26	.21	0.24
Variable Absent (Target) vs. Variable Absent (Distractor)	105.49	.15	.88	0.03

Note. An asterisk (*) signifies a p-value below .05. Significant p-values were controlled for Type 1 error with Bonferroni correction.

4.4.2.3. Attentional-Orienting d'. I analysed d' for memory-guided attentional orienting using a two-way mixed ANOVA with Association (Fixed or Variable) as a within-participants factor and Category (Target or Distractor) as a between-subjects factor. There was a main effect of Category, with participants performing at detecting Targets (M = 2.09, SD = 1.47; Figure 4.6b; Table 4.8) than Distractors (M = 1.45, SD = 1.22). There was also a

main effect of Association, with participants performing better for Fixed (M = 2.03, SD = 1.45) than Variable (M = 1.51, SD = 1.27) associations. There was also an interaction between Category and Association.

I ran a planned paired-samples t-test to investigate the interaction between Category and Association. For the group tested on learned Targets, participants showed higher perceptual sensitivity for objects with Fixed than Variable associations ($t(53) = 3.88$, $p < .001$, Cohen's $d = .59$). Alternatively, for the group that tested on Distractors, participants showed no difference in sensitivity between Fixed and Variable Associations ($t(53) = 1.32$, $p = .19$, Cohen's $d = .16$). Next, for Fixed associations, participants were more sensitive to Targets than Distractors ($t(53) = 3.30$, $p < .001$, Cohen's $d = .70$). But, for Variable associations, there was no differences in sensitivity between Targets and Distractors ($t(53) = 1.25$, $p = .11$, Cohen's $d = .26$).

Table 4.8

D' for Attentional Orienting

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	106	8.76	< .001	0.06
Association*	1	106	15.42	< .001	0.04
Category:Association*	1	106	5.76	.018	0.01

There were significant main effects Category and Association as well an interaction between Category and Association. An asterisk (*) signifies a p-value below .05.

4.4.3. Conclusion

The results in this section supported my hypothesis that fixed spatial associations during learning would benefit memory-guided attentional orienting compared to variable learning. In particular, BIS performance was facilitated when target objects were present and fixed compared to absent and/or variable. However, there was no evidence supporting the predicted benefit of variable associations for distractors compared to fixed distractors. Also, participants were more perceptually sensitive to target than distractor objects, indicating the importance of attentional selection based on task goals for encoding into memory and subsequent use of memory-guided attention. But, this effect was mainly driven by higher d' for fixed targets compared to fixed or variable distractors, with no significant benefits to the detection of variable targets, reinforcing the benefits to attentional guidance of spatially consistent targets. Importantly these results were supported by different measures such as BIS – a combined metric for accuracy and RT – and d', a measure for perceptual sensitivity to target presence or absence.

4.5. Discussion

During repeated blocks of visual search, participants became faster and more accurate at finding targets that had either fixed or variable spatial associations with scenes. Additionally, there was a comparative advantage to learning fixed compared to variable associations. Both types of association enhanced subsequent memory retrieval for targets compared to distractors, with some evidence that scene memory retrieval specifically benefitted by variable association learning. Alternatively, only fixed associations facilitated attentional orienting for targets compared to distractors and participants performed better at detecting fixed than variable targets. These findings demonstrate that participants can reliably learn object-scene associations with different

extents of spatial regularities while distractors are simultaneously present. Furthermore, the results show that the spatial regularity of learned associations has important and distinct consequences for performance in subsequent measures of memory retrieval and attentional orienting.

For this chapter, I designed a task that explored how the task relevance and spatial predictability of objects embedded within natural scenes influenced learning during a visual search task and subsequent utilisation of memories for memory retrieval and attentional orienting. Specifically, target and distractor locations were either highly predictable (fixed spatial associations) or difficult to predict (variable spatial associations).

During learning, participants showed improvement in both association conditions, with clear benefits emerging to learning of fixed associations compared to variable associations. Participants reached a high level of performance (BIS) in a single session of learning over 5 blocks. My prediction that fixed associations would lead to faster learning compared to variable associations was supported. A linear-contrast analysis showed that learning slopes were steeper for fixed associations compared to variable associations. Therefore, as in Chapter 3 and other related experiments (e.g., Geng & Behrmann, 2002; Jiang et al., 2013; Salovich et al., 2018), targets that appeared in a high-probability location (fixed) were learned more quickly than those in low-probability locations (variable). This facilitation for fixed targets occurred despite the presence of competing distractors during visual search. Overall, it was more advantageous to have fixed targets with variable distractors than vice versa, suggesting that the benefits of predictions that guide selecting targets outweigh those related to supressing distractors (Ferrante et al., 2018). For example, if costs and benefits to visual search related to target and distractor predictability were equivalent, learning performance would have been equivalent in both

association conditions. Specifically, the increased distracting effect of variable distractor locations (Kelley and Yantis, 2009; Pascucci and Turatto, 2015), would have nullified the benefits of fixed target locations, whereas enhanced distractor suppression for fixed distractor locations (Noonan et al., 2016; Reder et al., 2003) would have neutralized the detriments of variable target locations. Therefore, visual search performance would be equivalent in both cases. Instead, participants performed better on trials containing fixed compared to variable targets, indicating that the benefits and costs of predictions for targets and distractors are not symmetrical.

There were some notable differences between the learning task used in this chapter compared to the task used in Chapter 3 experiments. In the current learning task, participants learned associations between scenes and object locations (as in Chapter 3) as well as associations between scenes and object identity. As in Chapter 3, object locations could vary, making it difficult to measure specific location memories. However, in this chapter, each scene had unique target/distractor identities (whereas in Chapter 3, all the objects were bells or dogs). Using the unique object identities allowed for measuring memory for specific learned associations by testing object memory during the retrieval task and flashing the objects that matched the learning scene during the orienting task. One potential risk of using unique objects was that they might have varied in how difficult they were to find in any given scene due to the 'pop-out' effect which can result from an object's colour contrast from its background (Draschkow et al., 2014; D'zmura, 1991). To minimize this possibility, the objects and scenes appeared in grey scale. Nevertheless, it is possible that some objects were more salient than others and that this could have contributed to the ease of visual search.

During the explicit retrieval task, both fixed and variable learned spatial associations conferred significant and similar benefits to object memory. As in past

studies (Castelhano & Henderson, 2005; Draschkow & Võ, 2016), object identification memory was facilitated for target objects compared to distractor objects across behavioural measures (accuracy, response time, or BIS). However, for both target and distractor objects, there was no difference in performance between fixed and variable associations. This result was counter to my hypothesis, suggesting instead that object identification memory may not be greatly impacted by spatial predictability during learning. Also, even though participants performed better during visual search for fixed compared to variable targets, subsequent object memory was similar for both association types, showing that effective learning occurred in both conditions. Relatedly, the spatial predictability of distractors did not significantly influence their subsequent memory retrieval. The literature suggests that fixed-location distractors may be better suppressed (Wang & Theeuwes, 2018). As a result, variable distractors may have been found more often during search (Ferrante et al., 2018; Kelley and Yantis, 2009; Pascucci and Turatto, 2015). Yet, these potential modulations during visual search did not result in later differences in explicit memory retrieval.

Source memory for the scenes associated with the remembered objects was also better for targets than distractors according to BIS measures, though response-times were equivalent. The spatial regularity of associations had only subtle effects on scene memory, affecting only response times. Specifically, participants were faster at correctly recalling scenes that contained variable targets and fixed distractors during learning compared to fixed targets and variable distractors. This response-time facilitation is consistent with my initial hypothesis that greater exploration of scenes necessitated by variable targets during learning may have encouraged greater encoding of the scene itself. The increased time and exploration needed to find hard-to-predict (variable) targets would facilitate subsequent scene memory compared to fixed target scenes. It is interesting that

benefits to scene memory were not accompanied by similar benefits for object-identity memory for variable targets, potentially supporting the idea that engaging more with a scene does not necessarily imply engaging more with its embedded objects (Draschkow & Võ, 2016). These findings are in line with past work showing that active engagement with a virtual environment leads to better memory for the environment, but not for embedded objects (Brooks et al., 1999). It is also important to point out that the initial test of object recognition was a measure of item memory, i.e., relational information was not task-relevant (Zimmer et al., 2006), whereas scene memory was a test of 'relational' or 'contextual' binding between the item information (object identity) and context information (scene identity) that made up the study event (Yonelinas et al., 2019). This distinction is critical for memory performance, with different structures implicated in item vs relational memory (Cabeza, 2006; Davachi, 2006; Henke et al., 1997) and relational binding more sensitive to aging and memory disorders (Spencer & Raz, 1995). Therefore, the differential effects of variable associations on object recognition vs. scene memory may be due to different underlying mechanisms being tested.

In Experiment 8, both the goal-relevance of objects during learning (target/distractor) and the predictability of their spatial associations had strong consequences for subsequent memory-guided attentional orienting. For example, participants were more perceptually sensitive to targets compared to distractors. In particular, BIS and perceptual sensitivity were higher for fixed targets compared to fixed or variable distractors, but variable targets did not give the same benefits. For the participant group detecting previously learned targets in the orienting task, fixed associations promoted better performance compared to variable associations as measured by both Biased Integration Score and d'. However, for the group tested on distractors from the learning task, there were no performance differences for either measure based on association type. Therefore, the results support my original supposition

about spatial predictability for targets – that learning predictable, fixed object-location associations would facilitate memory-guided attentional orienting compared to unpredictable, variable associations. My predicted attentional orienting benefit for variable compared to fixed distractors from the learning did not emerge. The original prediction was based on the literature showing stronger suppression of predictable distractors during visual search (e.g., Wang & Theeuwes, 2018). The lack of any relative benefits at the locations of variable distractors could have multiple explanations. The consequences of fixed vs variable spatial associations on distractors may have been weak and therefore not sufficient to support a reliable effect on attentional orienting. Specifically, even if variable distractors were attended to more during learning than fixed distractors, which faced more attentional suppression, this effect was not sufficiently powered for a significant difference to emerge (Ferrante et al., 2018; Noonan et al., 2016). Instead, or in addition, there could be a dissociation between the functions that mediate behavioural effects of predictable distractors during visual search vs during memory-based orienting. Performance during visual search, whether accuracy or response times, can be affected by many more variables than that during memory-based orienting (e.g., searching for targets, selecting targets, inhibiting distractors, learning about the target and distractor locations, etc.; see Summerfield et al., 2006). In either case, these results also suggest that spatial predictability influences target selection and distractor filtering through different mechanisms (Couperus & Mangun, 2010; Houghton & Tipper, 1996; Luck, 1995).

Combined, the results from both experiments provide evidence supporting that the way in which learned associations can be utilized could differ between visual search, memory retrieval, and memory-guided attentional orienting. Because the learning task was identical in both Experiments 1 and 2, it is possible to compare how the different learned associations support memory-retrieval vs memory-guided attention. Notably, in the memory-retrieval task,

object identification was equally facilitated by both fixed and variable targets compared to distractors, whereas scene memory showed some evidence of benefitting from variable target associations specifically. Alternatively, memory-guided attentional orienting performance (i.e., BIS and perceptual sensitivity) was only heightened after fixed target association learning. Therefore, a low level of predictability (variable associations) during target learning appeared to have some benefits to memory retrieval (scene memory), whereas a high level of predictability of goal-relevant items (fixed associations) appeared to benefit memory-guided attentional orienting. This may indicate that the spatial priorities learned during visual search have a stronger bearing on subsequent attentional memory-guided attention than on explicit memory retrieval. These behavioural differences may tie into proposals that the neural basis of memory retrieval and memory-guided attention have significant differences (Hutchinson et al., 2009; see also Salvato et al., 2016). Finally, these results reinforce evidence from Chapter 3 supporting that the method used for forming associative memories has important, and potentially differential, consequences for the application of that memory, whether it be memory retrieval or memory-guided attentional orienting.

These results provide a steppingstone for a range of follow-up experiments that can further explore how learning occurs under different pairings of target-distractor associations and the consequences of this learning for subsequent behaviour. For example, future studies should replicate the finding that the predictability of object locations in visual search has little impact on subsequent object-identity memory during retrieval. Stronger evidence could also be sought regarding whether and how low target predictability (variable associations) can strengthen memory for the scene context. Finally, associative memories containing unique and specific stimuli, such as those formed in this study, are typically hippocampal-dependent (Davachi, 2006; Shohamy & Adcock, 2010). Follow-up projects can test for the hippocampal-dependence of the spatial-association learning during the visual search task. It

would also be interesting to explore and compare the neural basis of the behavioural consequences of these memories for memory retrieval vs. memory-guided attention. For example, an MR study could delve into whether the same or different brain networks that are responsible for the selection of targets or the filtering of distractors during learning were reutilized during memory retrieval and attention orienting (Marini et al., 2016, Ruff and Driver, 2006, Serences et al., 2004). Finally, an EEG or MEG study could elucidate the neural rhythms underlying attentional orienting to different association types at the fast time courses used in my study (Patai et al., 2012).

Designing an experiment that measured two types of associations governing target and distractor locations had its costs and benefits. This design allowed for as much balance between conditions as possible during the learning task. For example, benefits to visual search for fixed targets were paired with the detriments due to the presence of variable distractors. Therefore, if participants performed better on fixed than variable targets, it was likely that the benefits of the fixed targets outweighed the costs of variable distractors. However, because of the coupled manipulation of fixed vs. variable targets vs. distractors, it is impossible to separate the specific extent to which learning benefits to fixed targets were related to target selection or distractor suppression. A follow-up that uses a full factorial design and also examines the pairing of fixed targets with fixed distractors and variable targets with variable distractors could be used to separate fully the contributions of goal-based attention and the predictability of spatial associations. Running this study was not feasible within the time constraints of my DPhil, but it would be an interesting and important follow-up.

Also, though real-world objects and scenes were used, the pairings of objects with scenes did not follow semantic consistency, nor did the objects appear in locations that could be considered semantically congruent. As in Chapter 2, this was by design, such that

participants had to rely on their memory as much as possible to search for and subsequently retrieve or orient to object identities or locations rather than following semantic guidance (Võ & Wolfe, 2013). Also, there are only so many settings where toys and clothes (or any two object categories for that matter) could naturally occur together. Therefore, it would be difficult to choose a set of scenes that are not easily confusable where these or other object categories could simultaneously occur in various semantically congruent locations. Increased between-episode competition from less uniqueness of scene-object pairs may have reduced memory retrieval performance (Sohn et al., 2003), potentially confounding the effects that I sought to find. As a result, this study sacrificed some of its ecological validity in order to maintain the uniqueness and memorability of the formed associations. Next, though using grayscale scenes and objects would have reduced the extent to which objects 'popped-out' of scenes (Draschkow et al., 2014), this design choice reduced the ecological validity of the study, as we operate in a world that is in colour, not in greyscale. Finally, though as much as possible, natural scenes were used that did not contain distinguishable distracting objects, natural scenes are complex and contain multiple possible sources of distracting information (e.g., cars in an image of a road; Biederman et al., 1982; Brockmole et al., 2006b). Although these sources of distraction were unlikely to be as effective in drawing attentional selection as the actual distractor object, possible alternate sources of distraction should not be entirely discounted. Future studies should consider these design aspects when considering how to increase ecological validity while testing similar effects of learned spatial regularities on memory retrieval and/or attentional orienting.

One of the drawbacks of the experiments reported in this chapter was the difficulty of creating and balancing the object set. In the end, the pattern of participants performing better on fixed target search compared to variable target search was consistent for both object categories (toys and clothes) during learning. However, there

were some differences in performance between object categories, with participants scoring higher on BIS for toy objects than clothes objects. Despite these differences, the two categories were still overall quite well matched as the slight BIS differences during the learning task did not significantly impact performance in subsequent memory retrieval or attentional orienting – one of the important successes of this work. This result was not easy to achieve, as the object sets were created from scratch, rather than using an existing database. The objects populating the toys and clothes categories were chosen carefully for recognizability while maintaining uniqueness such that objects were not confused with other within-category exemplars. Furthermore, objects had to be paired with a matching foil that was still different enough to be discriminable. Narrowing down the specific objects, and the categories themselves, took rounds of piloting to reach the final task reported here, in which participants' performance (BIS) was similar between categories. The similar and significant effects of learning fixed compared to variable associations in these two categories suggest these effects may be more generalizable to object and scene learning rather than specific to a certain object category or scene category. Overall, the robust learning in this phase of the task provided a solid basis for exploring the consequences of spatial predictability of visual search on memory retrieval and attentional orienting in subsequent tasks and supports the feasibility of using this learning task for follow-up studies.

Chapter 5: General Discussion

Memories may be based in the past, but they influence our behaviour at each point along the arrow of time from the present to the future. Yet memory research tends to look back in time at the constitution of memories, rather than examining how our past experiences adaptively and dynamically guide our behaviour in the present (Nobre & Stokes, 2019). The proactive power of memory deserves further inquiry as our memories do not linger in the past, they continue to aid us in the challenges ahead (Bar, 2009; Biderman et al., 2020; Nobre & Stokes, 2019). Therefore, in this thesis, I investigated how past experiences shape and influence our ability to retrieve memories and attentionally orient in the present. In particular, I investigated how manipulating the ways in which memories are formed can have similar and different consequences for internal (memory retrieval) compared with external attention (attentional orienting). I began by investigating limitations on long-term memory retrieval, for example, whether an increased set size of to-be-remembered objects has detrimental effects on subsequent retrieval (Chapter 2). Then, I examined the relative consequences of different types of associative learning (Chapter 3) and spatial expectations (Chapter 4) for attentional orienting and memory retrieval.

Over these three studies, participants built associative memories during visual search tasks and were then tested on their learning in subsequent retrieval or attention orienting tasks. In my first study, participants demonstrated a remarkable ability to retrieval learned objects with no detriments to performance as the number of objects (set size) associated with a specific context increased. Similarly, manipulations to spatial overlap between targets and lures (between-episode competition) did not impact retrieval performance, except targets proved easier for participants to recognize when competing against novel compared with ‘old’ lures. In my subsequent two studies, learning of different types of spatial relationships between scenes and target objects impacted memory retrieval (internal attention) and

memory-guided attentional orienting (external attention) in different ways. Specifically, memory retrieval success was linked to congruency between learning and retrieval demands. For example, probabilistic learning improved subsequent hemifield memory, whereas contextual learning improved location memory. The predictability of spatial associations between scenes and target objects also impacted memory retrieval and attentional orienting in different ways. Scene memory retrieval speed was boosted by learning unpredictable (variable) target-location associations. Alternatively, memory-guided attentional orienting was specifically facilitated by learning predictable or fixed spatial associations. I will break down each of these findings and compare them across studies in the subsequent sections.

5.1. Memory Set Size does not have Significant Effects on Long-term Retrieval

As described in Chapter 2, over 3 experiments, participants learned to associate varying numbers of target objects (set size) with specific scenes. In contrast to my hypothesis, whether the set size was lower (1, 2 or 3 objects) or higher (3, 5, or 7 objects) than the standard working-memory capacity of 3-4 objects in memory (Fukuda & Vogel, 2019; Luck & Vogel, 1997), there was no related detriment to long-term memory retrieval (LTM) performance. This finding stands in contrast to studies showing impaired LTM performance when moving from 1 to 3 objects in memory (Čepukaitytė et al., 2022) or from 4 to 8 objects in memory (Fukuda & Woodman, 2017). Although it is difficult to identify a single reason why there was no effect of increased memory set size on LTM performance, one possible explanation it that allowing for similar encoding time per each learned object resulted in similar retrieval performance (Čepukaitytė, 2023). It is also possible that the lack of set-size effects on retrieval may be specific to young adults with impairment to this ability found in older adults and at-risk groups (Zokaei et al., 2019). Alternatively, in some studies which found effects of increasing set size on memory retrieval performance (Fukuda & Woodman,

2017), task backgrounds were identical, raising the possibility that effects of within-episode competition were influenced or added to by effects of between-episode competition. Therefore, the unique real-world scenes and objects used as backgrounds in my task may have contributed to participants' ability to recognize object identities and recollect their locations despite the increasing set size. Nevertheless, the results from my studies do call into question the role of working memory (WM) in LTM retrieval. For example, these results showing the lack of a capacity limit during retrieval may suggest that LTM was able to guide retrieval directly (Nobre & Stokes, 2019), rather than by retrieving objects into a WM buffer (Fukuda & Woodman, 2017). Subsequent work should further explore whether and when LTM traces operate through WM to guide retrieval (Atkinson & Shiffrin, 1968), for example, by determining differences between experiments which show that LTM is held to WM capacity limits (Sohn et al., 2003) and those which do not (Brady et al., 2008).

In Experiment 1, manipulations to between-episode competition did not influence memory retrieval based on the extent of spatial overlap between lure and target locations, however, participants' recognition memory was facilitated when there was no between-episode competition (novel lures). During the object recognition aspect of the retrieval task, participants' performance (accuracy and response times) was not impacted by whether lures were from the same or different screen location as the target. This result seemingly conflicts with other findings that the degree to which lures spatially overlap with a target can lead to increased competition and subsequent interference (Chanales et al., 2017; Pertzov & Husain, 2014). However, in other studies, the degree of spatial overlap was manipulated in the same context though in different trials, whereas in my study the degree of spatial overlap was manipulated in different contexts and different trials. This discrepancy may support that context or setting-based overlap is different from screen-based overlap in the degree to which it imposes between-episode competition. Subsequent work should compare setting and

screen-based overlap directly and systematically to more concretely establish their similarities and differences. It is also worth noting that in trials where the lure was completely novel, participants' recognition memory accuracy was much higher. This supports that the task of recognizing which object matches the scene was easier when choosing between a learned target that matches the scene and a novel lure versus a learned target that matches the scene and a learned target that does not (Migo et al., 2012). Therefore, it is possible that the learned foils did impose some effects of between-episode competition, even if this did not scale with the extent of screen-based overlap (Reagh & Yassa, 2014). Finally, even though object recognition accuracy was higher when a novel lure was present, there was no subsequent facilitation of location recollection. Given that familiarity is more involved in object recognition while recollection is more involved in recall (Aggleton & Shaw, 1996; Bastin & Linden, 2003; Migo et al., 2021; Parkin et al., 1994), these differences in recognition and recall performance potential support findings of mechanistic differences between familiarity and recollection memory (Aggleton & Brown, 2006; Mandler, 1980; Tulving, 1985; Yonelinas, 1994, 2002).

It is interesting to compare my finding of little of effects of set size during memory retrieval (internal attention) with evidence of effects of set size in external (perceptual) attention (Chun et al., 2011; Poskanzer & Aly, 2022; Tarder-Stoll et al., 2019). Specifically, during the learning task, each object associated with a scene was a target, but during retrieval, the learned targets that were not probed can be thought of as distractors in the process of internal attention or retrieval. Based on this logic, changing the set size during learning was also manipulating the number of retrieval distractors. Therefore, an inability to retrieve the identity of the target or to retrieve its location can be thought of as a failure to overcome interference and to ‘detect’ target memories among distractor memories (Long et al., 2018). Interestingly, the results showing that increasing the number of competing distractor

memories does not impact explicit retrieval differ from findings on how competing distractors impact visual search. In the contextual cueing literature, a “search slope” is an index of search efficiency that measures the increase in reaction time as the number of distractors in a target-distractor array increases (Chun & Jiang, 1998; Sisk et al., 2019; Wolfe., 1998). The extent to which contextual memory resulting from repeated search reduces this slope (benefits search in arrays with many distractors more than arrays with few distractors) is inconsistent (Kunar et al., 2007; Sisk et al., 2019). However, even in studies that do show reduced search slope on repeated trials, targets in arrays with a large number (e.g., 16) of distractors are found slower than those with a smaller number (e.g., 12 or 8) of distractors (Chun & Jiang, 1998). Therefore, this evidence suggests that internal attention may to an extent work differently from external attention as the number of objects that participants must search through to find targets may impact visual search performance but not memory retrieval.

Overall, the research presented in this chapter demonstrated that the set size of target objects may be increased up to 7 items in memory without related detriments to retrieval ability. This provides further evidence for the prospective power of memory to retrieve specific target-scene associations with high accuracy and precision despite competing alternatives stored within the same memory episode. Finally, prior to this study, it was unclear whether participants would have the attention span or focus necessary to complete the lengthy, multi-part, long-term memory experiments that were planned for my thesis. This study provided evidence to support the continued use of online testing in the subsequent studies of my thesis based on finding no significant differences between in-lab and online groups for any of the task-relevant measures.

5.2. Contextual and Probabilistic Associations Facilitate Memory Retrieval and Attentional Orienting Differently

As presented in in Chapter 3, over 3 studies, participants formed different types of associative memories and then applied this learning to retrieval and attentional-orienting tasks. Although significant learning benefits were demonstrated for both contextual and probabilistic associations, contextual associations showed comparatively more facilitation of visual search performance. Learning effects for both association types were accentuated when participants were able to learn over two consecutive days compared to only one day, indicating that sleep-related memory consolidation may benefit associative spatial learning (Barsky et al., 2015; Geyer et al., 2013). Facilitation of visual search learning by contextual associations is well-established by contextual cueing literature (Brockmole & Henderson, 2006; Chun & Jiang, 1998; Endo & Takeda, 2004; Goujon et al., 2015), while benefits to visual search by probability cueing is also well supported in literature (Druker & Anderson, 2010; Geng & Behrmann, 2002). However, this is the first study I am aware of that directly compares these different types of associative learning in a single task using scenes as contexts. One other study has directly compared probabilistic and contextual learning using a search task in a simple stimulus array (Goldfarb et al., 2016). Despite differences between my study and their study (e.g., use of complex scenes as contexts vs simple stimulus array), in both studies participants' rate of learning was slower with probability cueing to develop the same levels of learning as contextual cueing. This finding reinforces assertions that the time-course of learning in striatal-probabilistic learning (Salovich et al., 2018; Schmitzer-Torbert, 2007; Yin & Knowlton, 2006) may be slower than that of hippocampal-contextual learning (Spaak & de Lange, 2020). Future work should delve deeper into the similarities and differences between how learning benefits from contextual and probabilistic associations in simple stimulus arrays versus 2D and 3D naturalistic environments, including comparing

behaviour in scene settings that are semantically congruent versus incongruent. For example, one interesting topic would be to directly compare how these systems act in 3D environments, as initial findings suggest probability cueing may be more dependent on the target being in the initial field of view than contextual cueing (Marek & Pollmann, 2020; Sisk et al., 2021).

After repeating the learning task for two days in a row, participants demonstrated facilitation of attentional orienting by both association types on a third test day. This facilitation of attentional orienting by contextual associations is well supported (Doallo et al., 2013; Patai et al., 2012; Summerfield et al., 2006). However, this is the first study that I am aware of to show that a higher probability of target locations occurring in a specific spatial region (probability cueing) facilitates memory-guided attentional orienting. This finding suggests that learned attentional habits (e.g., in ocean scenes targets appear on the right) can be stored in memory and guide attentional orienting in subsequent tasks that differ from the initial learning. Next, the result that probabilistic and contextual learning facilitated attentional orienting to equal extents was unexpected. Specifically, it could be predicted that contextual associations would benefit attentional orienting more than probabilistic associations as contextual learning was based on specific location-scene associations – precisely what was tested during the orienting task by flashing a target in a specific location. One possibility is that a reported speed advantage for probabilistic (striatal) retrieval compared to contextual (hippocampal) retrieval (Vogel et al., 2017) may have made up for the lack of spatial specificity of probabilistic memory, resulting in similar attentional orienting performance. It is also worth noting that when participants were tested on their attentional orienting after only one learning session on the same day (Experiment 5), there was no significant facilitation of attentional orienting. This may indicate that there is also an important role for memory consolidation in memory-guided attentional orienting. Relatedly,

it is possible that the way in which contextual and probabilistic associations were stored in memory became less spatially specific or gist-like due to consolidation between days 2 and 3 of testing (Antony et al., 2021), again resulting in similar attentional orienting performance. Subsequent work should test the role of memory consolidation in attentional orienting to understand how it impacts guidance by different types of associative learning. It is feasible, for example, that memory consolidation benefits attentional orienting, but mainly because it facilitates initial learning (Barsky et al., 2015). Therefore, if robust learning occurs without over-night memory consolidation (as in Chapter 4, Experiment 8), attentional orienting may still be facilitated.

Different memory retrieval tasks were facilitated based on the type of associative learning. In comparison to the other learned association types, probabilistic association learning led to the strongest performance in retrieving the target's matching hemifield, e.g., in Experiment 6 during location report. The same pattern was apparent in Experiment 4 for hemifield recall, though accuracy was not significantly higher for probabilistic than contextual associations. On the other hand, contextual association learning uniquely improved localisation memory (Experiment 4: location memory, Experiment 6: location report precision). Therefore, memory retrieval was most facilitated when learning was well-matched to the demands of retrieval tasks. For example, during retrieval of probabilistic associations, participants could reduce the difficulty of retrieval by only needing to remember the association between scene category and hemifield (e.g., forest scene = target on right; Delgado et al., 2005; Geng & Behrmann, 2002; Salovich et al., 2017). This learned attentional habit was more suited to hemifield recall than contextual associative learning. Instead, during retrieval of contextual associations, participants could use the cued context to remember the associated specific target location (Summerfield et al., 2006), facilitating both their

hemifield and location recall. Therefore, contextual associative learning was spatially specific but also flexible, in that it was best utilized for recall of specific target locations but still effective at hemifield recall (Doeller & Burgess, 2008; Summerfield et al., 2006; Stokes et al., 2012). However, it is worth noting that probabilistic learning could not have facilitated location recall, as a specific, fixed location was never learned from which their recall could be compared (see Section 3.3.3). Therefore, though probabilistic learning was more suited for hemifield recall, contextual learning was uniquely suited for location recall as no other association could have enhanced memory in this task to the same extent. An intriguing follow-up study might more adequately test the extent to which probabilistic associations are 'inflexible' as found in literature (Geng & Behrmann, 2002; Jiang & Sisk, 2019; Salovich et al., 2018; Seger et al., 2018). For example, in the same task design as Experiment 4, asking participants to recall the last location where the target occurred during learning could test the extent to which probabilistic learning can also be specific.

Interestingly, performance in retrieval and attentional-orienting tasks appeared to have different learning requirements. Memory retrieval was facilitated regardless of whether participants were tested on the same day as a single learning session (Experiments 4 or 5) or on a third day following two days of learning (Experiment 6). Alternatively, overnight memory consolidation and/or additional learning blocks (Experiments 4 and 5 had five blocks whereas Experiment 6 had ten broken up over two days) appeared vital for the facilitation of attentional orienting in this study. This assertion is especially supported by results from Experiment 5 where participants' location memory for attentional orienting targets was facilitated despite no benefit to attentional orienting itself. It would be interesting to investigate if these differences in learning requirements are related to suggestions that the neural basis of the attention

and memory retrieval systems diverge (Hutchinson et al., 2009). Additionally, future studies that wish to replicate or extend my findings with a similar design should consider that measuring memory-guided attentional orienting may require more robust learning effects compared to explicit memory retrieval. Further, subsequent research should parse the contribution of additional learning blocks compared with overnight memory consolidation (between learning sessions or learning and attentional orienting sessions) to the facilitation of memory-guided attentional orienting. Overall, this chapter provides new evidence to support proposals that memory should not be combined into a single source of attentional control (Nobre & Stokes, 2019). Rather, the way in which different memories are built, e.g., by different association types, has important implications for their future utility.

5.3. Spatial Expectations have Important and Differential Consequences for Memory Retrieval and Attentional Orienting

As described in Chapter 4, across two studies, I measured how learned spatial expectations regarding the locations of targets and distractors impact subsequent memory retrieval (Experiment 7) and attentional orienting (Experiment 8). First, as hypothesized, participants demonstrated facilitated visual search for fixed compared to variable target locations, though participants' performance improved for both types of spatial expectation during the learning task. This result occurred despite fixed targets being paired with the same scene as variable distractors and variable targets being paired with fixed targets. Therefore, it was more advantageous to have fixed targets with variable distractors than vice versa, suggesting that the benefits of spatial predictions that guide target selection may outweigh those related to distractor suppression (Ferrante et al., 2018).

After learning, participants were tested on their ability to retrieval the target and distractors' identities and then had to match them to their associated scenes (Experiment 7).

Participants' object identity memory did not differ based on spatial expectations (fixed or variable). However, as in past studies (Castelhano & Henderson, 2005; Draschkow & Võ, 2016), identity memory was better for targets than for distractors. The lack of effect of spatial expectations on identity memory was counter to my hypothesis, suggesting that object identity memory may not be greatly impacted by learned spatial expectations. This result is in accord with past findings that engaging more with a scene does not necessarily imply engaging more with its embedded objects or having better memory for them (Brooks et al., 1999; Draschkow & Võ, 2016). Scene memory was also facilitated for targets compared to distractors. But, in contrast to identity memory, there were subtle effects of learned spatial expectations on scene memory. Specifically, participants were faster at correctly retrieving scenes that were associated with variable targets and fixed distractors during learning compared to fixed targets and variable distractors. This finding provides evidence in favour of the uncertainty principle outlined by Pearce and Hall (1980), where attention may be preferentially allocated to cues when their outcomes are surprising. In the variable condition, target locations were unpredictable, therefore participants were motivated to explore the scene to find each target location (Le Pelley et al., 2016). This additional attentional exploration may have benefitted their subsequent scene memory retrieval speed (Beesley et al. 2015). Additionally, these results suggest that learned spatial expectations have different consequences for memory retrieval depending on subsequent use (e.g., for identity memory versus scene memory).

Interestingly, one recent study (Bainbridge & Baker, 2021), found a similar performance discrepancy in semantically incongruent scenes for scene memory and object memory. In their study, scenes containing semantically incongruent objects were recalled more often (compared with semantically congruent scenes), but memory for related objects was weaker, indicating that there were binding deficits between the object and its scene. In

contrast, semantically inconsistent scenes, were recalled less frequently, but object-scene binding was more effective when scenes were recalled as demonstrated by improved object memory (Bainbridge & Baker). Therefore, some of the discrepancies in my study between object identity and scene memory may have been modified by the choice to use semantically inconsistent scenes (rationale for this choice is discussed in Section 4.5). Follow-ups should delve deeper into the consequences of semantic inconsistency and potentially investigate if benefits to scene memory by variable associations would still occur in semantically congruent settings. Also, subsequent work should attempt to replicate my findings with stronger evidence showing that inconsistent spatial expectations may facilitate scene memory due to additional attentional exploration (Beesley et al., 2015) with little consequence for item memory.

In Experiment 8, after learning, participants completed an attentional-orienting task where they were tested either on the learned targets or distractors. Memory-guided attentional orienting, as measured by perceptual sensitivity, was facilitated for targets compared to distractors. Therefore, for both memory retrieval and attentional orienting, attentional selection during learning promotes subsequent utility. Also, in agreement with my hypothesis, fixed associations facilitated attentional-orienting performance compared to variable associations. Specifically, BIS and perceptual sensitivity were higher for fixed targets compared to fixed or variable distractors, but variable targets did not provide the same attentional benefits. This finding replicates other work showing that consistent spatial expectations facilitate both visual search learning (Zhang et al., 2022) and memory-guided attentional orienting (Summerfield et al., 2006). Additionally, these findings align with the proposals of the predictiveness principle (Mackintosh, 1975), where attention is preferentially allocated to cues when their outcome is predictive. In other words, attentional exploitation of targets that occurred in predictable spatial locations appeared to facilitate performance both

during visual search and during memory-guided attentional orienting (Beesley et al., 2015). This may also support that whereas memory retrieval can be guided by attentional exploration (as measured by faster scene recall), attentional orienting may be predominantly guided by attentional exploitation.

Contrary to my hypothesis, there was no facilitation of attentional orienting to distractors that had occurred in variable compared to fixed locations. This proposal was based on findings from visual search tasks where distractors that vary in location are more distracting than fixed location distractors, and may thus be found more (Ferrante et al., 2018; Wang & Theeuwes, 2018). Instead, I found no differences in attentional orienting to distractors based on learned spatial expectations. Therefore, it is possible that attentional guidance by distractors differs between visual search and memory-guided attentional orienting, consistent with visual search being impacted by more variables than attentional orienting (Summerfield et al., 2006). These differing results for orienting to targets compared to distractors reinforce proposals that spatial predictability may influence target selection and distractor filtering through different cognitive mechanisms (Couperus & Mangun, 2010; Ferrante et al., 2018; Houghton & Tipper, 1996; Luck, 1995). Future research should delve deeper into whether variable distractors are remembered better and lead to stronger attentional orienting compared to fixed distractors. Results from studies in Chapter 3 support that attentional orienting performance is dependent on robust learning, therefore it is plausible that distractors were simply not attended to enough for their learning to benefit attentional orienting. Therefore, effects on attentional orienting might be detected in another study with a more difficult learning task, or more rounds of learning, where additional scene exploration could result in variable distractors being discovered more and thus learned better. Together, the findings from this chapter indicate that different learned spatial expectations

have important consequences for subsequent behavioural utility, but their usefulness is modulated by attentional selection based on task goals during learning.

5.4. Linking Findings Between Chapters

5.4.1. Spatially Predictable Targets Facilitate Attentional Orienting

In the experiments contained within Chapters 3 and 4, participants completed visual search tasks where scenes were associated with targets that occurred with a high to medium degree of spatial predictability (i.e., occurred in a specific location or a particular hemifield) or were unpredictable (i.e., occurred in a random location). In both studies, learning of spatially predictable targets facilitated both visual search and subsequent memory-guided attentional orienting compared to unpredictable targets. This finding is aligned with past research showing that attention is rapidly allocated to previously relevant locations within a scene (Becker & Rasmussen, 2008; Geng & Behrmann, 2002) and that contextual reinstatement of a learned scene facilitates attentional orienting towards that scene in memory-guided attention (Salvato et al., 2016; Stokes et al., 2012; Summerfield et al, 2006). Overall, these results suggest that spatial predictability plays a significant role in external attention more generally, i.e., in visual search or subsequent memory-guided attentional orienting.

5.4.2. Memory Facilitation is Linked to Congruency between Learning and Retrieval Demands

Across the studies described in Chapters 3 and 4, memory retrieval performance was best when learned associations were well suited to the demands of the retrieval tasks. For example, as presented in Chapter 3, hemifield retrieval was facilitated when target-hemifield

associations were learned (probabilistic learning). Similarly, location memory was facilitated by specific target-location associations (contextual learning). Then, as shown in Chapter 4, after learning variable target-scene associations, which may have required participants to explore scenes more to find targets (compared to fixed associations), the speed of scene memory was benefitted. However, in Experiment 4, participants showed no scene memory performance differences between variable (in this Experiment called 'random'), fixed (contextual), and probabilistic target-scenes associations. In Chapter 3, scenes were sorted into six categories (e.g., beach, desert etc.) of similar exemplars. As a result, the overall uniqueness of individual scenes was relatively low compared to the experiments in Chapter 4 where each scene was categorically unique. Therefore, effective scene memory may be related to the uniqueness and categorical diversity of the learned scenes.

Next, as measured in Chapter 4, item memory stands out in being unaffected by the type of learned association. It is important to note that item memory was measured independently from its contextual (scene) association. Therefore, it is possible that item memory would have been facilitated if the associated context had been shown first (e.g., as in the Chapter 2 explicit retrieval task). In this case, the scene, which was remembered better for variable targets, may have acted as a memory cue and promoted retrieval of the location and identity of the associated object (Chun & Jiang, 1999; Eckstein et al., 2002; Giesbrecht et al., 2013; Summerfield et al., 2006). This order of testing would also have been more aligned with the learning task, where the participants saw a preview of the context not containing the target and then searched for the target when the scene reappeared. Therefore, in this case, when the way learning occurred was not very well matched to the retrieval task, facilitation based on association type did not occur, aligning with my proposal that memory performance is linked to congruency between learning and retrieval demands. Overall, whether learning tasks were typified by attentional exploitation of spatially predictable targets or by attentional

exploration of unpredictable targets, as long as the memory retrieval test was well aligned with the learning, internal attentional could effectively select a versatile range of associations for retrieval.

5.4.3. Methodology

An important factor that unified the different parts of my thesis was a unitary methodology. Across three chapters, a common task structure was used: participants completed a visual search learning segment and then were tested on their memories in retrieval or attentional orienting tasks. This structure was adapted from past studies with similar designs (Doallo et al., 2011; Stokes et al., 2012; Summerfield et al., 2006). Having participants build memories via visual search was ideal because of the ease of adjusting task parameters to explore different research questions. For example, in Chapter 2, memory set size could easily be manipulated by adjusting the number of targets associated with each scene. Further, in Chapter 3, different types of associative learning (e.g., probabilistic vs contextual) could be measured implicitly by having different rules regulate the locations where targets appeared in specific scene categories. Finally, in Chapter 4, spatial predictability could be adjusted by altering whether targets or distractors occurred in fixed or varying locations. The tasks were also simple to fine-tune. For example, to make the task harder or easier for participants; the target size, opacity, or contrast from the background (e.g., black or white) could be adjusted, as well as the number of learning blocks. Learning was carried out to high levels before the effects of the acquired memories were probed on subsequent retrieval and attention tasks. The scene contexts were then reinstated in subsequent tests to cue participants' memory and have them retrieve or attentionally orient to associated targets or distractors. Finally, throughout this thesis, most data were collected online, meaning that, throughout COVID, it was still possible to continue the

experimentation. Though online data collection likely introduced increased variability and drop-outs in the datasets compared to in-lab data collection (Sauter et al., 2020), the findings from this thesis contribute evidence to support the use of online testing as an effective methodology for memory and attention research. Therefore, overall, a significant contribution of this thesis is the tasks themselves which have the potential for adaptation for a range of follow-up behavioural or neuroimaging studies.

It is also worth noting that the learning tasks and subsequent tests featured a common structure: incidental learning was followed by surprise explicit tests in the form of memory retrieval and/or attentional orienting tasks. Throughout the tasks, participants were never explicitly instructed that they should attempt to learn the objects or scenes for any given purpose. This was purposeful so that participants would not attempt to guess at the underlying conditions to aid their learning or memory or try to use strategies to complete the task (See Section 1.2.4.). For example, if participants because explicitly aware of the rules underlying the probabilistic association condition, they could use a heuristic (e.g., ocean scenes = target on right) to respond, mitigating the need to retrieve the learned association. It is nevertheless possible that participants became explicitly aware that target locations and identities were repeated within certain scenes as in past studies using complex scenes as contexts (Brockmole & Henderson, 2006b). It would be interesting in a follow-up study to provide participants with a debrief and ask them if they became aware of any rules governing the object locations and which scene categories these rules were true for. This could elucidate the extent to which participants' learning was truly implicit and whether they developed strategies despite the lack of explicit instructions. Finally, it is worth noting that incidental learning may actually facilitate subsequent memory compared to explicit instructions to learn, but this may only be the case in semantically congruent scenes, i.e., these benefits are lost when objects are presented against uniform, non-scene backgrounds (Draschkow et al.,

2014). As I've noted elsewhere, subsequent work should delve deeper into the impact of learning within semantically incongruent settings for memory retrieval versus attentional orienting. For example, though the contexts I used for my studies were semantically incongruent, it would be interesting to investigate if memory retrieval is still enhanced compared to when learning occurs in contexts with uniform, non-scene backgrounds, such as those used in Draschkow et al..

Finally, different tests of memory were used in the experimental chapters with different ramifications for systems and processes involved in the retrieval process. Specifically, Chapter 2 involved an object recognition test followed by a cued recall test. There were no differences in object recognition or recall based on manipulations to within episode competition (memory set size), however there was some evidence of differences based on between episode competition. Namely, in trials where novel lures were present, recognition memory was facilitated but not recall indicating that benefits to one type of memory may not necessarily transition to the other (Aggleton & Brown, 2006; Mandler, 1980; Tulving, 1985; Yonelinas, 1994, 2002). Next, in Chapter 3, all tests of memory involved recollection, e.g., scene memory (old/new) as well as cued recall of the hemifield or location the target object occurred in. Therefore, it is interesting to note that results differed for scene memory compared to cued recall. As I noted prior, this may be because in this experiment there was a great deal of category overlap between the scenes, which may have made it difficult to recall specific scene identities. However, others have found strong scene memory despite overlapping categories when testing familiarity memory with 2AFC tasks which test familiarity memory (Konkle et al., 2021). But, 2AFC tasks are generally easier than old/new tasks (Macmillan & Creelman, 2004), therefore using old/new responses may have resulted in my task being too difficult for the effects of experimental manipulations to emerge. Finally, in Chapter 4, both tests primarily involved familiarity memory (2AFC).

Nevertheless, memory performance differences were found as object recognition was a test of item memory and scene memory was a relational binding test (Yonelinas et al., 2019). Therefore, in the experimental chapters, different tests and mechanisms were involved in memory retrieval, potentially resulting from process-based performance differences (e.g., familiarity versus recognition memory as in Chapter 2), or task-based performance differences (i.e., performance differed based on the recollection or familiarity task used in Chapters 3 and 4). These findings highlight the complexities of the different processes involved in memory while emphasizing that task-based factors such as demands and difficulty can be important limiting factors to the retrieval process.

5.4.4. Limitations

Despite the use of online recruitment and data collection throughout this thesis, COVID was still a major impediment to planned studies. When COVID hit, data collection was underway for the studies in Chapter 3, with a plan to complete a follow-up fMRI study to investigate the neural underpinnings of the memory systems supporting the consequences of contextual and probability learning on different tasks. Planning continued for this fMRI study during COVID and an ethics application was submitted. But, by the time the numerous subsequent waves ended, and the ethics application was amended to account for changes to the landscape of in-person testing, time was running short to collect the fMRI data on time. Therefore, the energies shifted instead to designing and implementing the set of studies in Chapter 4, which were also time intensive.

A strength of the learning tasks that I used in my thesis is the sheer number of variables that can be manipulated. The counterpoint is that getting a task just right can take many rounds of piloting, so that performance is neither at floor nor at ceiling and that sufficient learning such that retrieval and/or attentional orienting are facilitated occurs within

a reasonable training period. For example, as discussed in Chapter 4 (Section 4.3.1.2.1), two additional learning data sets were collected in which performance was too low or too high to facilitate significant performance differences based on association type. Notably, completing the many rounds of piloting required was only feasible due to the speed of online data collection, reiterating the power of this method for psychological research. Therefore, overall, the difficulty of getting the learning tasks right should not dissuade follow-ups, but it is a caveat to consider.

Finally, it is worth considering that some of the experiments contained in this thesis may have been underpowered to detect an effect. In particular, in Chapter 2, there were numerous cases where main effects or interactions were significant but subsequent comparisons within or between levels of variables did not show significant differences (e.g., a main effect of Lure Type but no pairwise comparisons were significant) and the related effect sizes were quite low. Further, in Chapter 3 (Experiment 4), there were a few cases where tendencies were found when comparing performance between levels of experimental factors (e.g., for hemifield recall, accuracy was nearly significantly higher ($p = .051$) for probabilistic than contextual associations). In Chapter 2, power was based on a study with a very similar design (Zokaei et al., 2019), whereas in Chapters 3 and 4 power was estimated based on calculating the number of participants required for a medium effect size in the recall tasks. It seems that the latter method was more effective in powering the studies sufficiently, as though there were some cases where effects may have been underpowered, these were less common and less severe compared to the studies in Chapter 2. Also, in general, data from many more participants were collected in the experiments in Chapters 3 and 4 ($N = 108$ for learning tasks and 54 for recall or attentional orienting) compared to Chapter 2 ($N = 20$). Despite this discrepancy in participant counts, it seems unlikely that the main findings from Chapter 2 would have changed if more participants were included in the studies, as no effects

of set size on memory retrieval was a consistent finding across 3 studies. Nevertheless, future work that wishes to extend or replicate the studies found here should consider estimating effect size in line with methods from Chapters 3 and 4 rather than matching the participant count in Chapter 2.

5.5. Implications and Future Directions

This thesis contributes new evidence to a range of ongoing debates relating to memory and attention such as the role of working memory in long-term retrieval, the similarities and differences between attentional orienting and memory retrieval based on learned association type or spatial expectation, and whether target selection vs. distractor suppression have similar or different cognitive mechanisms. The research included in this thesis invites many interesting follow-up investigations that could, for example, elucidate the neural correlates of the reported results and their translational implications.

In Chapter 3 and 4, there were different tests of memory retrieval, but attentional orienting was tested in a similar way. For example, memory retrieval was tested via hemifield recall (Chapter 3), location recall (Chapter 3), object identity memory (Chapter 4), and scene memory (Chapter 4). In contrast, attentional orienting was tested in two ways: participants responded to the identity of a target that flashed briefly (Chapter 3) or they detected if a target was present or absent in a flashed scene (Chapter 4). Therefore, it could be argued that whereas the different memory retrieval tasks tested memory for a range of different types of learning, in general, the attentional orienting tasks tested participants' ability to respond to targets that flashed in specific locations. Nevertheless, there was some variance in what type of learning could facilitate attentional orienting, with contextual as well as probabilistic learning facilitating memory-guided attentional orienting in Experiment 6. But, this begs the question: is attentional orienting uniquely suited for attending to specific points in space, or

can it also demonstrate behavioural benefits in tasks where the attentional field is more distributed? For example, in Experiment 5 (Section 3.4.2.2.), I argued that probabilistic learning results in a more distributed or 'zoomed-out' attentional field because learned target locations were dispersed throughout a hemifield (Eriksen & James, 1988). Based on this argument, I included all trials (i.e., independent of orienting target identification accuracy) in analysis of orienting target location recall, resulting in probabilistic as well as contextual associations demonstrating recall benefits. But, could there be an attentional-orienting task that is more suited to probabilistic than contextual association learning? This would be an interesting idea for a follow-up. For example, after a similar learning task, participants could complete a task where either one or three targets flash in the same hemifield as the learned target and participants respond indicating how many have flashed. In this task, I would predict that probabilistic learning would facilitate detection in the three objects condition as the locations would be distributed throughout the learned attentional field and the response would be based on low-detail detection rather than high-detail identification (Druker & Anderson, 2010; Miller, 1988). Alternatively, as in Experiment 6, the contextual condition would facilitate detection in the one target condition, as the target would appear in the same location as the learned target.

Additionally, an fMRI study would be a natural follow-up to promising results from Chapter 3 showing dissociable behavioural effects of probabilistic and contextual associations during learning and memory retrieval. For example, in Experiment 6, a linear contrast analysis provided evidence that contextual learning was acquired quickly, whereas probabilistic learning was more gradual. This finding is aligned with the known learning rates of the hippocampal (Spaak & de Lange, 2020) and striatal systems (Salovich et al., 2018; Schmitzer-Torbert, 2007; Yin & Knowlton, 2006) respectively. An fMRI study could verify the neural correlates of these behavioural effects and investigate claims that the hippocampal

and striatal systems work in parallel: they receive the same information, but each system specializes in representing different aspects of the information (Dickerson et al., 2011; White & McDonald, 2002), which can be used to influence behaviour independently (Doeller et al., 2008), cooperatively (Duncan et al., 2018; Sadeh et al., 2011), or competitively (Foerde & Shohamy, 2011). One proposal is that differential activation of these memory systems may depend on task demands (Moody et al., 2004). Alternatively, these systems may cooperate during the learning of associations, but not during the performance of well-learned associations where a "bottleneck" may occur and only one system can be active at a time (Freedberg et al., 2020). Relatedly, co-activation of the stratum and hippocampus during episodic encoding tasks has been found to predict subsequent successful memory recollection (Sadeh et al., 2011), but the hippocampus and striatum may become engaged separately under different conditions (reliable vs. unreliable feedback respectively) during retrieval (Mattfeld & Stark, 2015, 2010). Resolving these strands of evidence by determining under what conditions the striatal and hippocampal memory systems work in tandem versus independently or competitively to support learning compared to attentional orienting and retrieval is an important area for future research. Finally, although the hippocampus has been shown to have a role in attentional guidance by contextual memories (Summerfield et al., 2006), whether the striatum supports attentional guidance by probabilistic memories would be worthwhile to test. Relatedly, a range of studies have also investigated the consequences of damage or impairment to the memory system implicated in these behaviours.

The hippocampal-striatal interactions are impacted by different psychiatric and neurological conditions. For example, stress (both acute and chronic) can modulate the relevant involvement of the hippocampal and striatal memory systems and tilt it towards dependence on striatal stimulus-response learning (E. V. Goldfarb & Phelps, 2017; Vogel et al., 2017). Stress is a risk factor for conditions such as PTSD and addiction (Goodman &

Packard, 2016), and it can exacerbate the progression of Alzheimer's disease symptoms (Justice, 2018). Studies have found impairment of contextual cueing in patients with hippocampal damage or amnesia (Chun & Phelps, 1999; Manns & Squire, 2001; but also see Preston & Gabrieli, 2008), whereas nondeclarative learning such as probabilistic cueing is impaired in patients with striatal dysfunction such as in Parkinson's or Huntington's disease (Gabrieli, 1998; Knowlton et al., 1996; but also see Sisk et al., 2018). Therefore, the pattern of memory impairments found in Parkinson's disease patients may be opposite to those found in patients with medial temporal lobe damage, as in Alzheimer's disease (Foerde & Shohamy, 2011). Interestingly, damage to one memory system may lead to compensatory behaviour from the other system, such as going from more hippocampal-cognitive and spatial memory to more habitual-striatal type memory (Ferbinteanu, 2016). Compared to contextual cueing (Negash et al., 2015), probabilistic cueing is relatively preserved in aging (Jiang, 2018). Additionally, interestingly, contextual memory-guided attentional orienting is relatively preserved compared to explicit retrieval (Salvato et a., 2016). Overall, these psychiatric and clinical factors indicate the importance of further research into the trade-off between the hippocampal and striatal systems in behaviour. The tasks that I have developed may have the potential to measure relative impairment to these systems in different neurodegenerative conditions. Disruption of the hippocampal-striatal relationship may enhance the risk for many conditions. Therefore, understanding better these systems and their interactions, and developing healthy ways of balancing them accordingly, may contribute significantly to cognitive resilience.

Another relevant domain that has important consequences for memory retrieval and attentional orienting is time. For example, probabilistic learning can be built up via spatial regularities, but temporal regularities (e.g., what happens after what) can also result in probabilistic learning (Aly & Turk-Browne, 2017). Specifically, temporal regularities at one

spatial location can be learned even when embedded among other random sources of input at different locations (Zhao et al., 2013). Also, using a temporal variant of the memory-guided orienting task described in Chapter 3, Cravo et al., (2017) showed that improved perceptual sensitivity and response times to detect and discriminate visual targets occurred at learned temporal intervals, which served as valid memory cues compared to invalid or unlearned intervals. Temporal and spatial predictability can also be combined to facilitate performance in "dynamic" visual search tasks (Boettcher et al., 2021). One way to combine some of the findings from my work with their results would be to run a study where search facilitation is compared between conditions where targets are either spatially predictable (probable quadrant of appearance but random appearance time), temporally predictable (equally probably in all quadrants but specific appearance time) or both. A study such as this could tease apart some of the relative search benefits of temporal and spatial predictions. Another way in which the role of time in memory and attention could be studied is by manipulated the timing of retrieval. For example, in Chapter 3, I manipulated the timing of memory retrieval by adjusting the inter-stimulus-interval between 150 and 750 ms to test for engagement of different striatal and hippocampal memory systems over shorter and longer time scales (Staresina & Wimber, 2019; Vogel et al., 2017). Though behavioural results did not differ significantly between intervals, it would be interesting to investigate with EEG/MEG whether this is one way in which the engagement of different memory systems can be controlled.

Neuroimaging studies would also contribute to our understanding of the behavioural effects reported in Chapters 2 and 4. For example, proposals have also been made suggesting that a hippocampal-midbrain network is involved in contextual novelty (Kafkas & Montaldi, 2015). Therefore, it would be interesting to see whether variable association learning (a form of contextual novelty as participants search for familiar targets in novel locations), as described in Chapter 4, may also be mediated by joint involvement of the striatal and

hippocampal systems. Also, the prefrontal cortex (PFC) has been shown to have a role in resolving competition in memory, with greater activation at increased competition or memory set-size (Sohn, 2003). Therefore, subsequent work could measure the engagement of the PFC with increased set-size (Chapter 2) or with competition for retrieval from learned distractors under differing spatial expectations (Chapter 4). Overall, this proposed work would provide support for the suggestion that memory is not modular (i.e., hippocampal and striatal structures independently support retrieval under different circumstances), rather it is a result of numerous systems working together fluidly to perform retrieval, perception, and action (Ferbinteanu, 2018; Goldfarb et al., 2017; Nobre & Stokes, 2019). For example, as we drive down the street, we naturally weave between using our contextual memories (e.g., recognizing specific businesses and oncoming road signs) and our probabilistic memories (e.g., checking for oncoming cyclists to the left as we prepare to make a turn) as these systems collaborate to guide our vision prospectively.

5.6. Conclusions

In this thesis, I set out to measure the prospective power of memory. Throughout the different experiments, the way in which memories were formed had important implications for their use. Even when I predicted that memory would fail, increasing set size within episodes did not interfere with participants' ability to retrieve specific object-scene associations. There was, however, some evidence of interference related to between-episode competition, with participants performing worse at recognition when lures were 'old' rather than 'novel'. Nevertheless, in my initial three experiments, participants demonstrated a remarkable ability to absorb massive input from the external visual world, sort it into digestible chunks, select the right chunk with internal attention, and then use it adaptively for behaviour. In my subsequent experiments, differences were found in how our memories can

be used for retrieval (internal attention) compared to attentional orienting (external attention). External attention benefitted most when directed to predictable spatial associations, whether during visual search or when LTM guided attentional orienting. In contrast, internal attention demonstrated more versatility: different ways of learning could facilitate future retrieval, as long as the key of learning fit the hole of retrieval. For example, learning that objects occur in specific points in space or within a particular hemifield can facilitate relevant memory tasks. Also, the way we search through the environments around us may relate to how we remember them. Specifically, if the targets of our visual search are hard to predict, greater resulting exploration may instead facilitate our memory of the surrounding environment.

Therefore, although learning, memory, and attentional orienting are intertwined behaviours, I found them to behave similarly or differently under different circumstances. What is clear from the interplay between these behaviours is that different means of engaging with the external visual world, whether paying attention to novelty or to predictability, have important consequences for how we build and subsequently utilize associations stored in our internal world. Further, differences in the utility of these behaviours suggest that we should not equate the processes of searching through the mind with searching through the eyes. Together, it may be that better understanding the interchange between the internal and external realms will help us to more effectively use our experiences to prepare for both the seen and unseen challenges ahead.

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Appendix A

Additional Analysis for Learning Task in Experiment 6 (Chapter 3)

I examined the effects of Association (Contextual, Probabilistic, Random), day (1 or 2), and block (1-5) on participants' response time and accuracy. On Day 1, Mean accuracy was 86% (*SD* = .35) in the Contextual condition, 85% (*SD* = .36) in the Probabilistic condition, and 85% (*SD* = .36) in the Random condition. RT data were log-transformed to approximate the normal distribution and meet ANOVA assumptions. On Day 2, Mean accuracy was 88% (SD = .08) in the Contextual condition, 87% (SD = .09) in the Probabilistic condition, and 85% (SD = .09) in the Random condition.

Table A1

Target Identification Accuracy

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association	2	106	2.54	.084	0.01
Day*	1	53	18.66	< .001	0.01
Block	4	212	0.85	.50	< .01
Association x Day*	2	106	3.69	.028	< .01
Association x Block	8	424	1.05	.40	< .01
Day x Block	4	212	0.74	.57	< .01
Association x Day x Block	8	424	0.76	.63	< .01

Note. There was a significant main effect of Day and an interaction between Association and Day. An asterisk (*) signifies a p-value below .05.

On Day 1, the means for log of RT were .33 (*SD* = .53) in the Contextual condition, .34 (*SD* = .52) in the Probabilistic condition, and .36 (*SD* = .54) in the Random condition. On Day 2,

the means for log of RT were .24 (*SD* = .18) in the Contextual condition, .28 (*SD* = .16) in the Probabilistic condition, and .32 (*SD* = .19) in the Random condition.

Table A2

Target Identification Response Time

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association	2	106	2.35	.10	0.01
Day*	1	53	21.28	< .001	0.03
Block*	1.37	72.84	16.10	< .001	0.05
Association x Day*	2	106	7.51	< .001	< .01
Association x Block	1.36	72.17	1.30	.27	< .01
Day x Block*	6.18	327.49	2.91	.008	< .01
Association x Day x Block	8	424	1.68	.10	< .01

Note. There were significant main effects of Block and Day. Interactions occurred between Association and Day and between Day and Block. An asterisk (*) signifies a p-value below .05.

It is worth noting that these results differ slightly from those in the Experiment 4 learning task, where there was an Association by block effect for accuracy and an association effect for RT. However, there are two significant differences between studies. First, the study above was conducted over the course of two days or 10 blocks of total learning, whereas the results from learning in Experiment 4 were from just 1 day or 5 blocks of learning. Second, Experiment 4 had 108 total participants engaging in the study, whereas the study above had only 54. Therefore, it is likely that these differences in results come down to statistical power, trial count differences, and effects of memory decay and/or consolidation (See Discussion for further review.

Appendix B

Additional Analysis for Attentional-Orienting Task in Experiment 6 (Chapter 3)

I examined the effects of the two within-participants factors: Association (Contextual, Probabilistic, Random) and ISI (Short or Long) on participants' response time and accuracy in a two-way ANOVA. Accuracy data were arcsin transformed, whereas RT data were log-transformed to approximate the normal distribution and meet ANOVA assumptions. Raw (untransformed) means for accuracy were 74% (*SD* = 11%) in the Contextual condition, 73% (*SD* = 8%) in the Probabilistic condition, and 69% (*SD* = 9%) in the Random condition.

Table B1

Orienting Accuracy

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association*	1.78	94.1	3.35	.045	0.02
ISI	1	53	0.01	.92	< .01
Association x ISI	2	106	1.31	.27	< .01

Note. There was a significant main effect of Association only. An asterisk (*) signifies a p-value below .05.

Table B2

Orienting Response Time

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association	2	106	1.25	.29	< .01
ISI	1	53	0.37	.55	< .01
Association x ISI	2	106	2.48	.088	< .01

Note. There were no main effects or interaction.

Appendix C

Additional Analysis for Chapter 4 Learning Task

I examined the effects of Target Association (Variable or Fixed), Block (1-5), and Target Identity (Toys or Clothes) on participants' reaction time and accuracy. Accuracy data were arcsin transformed, whereas RT data were log-transformed to approximate the normal distribution and meet ANOVA assumptions.

Descriptive Statistics for accuracy (proportion of correct responses) are as follows for Fixed associations: Block 1 (M = 90%, SD = 6%), Block 2 (M = 93%, SD = 6%), Block 3 (M = 93%, SD = 5%), Block 4 (M = 95%, SD = 5%), Block 5 (M = 95%, SD = 4%); and for Variable associations: Block 1 (M = 90%, SD = 6%), Block 2 (M = 91%, SD = 6%), Block 3 (M = 92%, SD = 6%), Block 4 (M = 92%, SD = 6%), Block 5 (M = 93%, SD = 6%).

Table C1

Target Identification Accuracy

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association*	1	160	13.74	< .001	0.01
Block*	4	640	28.07	< .001	0.04
Target Identity*	1	160	4.28	.04	0.01
Association x Block*	4	640	3.37	.01	< .01
Target Identity x Block	4	640	0.98	.42	< .01
Association x Target ID	1	160	2.21	.14	< .01
Association x Target ID x Block	4	640	0.96	.43	< .01

Note. There was a significant main effect of Association, Block, and Target Identity and an interaction between Association and Block. An asterisk (*) signifies a p-value below .05.

Descriptive Statistics for response times (log of response times) are as follows for Fixed associations: Block 1 (*M* = 0.91, SD = 0.13), Block 2 (*M* = 0.78, *SD* = 0.11), Block 3 (*M* = 0.69, *SD* = 0.10), Block 4 (*M* = 0.63, SD = 0.13), Block 5 (*M* = 0.52, SD = 0.18); and for Variable associations: Block 1 (*M* = .92, SD = .13), Block 2 (*M* = .84, SD = .12), Block 3 (*M* = .82, SD = .11), Block 4 (*M* = .78, SD = .12), Block 5 (*M* = .76, SD = .12).

Table C2

Target Identification Response Time

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Association*	1	160	176.85	< .001	0.06
Block*	4	640	205.70	< .001	0.14
Target Identity*	1	160	8.76	.004	0.04
Association x Block*	4	640	72.45	< .001	0.03
Target Identity x Block	4	640	1.43	.22	< .01
Association x Target ID*	1	160	5.40	.021	< .01
Association x Target ID x Block*	4	640	4.91	< .001	< .01

Note. There were significant main effects of Association, Block, and Target Identity. Interactions also occurred between each combination of variables. An asterisk (*) signifies a p-value below .05.

Appendix D

Additional Analysis for Experiment 7 (Chapter 4)

I examined the effects of Category (Target or Distractor) and Association (Variable or fixed) on participants' accuracy and response time. Means for Identification accuracy were 83% for Fixed targets (*SD* = 9%), 84% for Variable targets (*SD* = 11%), 64% for Fixed distractors (*SD* = 12%), and 65% for Variable distractors (*SD* = 13%).

Table D1

Object Identification Accuracy

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	52	151.99	< .001	0.30
Association	1	52	0.70	.41	0.28
Category:Association	1	52	0.06	.81	< .01

There was a significant main effect of Category on Object Identification Accuracy. An asterisk (*) signifies a p-value below .05.

RT data were log-transformed to approximate the normal distribution and meet ANOVA assumptions. RT data were only analysed for trials in which participants correctly identified the object.

Table D2

Object Identification Response Time

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	52	38.84	< .001	.031
Association	1	52	0.36	.55	< .01
Category:Association	1	52	0.57	.45	< .01

There were significant main effects of Category on Target Identification response time. An asterisk (*) signifies a p-value below .05.

Appendix E

Additional Analysis for Experiment 8 (Chapter 4)

I analysed accuracy and response times for memory-guided attentional orienting using a three-way mixed ANOVA with Association (Fixed or Variable) and Object Presence (Present or Absent) as within-participant factors and Category (Target or Distractor) as a between-subjects factor. Means were 79% (*SD* = 10%) for Fixed Targets, and 70% (*SD* = 10%) for Variable Targets, 68% (*SD* = 8%) for Fixed Distractors, 65% for Variable distractors (*SD* = 8%),

Table E1

Attentional-Orienting Accuracy

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category*	1	104	13.36	< .001	0.04
Association*	1	104	22.80	< .001	0.02
Object Presence*	1	104	75.90	< .001	0.24
Category:Association*	1	104	5.78	.018	0.02
Category: Object Presence*	1	104	5.11	.026	0.02
Association:Object Presence*	1	104	13.17	< .001	0.01
Association:Category:Object Presence*	1	104	6.78	.011	0.01

There were significant main effects of Category, Association, and Object Presence as well interactions between each combination of the variables. An asterisk (*) signifies a p-value below .05.

RT data were log-transformed to approximate the normal distribution and meet the ANOVA assumptions. RT data were only analysed for trials in which participants responded correctly.

Table E2

Attentional-Orienting Response Time

Effect	*DFn*	*DFd*	*F*	*p*	*η2*
Category	1	104	0.01	.91	< .01
Association*	1	104	8.67	.004	< .01
Object Presence*	1	104	71.50	< .001	0.08
Category:Association	1	104	3.76	.053	< .01
Category: Object presence	1	104	2.95	.089	< .01
Association:Object Presence	1	104	< .01	.99	< .01
Association:Category:Object Presence	1	104	2.09	.15	< .01

There was a significant main effect of Association and of Object Presence. An asterisk (*) signifies a p-value below .05.