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Automaticity and Cognitive Control
in the Learned Predictiveness Effect

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A thesis submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy
Acknowledgements

In the exhilaration of being accepted as a PhD student, there is no way I could have anticipated the ways in which the experience would change me. Those first moments were filled with nothing but bright optimism at the thought of venturing into territories of knowledge previously undiscovered, however small they may be. The reality was less an adventure so much as a torrid love affair in which research was my unrequited love, something I poured myself into that didn’t seem to appreciate my affection. Combined with the long hours of solitary thought that belong to the rituals of university life, it often took me to a place of deep reflection that was lonely, distressing, and inert. It was also a place filled with important insight, empowerment, and Dr. Seuss.

Emerging from the place of reflection to complete this piece of work is an emotionally complex moment, and inserting instances of first person singular have felt wonderfully indulgent. They are also very misleading, as this journey has been a guided one. I have boundless gratitude towards my two supervisors, Irina Harris and Evan Livesey. I applaud your insight and integrity as researches and I have enjoyed working with you both immensely. Your ability to grasp and communicate complicated ideas often helped me to find a footing in my own thoughts, and I now also have an unhealthy appreciation of complex research designs (that one belongs to Evan, I would not blame that on you Irina). More than that I thank you for being compassionate, kind, and just all round awesome people.

I am thankful to all those who were generous with their time and expertise. The research community is filled with weird and wonderful creatures and a sense of sharing and interest in the world is one of its best qualities. The support of fellow students was particularly vital, and I thank you all for the days and nights of shared
understanding. Insights and honesty shared with Bec have been very therapeutic. Nicky and Ash, I thank you both dearly for your ability to always make me laugh with abandon, as well as the numerous other ways in which you enrich my life. I am very happy to be taking you along into the next chapter as friends.

The support of those who don’t understand but are there anyway is just as vital, from my homegirl Cara to my family away from home Nik and Sioux. I thank the friends who were patient, confused, and always there to provide release, laughter, and happy memories. Days spent singing in the bush with Adina, who is the human embodiment of a ray of sunshine, are very dear to me. As are the hours upon hours spent with Vanessa over lentils, chai tea, or old fashions. The insight and honesty with which you view the world has saved me in many moments. I am deeply grateful.

No creatures are weirder or more wonderful than ones family. Thank you all for being the distinct strong people that you are. Jessie, Dad, Mom, Lyn, Zack, and Kath, you gift me an array of qualities that I could never fully list here, and the beautiful little faces and escapades of Tommie, Eve, Tallulah, and Ben have been my fail-safe go to feel-good medicine.

Now it is done and I can happily report that I am full of bright optimism at the thought of venturing into territories of knowledge previously undiscovered, however small they may be. Though finally, given the circular nature of the endings embedding in this process, I am stealing the last part of this page to celebrate myself and also someone who is very much a part of me. Enis, you have made post PhD existence sweeter than I could imagine. I happily paste you permanently into these pages of my life. These and many more.
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Abstract

This thesis explores changes in attention that occur in response to predictive learning. Learned predictiveness is a bias in learning towards cues with prior predictive utility, or indeed a bias away from cues that have poor prior utility. In a typical learned predictiveness experiment, predictive validity is first manipulated such that cues are either predictive or non-predictive of a set of outcomes. In a subsequent and seemingly unrelated task involving novel outcomes, new learning is biased in favour of the previously predictive cues. This bias has been interpreted as a shift in attention towards items with predictive utility. However, the relative contribution of automatic and controlled selection mechanisms in producing the bias remain to be fully characterised. The studies reported here examine the expression of learned predictiveness using cognitive tasks that involve competition for stimulus processing. Chapter 2 measured the processing of predictive and non-predictive items in the attentional blink, a visual detection task that limits the availability of controlled attention. There was no evidence that the predictive history of targets was associated with variations in their detection. However, predictiveness did influence target detection indirectly by virtue of the predictive history of critical distractors, such that targets were easier to identify when they were immediately flanked by non-predictive stimuli. In contrast, novelty was a potent source of processing bias for both targets and distractors: Novel targets were easier to detect than familiar targets. In Chapter 3, controlled attention was manipulated by issuing instructions about the causal nature of cues, and differentiating between measures of associative memory and causal reasoning. Experiment 7 – Experiment 8 attempted to tease apart inferential and automatic contributions to the bias by presenting instructed causes that were predictive and non-predictive in initial training, as well as instructed non-causes that were predictive and non-predictive in initial training. The results showed that the
predictive history of cues influenced subsequent learning over and above the effect of explicit instruction, suggesting an automatic bias that persists in the presence of top-down control. However, the results for cues instructed as non-causes suggest that the relationship between explicit instruction and predictiveness was interactive rather than additive. Chapter 4 extended this procedure to include the presence of novel stimuli. Learned predictiveness in the presence of novelty was first assessed in the absence of explicit instruction about which cues were causal. There was no evidence for the bias when predictive and non-predictive cues appeared alongside novel items at the start of the second task. When instructions about the causal structure of the task were reintroduced, novelty was once again a potent source of selection bias, such that learning favoured novel items instructed as causal. In Experiment 11, there was evidence that the predictive history of items was influencing associative memory for cues known to be non-causal of an outcome, though this pattern of results was slightly different to those observed in Chapter 3. This suggests that the presence of novelty changes the way in which the automatic effects of predictive history interact with top-down control. The results are discussed in Chapter 5 in relation to the interaction between automatic and controlled selection mechanisms, as well as theories of learning and attention.
Chapter 1: Making sense of a complex world

We live in a complex world, rich with information about where to look, what to think, and what actions to take at any given moment. Our ability to successfully navigate this environment depends on selecting and responding to the most relevant aspects of what lies before us. Indeed, our capacity to process information is severely limited (Allport, 1989; Broadbent, 1958; Carrasco, 2011), suggesting that the way in which we prioritise signals is a critical mechanism driving detailed perception and goal-driven action. Given this limited capacity, it is broadly held that signals compete in order to achieve detailed analysis (Desimone & Duncan, 1995; Knudsen, 2007; Rescorla & Wagner, 1972). Adding to the complexity of the problem, there are several sources of bias influencing the outcome of this competitive process, originating from the physical properties of the world (Itti & Koch, 2001; Wolfe & Horowitz, 2004), as well as a variety of internal states (Le Pelley, 2010).

The general ideas put forward in this opening paragraph are pervasive in Psychology, taken as fundamental aspects of broad areas of research such as attention (Beck & Kastner, 2009; Desimone & Duncan, 1995; Pashler, 1998), learning (Le Pelley, 2010; McLaren et al., 2014), decision making (Evans, 2008), and perception (Carrasco, 2011). This thesis deals with the interaction between two potent influences on one’s behaviour, namely learning and attention. The importance of attention in facilitating the selection of behaviourally salient signals is well established (e.g., Pashler, 1998). However, the utility of those signals isn’t always an intrinsic feature of the environment. Learning is an important way in which we come to know the usefulness of information, by observing the relationship between cues and outcomes. I start this chapter by briefly outlining the key properties of attention according to current understanding within the cognitive literature. In doing so, I highlight the
distinction between top-down and bottom-up biases in selection, which form a critical component of many theoretical frameworks of attentional control. However, a recent line of research demonstrates that learning has a distinct influence on selection, suggesting that a greater understanding of the relationship between learning mechanisms and stimulus selection is required. Accordingly, this provides the basis for contrasting operational measures of attention across the cognitive and learning domains. This reveals an important theoretical consequence of the way in which attention is measured in the learning literature, namely that the construct is open to numerous interpretations. As a result, there is uncertainty as to the role of specific selection processes in learning. It is this uncertainty that provides the motivation for the current thesis.

1.1. Learning to attend: Effects of predictiveness on perception and cognition

While the importance of selective attention has been recognised since the emergence of experimental psychology (Helmholtz, 1867; James, 1890/1981), the construct has often eluded complete explanation. For example, a favoured tradition in discussions of attention is to cite these words from William James:

Everyone knows what attention is. It is the taking possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought… It implies withdrawal from some things in order to deal effectively with others. (1890/1981, p. 381)
Indeed, while James eloquently captures some of the fundamental properties of attention, the intuitively appealing explanation requires further elaboration. More recently, attention has been associated with a wide-ranging number of more specific cognitive phenomena, leading to the less poetic insistence that, “no one knows what attention is” (Pashler, 1998, p. 1). Nonetheless, it is broadly held that the critical purpose of attention is stimulus selection in the face of our limited capacity for the detailed analysis of sensory information (Carrasco, 2011; Desimone & Duncan, 1995).

Stimulus selection is pivotal in characterising a broad variety of processes that influence the way in which we make use of information. Accordingly, a central theme in empirical work has been to map out various modes of selection. For example, selection has been investigated at the level of object-based processing (e.g., Duncan, 1984), feature-based processing (e.g., Wolfe, 1994), spatial processing (e.g., Posner, 1980), temporal processing (e.g., Raymond, Shapiro, & Arnell, 1992), and category-level processing (e.g., Peelen, Fei-Fei, & Kastner, 2009). These are traditionally explored within paradigms designed to engage each process independently. Spatial processing is revealed in cueing paradigms (Posner, 1980), whereas feature-based attention is studied making use of search paradigms (Wolfe, 1994). However, given the central assumption that selection is necessary in order to accommodate our limited ability to process information, a common characteristic of these operational measures is that they test performance under conditions in which processing capacity is taxed, and therefore when selective attention is thought to be most crucial.

The way in which selection is biased under such conditions has been conceptualised according to a number of functional distinctions. A critical theoretical division is the difference between top-down and bottom-up mechanisms
of selection (e.g., Carrasco, 2011; Desimone & Duncan, 1995). Top-down, or endogenous attentional control, also known as goal-driven attention, reflects a bias in selection originating from the goals and intentions of an observer. This form of attentional control enables us to prioritise incoming signals on the basis of pre-existing knowledge, goals, and expectations. Indeed, detecting and responding to information from a scene is facilitated by prior knowledge of important characteristics, such as spatial location (Dosher & Lu, 2000; Posner, Snyder, Davidson, 1980), features (Egeth, Virzi, & Garbart, 1984), or category (Peelen, Fei-Fei, & Kastner, 2009). Alternatively, bottom-up, or exogenous, stimulus-driven selection, reflects the control of attention by the physical properties of a stimulus. Given the key role ascribed to the external cue in driving responding, this form of attentional control is often thought to operate in a more involuntary, automatic fashion. Accordingly, responding to certain classes of stimuli, such as the sudden onset of new objects (Yantis & Hillstrom, 1994), or cues that differ dramatically from their surrounds (Wolfe, 1992), appears to be automatic in the sense that performance is impeded or facilitated independently of the intentions of the observer.

While this dichotomy provides a useful framework for operational measures of attention, it is unlikely that behaviour emerges exclusively from one form of selection. Rather, it is widely argued that behaviour reflects the dynamic interplay between top-down and bottom-up control (Carrasco, 2011; Desimone & Duncan, 1995; Knudsen, 2007; Pashler, Johnston, & Ruthruff, 2001). Indeed, it is this interplay that forms the basis for the influential framework of attentional control put forward by Desimone and Duncan (1995), namely the biased competition theory of selective attention. The fundamental principle of this theory is the idea that the processing of sensory information is a competitive process. This means that the detailed analysis of one piece of information comes at the expense of another.
Critically, this ongoing competition is controlled. In particular, it is the mechanisms of top-down and bottom-up control that in combination influence the resolution of the competitive process. Thus, the nature of the competition will rely on the kind of incoming perceptual information as well as the behavioural goals of the observer. Formulated in this manner, attention is an emergent property of the mechanisms required to resolve perceptual conflict and control motor output.

There is now much evidence in support of the biased competition model of attention (see Beck & Kastner, 2009; Duncan, 2006, for reviews). However, the distinction between top-down and bottom-up mechanisms of stimulus selection is a pervasive one, incorporated within numerous theoretical frameworks that vary in specificity from general descriptions to more formulated computational models (e.g., Itti & Koch, 1998; Mozer, 1991; Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989). Recent findings suggest that this distinction may be insufficient to fully characterise the sources of selection bias that determine the resolution of perceptual competition. There is now a growing body of work that points to learning as a distinct source of attentional control.

For example, various attentional paradigms have incorporated the delivery of monetary rewards on a trial-to-trial basis in order to demonstrate the modulation of selection by value. Kiss, Driver, and Eimer (2009) showed that the selection of targets associated with high reward is facilitated relative to low reward targets during visual search. This occurs when both high and low reward targets are physically salient, and therefore assumed to be equally prioritised via bottom-up processes (e.g., Theeuwes, 1991). Indeed, it is likely that value-driven and physical bottom-up processes operate independently. When visual salience and value information vary independently within a complex perceptual context, both variables
combine to influence performance in a way that maximises reward (Navalpakkam, Koch, Rangel, & Perona, 2010).

Value-driven selection biases appear to influence cognitive control as well as perceptual decisions. Indeed, cognitive control has been formulated as an attentional mechanism biasing competition in favour of current task demands (Miller & Cohen, 2001). Broadly speaking, demonstrations of cognitive control rely on one’s ability to flexibly switch to the relevant components of a task in the face of interfering information (e.g., Posner & Snyder, 1975; Stroop, 1935). Reward associations have been shown to influence the way in which this conflict is resolved. For example, Della Libera and Chelazi (2006) provided some initial evidence that the delivery of reward affects the balance of inhibitory control evident in negative priming. In the Stroop task, when the colour of the word and its meaning do not correspond, interference from word meaning is selectively reduced for highly rewarded colours (Krebs, Boehler, & Woldorff, 2010). Similar effects have been reported in flanker and task-switching tasks (Braem, Verguts, Roggeman, & Notebaert, 2012), as well as the Simon task (Sturmer, Nigbur, Schacht, & Sommer, 2011), all classical indexes of cognitive control.

The studies reviewed thus far all make use of procedures in which rewards are issued on an immediate trial-by-trial basis, suggesting that learning-driven changes in attention arise rapidly in order to guide performance in an on-line manner. However, it appears that these changes in processing are relatively stable. That is, learning in one context can influence selection in a subsequent task. In one demonstration by Raymond & O’Brien (2009), faces were associated with varying monetary rewards in an initial training phase. Those same faces were then used as stimuli in a version of the attentional blink task, a visual detection task with severe temporal constraints, in which competition for target selection is high. Importantly,
the goal of the task was visual detection independent of any reward. In line with the
evidence reviewed thus far, high reward faces showed a benefit in detection
compared to faces associated with low rewards. In a related finding, Della Libera
and Chellazzi (2009) provided extensive training associating shapes with high
versus low rewards. In a subsequent, unrewarded test phase, shapes associated with
high rewards were more easily selected as targets, and harder to reject as distractors.

Thus, there is consistent evidence to suggest that learning, in the form of value
associations, can alter the selection priority of sensory signals. The findings outlined
above share the characteristic that reward is directly associated with target
information. This raises the possibility that learning influences selection indirectly
by altering the motivational components of a task. According to this possibility,
learning influences stimulus selection by changing the salience of goals and can
therefore be interpreted as enhancing voluntary, top-down attentional control.
Indeed, incentive driven motivation has been explicitly conceptualised as a means of
increasing executive control processes in order to facilitate performance (Pessoa &
Engelmann, 2010). For example, some theories of cognitive control (e.g., Botvinick,
2007) suggest that the conflict generated by the presence of interfering information
on a given trial acts as a learning signal motivating observers to adapt their
behaviour in subsequent trials. If the presence of explicit learning in the form of
reward-associations simply adds to the strength of that signal, the findings above can
be thought to reflect changes in motivation as opposed to a more distinct role of
learning in affecting attentional control.

However, this explanation does not account for situations in which value-
driven selection runs counter to the physical salience of a scene as well as the goals
of the observer. In a visual search procedure initially developed by Anderson,
Laurent, and Yantis (2011a), participants were trained on an initial task in which the
display consisted of equally salient coloured circles, one of which was a target. One target colour was associated with high reward, and another target colour was associated with low reward. This was followed by an unrewarded test phase. Now, the target was a diamond amongst circle distractors. On some trials, one of the distractor circles was either a high or low value circle from prior training. What is important to note is that the salience of colours was equated across shapes, and the target consisted of a shape singleton. Given that shape singletons capture attention, both top-down and bottom-up factors favour the selection of the target. However, a detriment in target selection was observed on trials in which value associated distractors were present. Thus, rewarded stimuli involuntarily captured attention over and above the influences of stimulus-driven and voluntary attentional control. Subsequent work has replicated this basic effect under a number of conditions (Anderson et al., 2011b; 2012; Hickey, Chelazzi, & Theeuwes, 2010a; 2010b; 2011; Le Pelley, Pearson, Griffiths, & Beesley, 2015).

Taken together these findings are consistent with a unique role for learning in influencing selection processes. Interestingly, within the cognitive literature reviewed thus far, stimulus-reward associations have been the primary focus for examining changes in selection that arise with learning. This has implications for understanding the way in which learning influences selection processes. For example, if it is taken that learning modulates the specific selection processes responsible for an outcome (Della Libera, Perlato, & Chelazzi, 2011), then the attentional change associated with reward might be quite different to that associated with other forms of learning, such as reasoning about the causal relationships between events.

Within the learning literature, the study of predictiveness, that is, the extent to which a stimulus reliably signals an outcome, has been central to demonstrations
implicating attentional processes (e.g., Le Pelley & McLaren, 2003). Such demonstrations have been critical for attentional theories of associative learning (e.g., Kruschke, 2001; Pearce & Mackintosh, 2010). Given that there is no unitary understanding of attention, a valuable extension of current work would include characterising the relationship between additional learning mechanisms and specific stimulus selection processes. In the next section I review in more detail how attention has been viewed within the learning literature.

1.2. Attending to learn: Effects of predictiveness on associability

As with attention, learning is a strong form of processing bias. Indeed, some of the concepts outlined in the previous section share some resemblance to many of the ideas embodied in the learning literature. For example, the notion of stimulus competition, or cue competition, in the face of limited processing resources lies at the heart of many models of associative learning (e.g., Mackintosh, 1975; Pearce & Hall, 1980; Rescorla & Wagner, 1972; Wagner, 1978). Perhaps most influentially, Rescorla and Wagner (1972) formalised the acquisition of associations between events based on algorithms predicting that cues compete in order to gain control of behaviour, given the assumption that the magnitude of learning is finite. While the model allows for the physical salience of cues to influence this competition, the primary means by which associations are modified is the predictive validity of cues, that is, the extent to which a cue reliably predicts the presence of an outcome. Thus, predictive cues gain a stronger association with events compared to less predictive information. It should be noted that while cue competition implies that selection is incorporated into the model, at its core it is not strictly attentional in nature. On any given trial, the formation of
associations is not selective, as learning is limited for all available cues on the basis of their combined predictive validity. Rather, the processing inherent in the Rescorla-Wagner model (Rescorla & Wagner, 1972) is conceptualised as an automatic association between two events that is non-attentional in nature.

Subsequent work has taken these mechanisms as a foundation for including attention in learning more explicitly. Many models of associative learning (e.g., Kruschke, 2001; Mackintosh, 1975; Pearce & Hall, 1980) now accept that the stimulus selection necessary for the acquisition of associative relationships is influenced by some form of selective attention. Such models share the same basic assumption that the attention devoted to a stimulus is flexible and governed by its past utility in predicting events. More specifically, attention is formalised within model predictions as an associability parameter, which is determined by previous learning about a stimulus and in turn influences the rate of future learning about that stimulus. As such these models view attention and learning as having an interdependent relationship. Associability, or $\alpha$, describes the property of a stimulus that determines the rate at which it will enter into associations. Associability changes according to the associative strength between a cue and the outcome with which it is paired. Thus, the rate of learning provides an index of attentional change, whereby cue competition is biased in favour of cues with high associability. While many such models remain largely agnostic as to the mechanisms by which associations and therefore associability emerge, it has been widely argued that the formation of associations is automatic (McLaren et al., 1994; McLaren et al., 2014). Thus, to the extent that one assumes that the mechanisms of association are automatic, in that they operate independently of the intentions of the participant, the implicit assumption here is that attentional change is relatively automatic.
An important example of one such model is that proposed by Mackintosh (1975). According to this model, the associability of a cue increases if that cue is a more effective predictor of an outcome relative to other cues available at the same time. If the associative strength between the cue and the outcome is high, that is, if a cue is a reliable predictor of the correct outcome, then associability will increase. If a cue is a poor predictor of the outcome, because its associative strength is relatively low, associability will decrease. Thus, attention to a stimulus is maintained and preferentially supports further learning provided it remains a good predictor relative to other cues present at the same time. Certainly, alternative models have been proposed in which the relationship between associability and associative strength differs (e.g., Pearce & Hall, 1980; Le Pelley, 2004), however, such models share the same premise that attention changes according to the mechanisms of associative competition.

Importantly, it is rarely argued that such models provide a comprehensive account of the mechanisms involved in learning. Rather, they are taken to characterise the more automatic components of attentional change within a dual-system approach. According to this view (e.g., Mackintosh, 2003; McLaren, Green, & Mackintosh, 1994; McLaren et al., 2014; Evans, 2008), learning is the result of both automatic associative processes and higher-order propositional processes operating together, though sometimes in competition (see Le Pelley, Oakshott, & McLaren, 2005). While this position is amenable to characterising the effect of various sources of attentional bias alongside the emergence of learning, much work has traditionally focused on interpretations relating to associability. That is, changes in attention are thought to occur automatically, independent of the intentions of the observer.

However, some theorists have made the claim that learning relies exclusively on propositional processes (Lovibond & Shanks, 2002; Mitchell, de Houwer, &
Lovibond, 2009). According to this view, all learning relies on reasoning about the relationship between events in an attentionally demanding process, the outcome of which is declarative knowledge about that relationship. While this controlled learning is thought to be an effortful process, the role of attention has been less explicitly outlined in such single-process accounts of learning.

The issues raised by this comparison can be emphasised by examining the way in which attention has been implicated in learning tasks. Traditionally this rests on demonstrations of transfer. In particular, the predictive value of cues is manipulated in one context, and the effect of this manipulation on learning about those same cues in a subsequent context is observed. If prior predictiveness influences new learning, it is taken that learning has altered the selection priority of cues, thus affecting the ease with which they can enter into further associations. A robust example of this methodological approach, and one critical to this thesis, is the learned predictiveness effect first reported by Le Pelley and McLaren (2003; see also Lochmann & Wills, 2003). The basic experimental design used to demonstrate this effect is shown in Table 1.

In the original demonstration, participants completed a causal learning task in which they were asked to play the role of a doctor in order to learn which of a variety of foods led to allergic reactions in a fictitious patient. Each trial in the first phase consisted of a compound of two food cues, leading to one of two allergic reactions. The critical manipulation was that each compound consisted of one perfectly predictive cue, represented by A – D, and one non-predictive cue, W – Z. For example, cue A consistently predicted the presence of Outcome 1 (O1), and therefore
had perfect predictive utility. In contrast, W had no predictive utility because it was equally predictive of both O1 and O2.¹

Table 1
A basic learned predictiveness design (e.g., Le Pelley & McLaren, 2003).

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>AW – O1</td>
<td>AY – O3</td>
<td>AC</td>
</tr>
<tr>
<td>AX – O1</td>
<td>BZ – O4</td>
<td>WY</td>
</tr>
<tr>
<td>BW – O2</td>
<td>CW – O3</td>
<td>BD</td>
</tr>
<tr>
<td>BX – O2</td>
<td>DX – O4</td>
<td>XZ</td>
</tr>
<tr>
<td>CY – O2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CZ – O2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DY – O1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DZ – O1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Letters (A – D and W – Z) refer to individual food cues. O1 – O4 refer to four outcomes.

In Phase II, a novel patient was introduced and again participants were required to learn the causal relationship between food cues and their respective allergic reactions. The same cues, in novel combinations, served to predict the occurrence of these novel reactions. In this phase, both components of the compound discrimination were equally predictive. That is, both A and W shared the same

¹ It could be argued that describing W as non-predictive is not entirely accurate, given that it predicts the presence of an outcome (either O1 or O2) on every trial. However, in line with prior literature on learned predictiveness, “non-predictive” here indicates that a given cue is equally paired with both available outcomes during Phase I and therefore provides no benefit in making correct predictions during this phase. That is, participants would be expected to demonstrate chance performance during training if using the cue W to make predictions.
objective relationship with O3 and O4 respectively. The critical difference between components was their status as a predictive or non-predictive cue in the initial phase of learning. The test phase assessed learning by means of novel compounds. Half of these compounds consisted of previously predictive components that signalled the same outcome during Phase II (AC and BD), and the remainder consisted of previously non-predictive components signalling the same outcome during Phase II (WY and XZ). Test ratings, as shown in Figure 1, revealed that previously predictive compounds were more easily paired with their correct outcomes, suggesting better learning for these cues.

Figure 1. Learning scores reflect a linear transformation of the data reported by Le Pelley & McLaren (2003) in order to remain consistent with the measures used in this thesis. Scores range from 0 to 100, with a score of 50 indicative of chance, as represented by the dotted line. These are shown for test compounds consisting of predictive components and test compounds consisting of non-predictive components. Error bars represent standard error of the mean difference between predictive and non-predictive cues.
This effect, repeatedly found across various scenarios (see Le Pelley, 2010, for a recent review), is consistent with some models that predict attentional change according to the mechanisms of associative competition (e.g., Mackintosh, 1975; Le Pelley, 2004; Pearce & Mackintosh, 2010). According to such models, attention will be biased towards predictive cues A – D and away from non-predictive cues W – Z throughout Phase 1. This means that cues A – D will have an advantage when entering into new associations during the second phase, resulting in the observed preference in learning for these cues. Importantly, the hypothesised process does not rely on a deliberate attempt by the individual to control attention in a biased fashion according to the nature of the Phase I relationships. Instead, given the proposed relationship between associative history and associability, this explanation relies on the assumption that the attentional processes underlying the emergence of this bias are automatic to the extent that they follow as a consequence of associative learning, and to the extent that associative learning is thought to reflect an automatic process.

However, this assumption can be questioned. In demonstrations of learned predictiveness, there is often a high degree of conceptual similarity between the scenarios across the two phases of learning. One possibility, therefore, is that the effect is governed by a simple heuristic arising from inferential reasoning. It may be that participants make the explicit assumption that the predictive utility of cues A – D will transfer across similar contexts resulting in the controlled, volitional selection of those cues throughout the second phase of learning (Mitchell, Griffiths, Seetoo, & Lovibond, 2012). Such an explanation accords well with claims that associative learning relies exclusively on propositional knowledge (e.g., Mitchell, de Houwer, & Lovibond, 2009), and that the attentional mechanisms responsible for the effect are controlled selection processes (Mitchell et al., 2012).
Consistent with this possibility is evidence suggesting that learned predictiveness is susceptible to manipulation of inferred beliefs. In their Experiment 2, Mitchell et al. (2012) directly manipulated inferential beliefs across the two phases of a learned predictiveness design by way of instruction. At the onset of the second phase, participants in their continuity condition were explicitly instructed that the same cues would be relevant. In contrast, those in the change condition were instructed the opposite, that previously predictive cues were now irrelevant. Critically, this condition revealed a complete reversal of the effect whereby more was learned about the relationship between previously irrelevant cues and the novel outcomes. That learned predictiveness is sensitive to variations in explicit reasoning suggests a role for controlled, volitional processes in explaining the effect.

There is, however, evidence to suggest that the presence of the inference alone is not sufficient to produce the learned predictiveness effect. For example, Le Pelley et al. (2010a) investigated the expression of learned predictiveness adopting a procedure in which the use of higher order reasoning was encouraged. In this demonstration, the critical relationships were explained to participants in written statements highlighting the summary of cue-outcome pairings as well as the frequency with which they occurred. Such a manipulation should indeed strengthen the ability of participants to engage in deductive reasoning, given the minimal demands on working memory. Interestingly, they failed to observe learned predictiveness under these conditions. The bias was only observed when the relevant information was presented in trial and error form across multiple trials. This is contrary to what would be expected if explicit causal attribution were the sole mechanism responsible for the effect.

Similarly, related attentional effects in predictive learning appear to be inconsistent with an explanation based solely on inferential processes. For example, in
a two-stage causal learning paradigm similar to that of learned predictiveness, Le Pelley, Mitchell, and Johnson (2013) observed an attentional bias towards cues previously experienced as predictors of a high value outcome. However, instructions issued following training appeared to bias attention towards cues previously experienced as predictors of low value outcomes. Thus, opposing influences of training and instruction on learned attentional responses have been found. Taken together these findings raise the possibility that learned predictiveness reflects the operation of a combination of inferential and non-inferential processes.

This highlights a problem associated with the different ways in which attention is measured across the cognitive and learning domains. Learning tasks rely on the rate of learning as a measure of attention. It appears that this leaves open multiple interpretations as to the specific nature of the attentional change observed in effects such as learned predictiveness. Quinlan (2010) has further suggested that this poses a more fundamental issue. Given that operational observations of attentional selection within the cognitive literature rely on paradigms designed to stress processing capacity, selection is engaged in different ways across learning and attentional paradigms. This raises the possibility that although selective attention may be operating in demonstrations of learning, it might not be the primary determinant of performance. More direct evidence as to the selection mechanisms operating during learning may help to clarify the theoretical similarities between the two lines of research.

As such, recent work has moved towards examining the relationship between predictiveness and attention by employing direct measures of attention, as established within the cognitive literature. The advantage of such measures is that they can assess changes in stimulus processing over and above the rate of learning. For example, measures of eye gaze have been used to look at the relationship between the rate of
learning in a learned predictiveness procedure and the overt orienting response. Le Pelley, Beesley, and Griffiths (2011) showed that a bias towards learning about predictive cues in Phase II corresponded to an increase in eye gaze to predictive cues. While it is generally argued that eye gaze corresponds quite closely to attention (Deubel & Schneider, 1996), it can be unclear as to what kind of attentional process one might be referring to. For example, Mitchell et al. (2012) measured eye gaze when they employed an instructional manipulation on learned predictiveness. They found that gaze was biased towards cues instructed as important, even when this instruction conflicted with predictiveness established through prior training. Accordingly, they argued that changes in gaze reflect the product of controlled attentional changes, which rely on the beliefs of the observer. Indeed, it is difficult to interpret changes in eye gaze during such tasks. Given that in such designs the bias in gaze is also towards a cue indicating a correct prediction, the bias could be thought to reflect decision or response processes.

Subsequent studies have used alternative paradigms, thought to be adaptable to the measurement of nonstrategic processes. For example, the spatial cuing paradigm (Posner, 1980) has been foundational in demonstrating the distinction between voluntary and automatic spatial selection (e.g., Jonides, 1981). Le Pelley, Vadillo, and Luque (2013) used a version of spatial cuing coupled with a learned predictiveness categorisation task. They showed that the predictiveness of irrelevant distractors influenced spatial attention. Predictive distractors captured attention, facilitating subsequent target detection in that location relative to non-predictive distractors. This effect was only found when the temporal distance between the distractor and the target was short, indicating that the effect relied on rapid, nonstrategic selection. Similar effects have been found in methods using temporal selection (e.g., Livesey,
Harris, & Harris, 2009; Raymond & O’Brien, 2009), as well as spatial motor selection (Beesley & Le Pelley, 2010).

1.3. This thesis

In summary, the interaction between learning and attention has been of interest in both cognitive and learning areas of research. However, operational measures of attention differ between the two domains, which has led to uncertainty concerning the selection processes that vary with learning. In the cognitive domain, attention is measured under situations in which processing resources are taxed, and therefore when selection is crucial. Alternatively, changes in associability, or the rate of learning, provide an indirect measure of attentional change in demonstrations of learning. This focus on associability carries with it assumptions about the automatic nature of attentional change during learning. As a result, the role of top-down attentional control has received less discussion. Given that controlled, voluntary processes are thought to play a role in learning either exclusively, or in combination with automatic association, a useful addition to current knowledge would be an extension of the attentional manipulations employed in learning tasks.

The learned predictiveness paradigm presents a task that is adaptable to various manipulations of attentional selection. Indeed, the study of this effect has been critical in discussions of attention as it highlights a bias in learning that appears to reflect the operation of inferential and non-inferential processes. As such, recent work incorporating direct measures of attention into learned predictiveness procedures provides a promising means of characterising the selection mechanisms...
responsible for the effect, and by extension the attentional processes involved in predictive learning more generally.

The overall aim of this thesis is to examine the stimulus selection processes that vary with predictive learning. To this end, the original contribution of the work presented here assesses the learned predictiveness effect using novel cognitive tasks that involve competition for stimulus processing. Such manipulations should provide insight into the relative contribution of controlled and automatic selection processes in producing the bias.

Chapter 2 presents a series of experiments that combine the first phase of learned predictiveness training with a measure of visual detection, the attentional blink task. The attentional blink provides an index of how visual information is prioritised under conditions where processing resources are taxed due to high temporal processing demands. If predictiveness influences the selection priority of cues, changes in selection should be evident immediately following Phase I. First, I establish the presence of learned predictiveness in an extended learning design. I then examine the detection of predictive and non-predictive targets in a skeletal attentional blink task, a version of the paradigm in which only targets and their masks are presented by varying temporal separation (Experiment 2). In subsequent experiments, additional distractors are included in the design in order to increasingly engage competitive processing. Experiment 3 employs the fully familiarised predictive and non-predictive stimuli, while Experiment 4 and Experiment 5 introduce novel stimuli as well in order to provide a means of assessing the effect of predictiveness on selection over and above the influence of familiarity.

In Chapter 3, top-down attention is manipulated by the use of instructions about the causal components of the task. Mitchell et al. (2012) first made use of an instructional manipulation during learned predictiveness to suggest that the bias
emerges as a result of inferential, controlled attentional processes. However, the initial design was not well equipped to test the potential involvement of automatic selection. As such, this approach was extended in order to provide a more sensitive measure of both automatic and controlled selection by using orthogonal manipulations of predictive history and instruction at the start of the second stage of learning, as well as measuring associative memory and causal reasoning separately at test.

Given the use, and importance, of novel items in Chapter 2, a beneficial comparison would be the introduction of novelty within the manipulation of volitional attention employed in Chapter 3. This is the aim of Chapter 4, which first examines the emergence of learned predictiveness in the absence of instruction when predictive and non-predictive cues appear alongside novel items at the start of the second stage of learning (Experiment 9). Experiment 10 and Experiment 11 then test how instructions influence the effect of novelty on predictiveness.

The General Discussion of this thesis is presented in Chapter 5, which provides a summary of the results as they relate to automatic and controlled processing. These findings are discussed in relation to theories of learning and attention.
Chapter 2: Learned predictiveness and the attentional blink

If learned predictiveness reflects the kind of automatic attentional change predicted by attentional models of associative learning, then differences in processing should be evident immediately following the first phase of learning in a task that directly manipulates the cognitive control of selective attention. Accordingly, this chapter investigates the relationship between learned predictiveness and visual identification under conditions where the availability of cognitive resources is constrained. Rapid serial visual presentation (RSVP, Potter & Levy, 1969) is a widely used visual attention paradigm allowing investigation into the temporal limits of stimulus identification and encoding. During RSVP, stimuli are presented consecutively at the same spatial location at rates typically a fraction of a second (e.g., 100 ms per item). A rather striking property of stimulus identification under these conditions is the relatively preserved ability to extract complex visual information from a single item (Lawrence, 1971; Potter, 1975; Potter & Levy, 1969). However, whether this performance holds for multiple items depends on the temporal distance between them. The attentional blink (AB) refers to a transient deficit in the ability to report the second of two targets (T2) when it is presented within 200 ms – 500 ms of an initial target (T1) during RSVP (Raymond, Shapiro, & Arnell, 1992; see also Broadbent & Broadbent, 1987). In traditional demonstrations of the AB, the task is to detect two targets embedded amongst a stream of distractors. The serial position of T2 following T1 is manipulated in a variable known as lag. For example, if T2 appears at lag 1, this means that it appears immediately following T1 in the RSVP stream with no intervening distractors. The main dependent variable of interest is the ability to report T2 as a function of lag. Figure 2.1 shows a schematic of the trial structure in an AB task, along with the commonly observed pattern of results. As is shown in the
figure, despite preserved T1 accuracy across lags, there is a relatively long lasting deficit in the ability to report T2 at shorter lags. This deficit is not observed at longer lags, when T2 accuracy recovers.

Figure 2.1. Shown above is an example of trial structure in the attentional blink. Items are presented centrally, offset by approximately 100 ms in time. Participants search for two targets, here defined by colour. A typical pattern of results is shown below. When the temporal distance between targets is short, T2 detection is poor despite preserved T1 performance. As lag increases, T2 detection recovers.
It is now well established that the AB is a robust effect observed across a range of stimuli, including alphanumeric characters (Chun & Potter, 1995; Raymond, Shapiro, & Arnell, 1992), words (Barnard et al., 2004; Luck, Vogel, & Shapiro, 1996), objects (Harris, Benito, & Dux, 2010; Livesey & Harris, 2011), and faces (de Jong, Koster, van Wees, & Martens, 2009; Fox, Russo, & Georgiou, 2005), suggesting that the phenomenon reflects a fairly central characteristic of limited perceptual awareness (Dux & Marois, 2009; Martens & Wyble, 2010). There is now strong evidence consistent with the proposal that this limitation occurs at a postperceptual stage of stimulus processing. For example, items presented within the duration of the T2 deficit, including targets that have failed detection (Shapiro, Driver, Ward, & Sorenson, 1997), as well as distractors (Harris, Benito, & Dux, 2010; Harris & Little, 2010; Maki, Frigen, & Paulson, 1997), can prime subsequent items within the stream. Similarly, electrophysiological evidence has shown that ERP components associated with perceptual as well as semantic processing are present during the AB deficit, whereas components tied to working memory consolidation are suppressed during that period (Luck, Vogel, & Shapiro, 1996; Sergent, Baillet, & Dehaene, 2005; Vogel, Luck, Shapiro, 1997). This means that stimuli failing to reach the level of identification nonetheless undergo substantial processing, to the point of at least partial semantic recognition.

Thus, it appears that the deficit in T2 report arises from the more coordinated processing requirements of consolidation in working memory and explicit target report (Dux, Ivanoff, Asplund, & Marois, 2006). While several theoretical models have been put forward to account for the presence of the AB, a common component of many explanations is the distinction between two stages of processing (e.g., Chun & Potter, 1995; Giesbrecht & Di Lollo, 1998; Jolicoeur & Dell’Acqua, 1998; Ward, Duncan, & Shapiro, 1996). During an initial, high-capacity stage, fleeting perceptual
and conceptual information is registered for multiple items in the stream. Given this relatively shallow form of initial registration, the information for each item in this stage is relatively short-lived, with subsequent items causing rapid decay. In order to reach the level of full report, an item needs to be taken up by the subsequent, limited capacity stage of effortful processing. This stage is initiated once the first target, T1 is detected. Due to the close temporal proximity of the stimuli, T1 and potentially a subset of surrounding items are included in this window of effortful processing. According to many models (e.g., Potter et al., 2005; Potter et al, 2002; Shapiro, Arnell, & Raymond, 1994), this leads to competition between items in order to gain the limited resources needed for consolidation and response selection. T1, by virtue of its temporal position generally wins, leaving subsequent stimuli vulnerable to interference. The AB is thus predicted to occur as a result of the delayed attentional response to T2, causing a subsequent loss of competition for resources.

Importantly, the deficit observed in the AB is sensitive to target and distractor manipulations designed to alter the selection priority of stimuli. For example, targets with a degree of learnt salience, such as one’s own name (Shapiro, Caldwell, & Sorenson, 1997), a famous face (Jackson & Raymond, 2006), or an emotionally salient word (Anderson, 2005; Anderson & Phelps, 2001) show a reduced impairment relative to more neutral stimuli. Similarly, when a stimulus that has been previously paired with an unpleasant outcome is used as a distractor in an RSVP task, it can automatically generate an impairment for subsequent targets, similar to that observed in the AB (Smith, Most, Newsome, & Zald, 2006). Thus, there is some evidence to suggest that stimuli with either familiarised or conditioned importance gain a competitive advantage under conditions of constrained attention.

Further studies have examined the effect of learning within the AB paradigm more explicitly. Raymond & O’Brien (2009) examined the transfer of learnt value
associations to visual detection in the AB. In an initial learning task, different faces predicted outcomes with either a high or low probability. These outcomes were both gains and losses. Thus, there were high probability and low probability gains, as well as high and low probability losses. Recognition of those faces as T2 was then measured at one short lag and one long lag in a subsequent AB task. For faces associated with positive gains, the probability with which those faces predicted gains modulated visual detection. Thus, for faces associated with wins, recognition was better for high probability win faces compared to low probability win faces at both lags. In a single target detection task, similar effects were reported by O’Brien and Raymond (2012), in which there was a clear benefit in recognition for faces more likely to predict a specific outcome, regardless of whether that outcome was a win or a loss. While it is worth noting that recognition effects may be interpreted according to a number of processes, what these studies clearly demonstrate is an effect of prior learning on subsequent visual detection in a largely unrelated task.

Livesey, Harris, and Harris (2009) further investigated the influence of target predictiveness during RSVP. They employed a procedure in which two targets requiring subsequent report were embedded within a stream of distractors, as in traditional AB tasks. Shortly following the presentation of the second target a cue would appear to the left or right of the stream requiring a speeded response. Throughout the experiment, some targets consistently predicted the direction of a subsequent response, while others were irrelevant to the cueing task as they predicted either response equally. Eventually, when targets that were predictive of a particular response were presented within the duration of the blink, they were protected from the processing constraint. That is, identification was facilitated for cues that were predictive of a particular response. This occurred independently of any need to use those cues strategically, given that two targets required detection in every trial and
were thus important regardless of their signal validity in the seemingly unrelated cueing task. This suggests a fairly automatic change in visual selection for predictive cues.

In summary, the AB is a task in which the availability of processing resources can be manipulated without varying the perceptual or response properties of the task. One factor that contributes to the deficit appears to be visual competition, whereby items compete in order to gain the limited capacity resources necessary for explicit identification. Importantly, this competition is influenced by learning in a manner that does not appear to rely on the intentions of the observer. That is, there is evidence to suggest that the AB is sensitive to fairly automatic changes in stimulus selection, even when learning has occurred in a prior task. If changes in predictiveness within the learned predictiveness paradigm correspond to variations in attentional selection, then the AB should provide an appropriate way in which such changes can be measured. In particular, the task should be sensitive to the more automatic components of attentional change, providing a means of assessing the presence of an automatic process in learned predictiveness. Accordingly, based on the evidence that the AB is sensitive to both learning and an automatic change in stimulus processing, the following studies examine transfer between the first stage of learned predictiveness, in which cues are rendered either predictive or non-predictive, and visual detection in the attentional blink. I start by establishing the presence of the learned predictiveness bias in a novel extended design.
2.1. Experiment 1

In this experiment, participants were asked to complete a learned predictiveness task that was modelled on the commonly used allergist task. The stimuli that were used in this chapter consist of line drawings of everyday objects, taken from the set of Snodgrass and Vanderwart (1980). These objects provide an ideal stimulus set as they have been used in both demonstrations of learned predictiveness (e.g., Livesey, Thorwart, De Fina, & Harris, 2011) as well as the attentional blink (e.g., Livesey & Harris, 2011). Given the nature of the cues, a scenario was presented in which participants were asked to observe the reactions of an alien who had come to earth and was suffering allergies after eating everyday objects. As per previous procedures, some of these objects were perfectly predictive of certain allergies, while others were non-predictive, having been paired with either outcome equally. Following this, a new alien was introduced who had also come to earth and was eating everyday objects. This alien, despite eating the same objects, suffered novel allergic reactions. Again, as in traditional demonstrations, each trial consisted of an object that was predictive in the first phase, and one object that was non-predictive in the first phase. Both objects were now perfectly predictive of a specific outcome, and the bias towards previously predictive versus previously non-predictive objects was assessed at test. Thus, the scenario and basic structure of the task mimic traditional demonstrations quite closely.

What diverges from past procedures is the extent of the design. The number of compounds appearing in Phase I was increased. While each compound still consisted of two components, each predictive component was paired with an increased number of non-predictive components across trials. Thus, instead of predictive cue A
appearing alongside non-predictive cues W and X on separate trials, a predictive cue A would now appear alongside non-predictive components W, X, Y, and Z on separate trials. This extended design is shown in Table 2.1.

Table 2.1  
*Design of Experiment 1*

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>AW – O1</td>
<td>ES – O1</td>
<td>AS – O3</td>
</tr>
<tr>
<td>AX – O1</td>
<td>ET – O1</td>
<td>BT – O4</td>
</tr>
<tr>
<td>AY – O1</td>
<td>EU – O1</td>
<td>CU – O3</td>
</tr>
<tr>
<td>AZ – O1</td>
<td>EV – O1</td>
<td>DV – O4</td>
</tr>
<tr>
<td>BW – O2</td>
<td>FS – O2</td>
<td>EW – O3</td>
</tr>
<tr>
<td>BX – O2</td>
<td>FT – O2</td>
<td>FX – O4</td>
</tr>
<tr>
<td>BY – O2</td>
<td>FU – O2</td>
<td>GY – O3</td>
</tr>
<tr>
<td>BZ – O2</td>
<td>FV – O2</td>
<td>HZ – O4</td>
</tr>
<tr>
<td>CW – O2</td>
<td>GS – O2</td>
<td></td>
</tr>
<tr>
<td>CX – O2</td>
<td>GT – O2</td>
<td></td>
</tr>
<tr>
<td>CY – O2</td>
<td>GU – O2</td>
<td></td>
</tr>
<tr>
<td>CZ – O2</td>
<td>GV – O2</td>
<td></td>
</tr>
<tr>
<td>DW – O1</td>
<td>HS – O1</td>
<td></td>
</tr>
<tr>
<td>DX – O1</td>
<td>HT – O1</td>
<td></td>
</tr>
<tr>
<td>DY – O1</td>
<td>HU – O1</td>
<td></td>
</tr>
<tr>
<td>DZ – O1</td>
<td>HV – O1</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Letters refer to individual food cues across both stages of learning. O1 – O4 represent the four different outcomes.

The motivation for this design is that it should encourage increased selective attention to the predictive cues of the task. It has been widely argued that the mechanisms of working memory and selective attention are closely linked whereby attention serves to bias the contents of working memory towards goal directed information (Awh, Vogel, & Oh, 2006; Gazzaley & Nobre, 2012). Given the large
number of compounds and different pairings, any strategy that relies on memorising the relationship between whole compounds and outcomes would be unlikely to yield performance above chance. Thus, selection of predictive components in particular becomes necessary in order to attain a reasonable level of performance. This should facilitate a change in the selection priority of stimuli, and thus increase the ability to observe a difference in selection in subsequent experiments.

2.1.1. Method

Participants and apparatus

Sixteen first year psychology students participated in this experiment in exchange for partial course credit (7 female, mean age = 18.9). The experiment was conducted on Apple Mac Mini computers attached to a 17-in. CRT monitor, running software programmed in PsychToolbox for Matlab (Brainard, 1997; Pelli, 1997).

Stimuli

The stimuli for this experiment consisted of 16 black and white line drawings of items taken from Snodgrass and Vanderwart (1980). The items consisted of a bicycle, glove, barn, piano, rocking chair, umbrella, anchor, bell, aeroplane, bed, hammer, trumpet, toaster, kite, kettle, and sailboat. The allocation of these images to serve as cues A – H and S – Z was counterbalanced across participants such that each image appeared as each cue across the experiment. Thus there was one participant per counterbalanced condition. At a viewing distance of approximately 57 cm, these subtended a visual angle of 3 - 7 ° horizontally, and 3 - 5 ° vertically, and were presented in pairs in the upper half of the screen separated by 8.5 °. The allergic reactions serving as outcomes consisted of fever, nausea, headache, and rash. These
were randomly allocated to O1 – O4 for each participant, and were presented in text form in the lower half of the screen.

**Procedure**

Participants were instructed that they would be playing the role of a doctor whose patient, an alien named Mr Green, had come down to earth and was experiencing allergic reactions after eating everyday objects. They were informed that on every trial they would be observing two things that Mr Green had eaten. Once the two objects appeared, they were required to predict which of two allergic reactions Mr Green would suffer by clicking on one of the two allergic reactions presented for that patient. Upon making a self-paced selection, feedback was issued for the duration of 1 second in the form of a green tick or a red cross as well as the name of the allergic reaction experienced on that trial.

Phase 1 consisted of the 32 trial types shown in Table 2.1. Each trial type was presented twice per block in 5 blocks of trials. The order of trials was randomised within each block, and the left and right position of the cues was counterbalanced within each block.

At the beginning of Phase 2, participants were told that they would now be observing a new patient, Mr Blue. They were informed that Mr Blue was also an alien who had come to earth, but was suffering different allergies after eating everyday items. Participants were asked to again observe the allergies of Mr Blue in order to learn which items were causing which allergic reactions. Each of the 4 blocks of trials in Phase 2 consisted of 2 presentations of the 8 trial types shown in Table 2.1. These appeared in random order within each block, with the position of the cues counterbalanced across the left and right.
The test phase occurred immediately following Phase 2. During the test, all cues were again presented in compound. These compounds are shown in Table 2.1. Participants were told that they would now be presented with a variety of foods that Mr Blue had eaten, and that they were required to make a judgement about each meal. For each compound, they were asked to judge the likelihood that Mr Blue, having eaten those items, would suffer from the allergic reaction allocated to O3, or whether he would be more likely to suffer from the allergic reaction serving as O4. This judgement was made on a linear analogue scale, labelled “Very confident that [outcome 3] will occur” on the left, and “Very confident that [outcome 4] will occur” on the right. This rating appeared in the lower half of the screen, and yielded a score out of 100 for each compound, with low scores reflecting a judgement that the compound would lead to O3, and high scores reflecting a judgement that the compound would lead to O4. Each compound appeared in random order, and the left and right position of the cues was randomised for each trial.

2.1.2. Results

Exclusions. Given that the critical predictions relating to learned predictiveness rely on the sufficient acquisition of the initial component discriminations, an exclusion criterion based on Phase 1 performance was adopted whereby participants were excluded if they failed to achieve 60% accuracy by the last block. This is consistent with previous learned predictiveness protocols (e.g., Le Pelley & McLaren, 2003) and was applied to the first phase of learning in all subsequent experiments reported in this chapter. Two participants were excluded and replaced on the basis of this criterion for Experiment 1.
Phase I. Acquisition of the Phase I and Phase II discriminations was assessed by averaging the prediction accuracy across compounds within each block. This is shown for both stages of training in the left and right panel of Figure 2.2. Accuracy increased steadily across Phase I. Scores were analysed by means of a one-way repeated measures analysis of variance (ANOVA) with Block (1 – 5) as a factor, which revealed a significant main effect of block on accuracy, \( F(4, 60) = 42.71, p < .001, \eta^2_p = .74 \).

Phase II. Similarly, accuracy increased across Phase II. A one-way repeated measures ANOVA revealed a significant main effect of Block on accuracy, \( F(3, 45) = 9.47, p < .001, \eta^2_p = .55 \).

Test. The test rating for each compound was recoded as a score out of 100, such that a higher score reflects a more confident pairing of the test compound with its correct outcome, and 50 is indicative of chance. These were averaged according to whether cues were predictive or non-predictive in the first phase and are shown in Figure 2.3. Scores were compared by way of a paired-samples t-test, which showed
that test scores were significantly higher for compounds comprising previously predictive components compared to previously non-predictive components, \( t(15) = 2.5, p = .025, \eta^2_p = .29 \).

![Graph showing learning scores for test compounds consisting of predictive and non-predictive components.](image)

**Figure 2.3.** Learning scores for test compounds consisting of predictive components and test compounds consisting of non-predictive components. Scores range from 0 – 100, with a score of 50 indicative of chance, as represented by the dotted line. Error bars represent the standard error of the mean difference between predictive and non-predictive cues.

2.1.3. Discussion

Experiment 1 successfully demonstrates the learned predictiveness bias making use of a modified extended design. Participants were better at identifying the relationship between test compounds and their predicted outcome for compounds consisting of cues that were predictive in the first phase compared to test compounds consisting of non-predictive cues from the first phase.
The observed pattern of results mimics those observed by Le Pelley and McLaren (2003) in the original demonstration of learned predictiveness quite closely. It is worth noting that the learned predictiveness effect is robust across variations in the scenario (e.g., Le Pelley, Beesley, & Griffiths, 2011; Le Pelley et al., 2010a) as well as the design (e.g., Le Pelley, Turnbull, Reimers, & Knipe, 2010), and thus there is no reason to believe that the bias observed here reflects any qualitative difference in the nature of learning despite the greatly extended version of the task.

2.2. Experiment 2

Following on from the successful demonstration of learned predictiveness above, Experiment 2 combines the first phase of this procedure with a subsequent AB task. The initial stage of learning provides a set of predictive and non-predictive cues. Of interest in this experiment is whether differences in predictiveness correspond to differences in visual selection during the AB.

Given that Raymond and O’Brien (2009) observed an effect of prior learning that transferred to performance in the AB, a similar procedure was also used here whereby a learning phase preceded the presentation of critical stimuli as T2 in a skeletal AB task. In this procedure, only the two temporally separated targets as well as their backward masks are shown. Making use of one short lag and one long lag condition, this procedure has been shown to produce a deficit in target report similar to more traditional trial sequences. That is, a deficit for T2 report at the short lag and restored identification at the long lag (Ward, Duncan, & Shapiro, 1997). Structured in this way, the skeletal AB task creates two conditions of attentional availability for T2 processing. At the short lag, T2 appears under the condition of limited attention, whereas at the long lag, given that initial target processing has had time to conclude,
T2 appears when attention is fully available for identification. Thus, the skeletal design provides a straightforward measure of the temporal resolution of the sustained coordination of limited capacity resources once target processing has been initiated.

T2 items consisted of predictive or non-predictive cues from the initial phase of the procedure outlined in Experiment 1. These followed a novel image presented as T1. Based on prior findings showing an advantage in selection for cues predicting important outcomes both within the AB literature (e.g., Livesey, Harris, & Harris, 2009; Raymond & O’Brien, 2009), as well as spatial attention paradigms (Le Pelley, Vadillo, & Luque, 2013), it was anticipated that predictive items would show an advantage over non-predictive items under conditions in which attention is limited, that is, at the short lag. Once attention has recovered at long lags, equivalent performance would be expected across predictive and non-predictive items.

2.2.1 Method

Participants and apparatus

Thirty-two first year psychology students from the University of Sydney participated in this experiment in exchange for course credit (17 female, mean age = 19.7). Apparatus was the same as Experiment 1.

Stimuli

The two allergic reactions acting as outcomes O1 and O2 in the learning phase were again presented in text form in the lower half of the screen and were randomly allocated for each participant from the outcomes employed in Experiment 1. Following Experiment 1, cues comprised line drawings of everyday items taken from Snodgrass and Vanderwart (1980). The original 16 items were again counterbalanced
across participants to serve as cues A–H and S–Z in the learning phase, leading to two participants per counterbalanced condition. An additional 16 images were employed in order to complete the required stimulus set of 32 images. These items, which served as the images for T1, consisted of: an accordion, a basket, wheeled cart, candle, couch, cup, desk, bag, hat, iron, watch, scissors, shoe, oven, television, and watering can. The stimulus set subtended a visual angle of 3–7° horizontally, and 3–6° vertically at a viewing distance of approximately 57 cm. Image masks consisted of abstract black lines with a similar spatial frequency and curvature to that of the Snodgrass and Vanderwart (1980) images, within a white 7-7° area.

Procedure

Learning phase. The learning phase was identical in all ways to the first phase of Experiment 1.

RSVP phase. Immediately following the learning task, participants were informed that on each trial in the second half of the experiment, they would be viewing two objects that the alien would be eating displayed very rapidly. They were told that they would be required to report the identity of both items following each trial.

Two independent variables were manipulated in a 2 × 2 design with T2 predictiveness (predictive vs. non-predictive) and lag (short vs. long) as within subject factors. Figure 2.4 shows a graphic depiction of the trial structure and design for this phase. Each trial began with a fixation cross displayed on a white background in the centre of the screen for 500 ms. This was followed by T1 and its mask displayed in immediate succession for 59 ms each. A blank white screen then appeared for either 59 ms, in the short lag condition, or 472 ms in the long lag condition. Thus, the
stimulus onset asynchrony (SOA) between T1 and T2 was 177 ms in the short lag condition, and 649 ms in the long lag condition. T2 and its accompanying mask immediately followed the blank screen for 59 ms each.

Figure 2.4. Illustration of the trial structure employed in Experiment 2. Each stimulus was presented for 59 ms. At short lags, the blank inter stimulus interval was 59 ms, and 472 ms in the long lag condition. Participants were required to report the identity of the two objects immediately following each trial. T2 consisted of either a predictive cue, or a non-predictive cue from the learning phase.

The 16 images not previously experienced in the learning phase comprised the stimulus set for T1, while T2 was always taken from the items seen during the learning phase. Thus there were 8 images that were predictive during the initial learning phase, and 8 images that were non-predictive during learning. Each image appeared an equal number of times throughout the experiment. The total 192 trials were divided into 6 blocks of 32 trials, however there was no discernable break in between blocks. Thus there were 48 trials per condition. Each T2 item appeared twice
per block, once each at the two lag conditions. The same pairings of T1 and T2 were never repeated across the experiment and the identity of T1 was evenly distributed between the two lags. Otherwise, the allocation of T1 to each trial was random. No more than 3 of the same lag appeared in succession across trials.

Following each trial, a screen appeared allowing participants to make their responses for the first target. The top of the screen contained the instruction, “Select 1st target”. Beneath the text 15 images were displayed in a random order. These contained the two targets, as well as 13 distractors. Overall, the display contained an equal number of items taken from the T1 stimulus set, the predictive T2 stimulus set, and the non-predictive T2 stimulus set. The frequency of individual items as distractors was approximately equated across trials. This was followed by an identical screen labelled, “Select 2nd target”. Participants selected targets by using the mouse, and the space bar was used to transition to the next screen.

2.2.2 Results

Exclusions. As in Experiment 1, participants were excluded if they failed to achieve 60% accuracy during the last block of training. An additional criterion was applied to T1 performance across all subsequent experiments. If participants failed to reach a level of T1 accuracy, averaged across conditions, of 60%, they were excluded from further analyses. Given that T2 accuracy is calculated as conditional upon the correct identification of T1, this reduces the likelihood that a deficit in one condition arises from overall poor performance in T1. One participant failed both criteria, three failed the learning criterion, and one failed the T1 criterion. These participants were replaced.
Learning. Accuracy was averaged across compounds and is shown for each block in Figure 2.5. Accuracy increased steadily during training, as shown by a significant effect of block on accuracy as revealed by one-way repeated-measures ANOVA, $F(4, 124) = 54.99, p < .001, \eta^2_p = .64$.

![Graph showing accuracy across blocks](image)

**Figure 2.5.** Prediction accuracy averaged over compounds across training blocks during Phase I of Experiment 2. Error bars show SEM.

RSVP. In all experiments, the order in which participants reported items was not taken into account when calculating target accuracy. That is, if a target was correctly identified in either response screen a correct response was recorded. T2 accuracy was calculated conditional upon the correct identification of T1 (T2|T1). Thus, only trials in which T1 was reported accurately were used to assess T2 performance. This is the most common way to report T2 accuracy during the attentional blink. Although the order of report of T1 and T2 was allowed to vary, it is not typical to make T1
accuracy conditional upon the identification of T2. Given that T2 accuracy is very low in some conditions, that is, at short lags, this does not provide a sufficient number of trials to render T1 analyses meaningful.

**T1.** T1 accuracy was analysed for conditions in which T2 was predictive and for conditions in which T2 was non-predictive. This is shown for the short lag and the long lag in Figure 2.6. There was no evidence to suggest that either lag or the predictiveness of T2 influenced the ability of participants to report the identity of the novel T1. A $2 \times 2$ repeated measures ANOVA with Lag (short vs. long) and T2 predictiveness (predictive vs. non-predictive) as factors revealed no significant main effect of lag, no significant main effect of T2 condition, and no significant lag $\times$ T2 predictiveness interaction, all $F_s < 1$.

![Figure 2.6](image-url)

**Figure 2.6.** Accuracy for T1 at the short and long lag, for conditions in which T2 was predictive, and conditions in which T2 was non-predictive. Error bars represent the standard error of the mean difference between predictive T2 and non-predictive T2 conditions.
Conditional T2 accuracy is shown for the short lag and long lag condition for targets that were predictive and for targets that were non-predictive in Figure 2.7. Conditional accuracy was subjected to repeated-measures ANOVA with Lag (short vs. long) and T2 predictiveness (predictive vs. non-predictive) as factors. This showed a main effect of Lag, $F(1, 31) = 135.31, p < .001, \eta^2_p = .81$, but no main effect of T2 predictiveness, and no Lag $\times$ T2 predictiveness interaction, all $F_S < 1$.

Figure 2.7. Conditional T2 accuracy across lags according to whether targets were predictive or non-predictive. Error bars show the standard error of the mean difference across conditions in which target predictiveness varied.

2.2.3. Discussion

The present experiment failed to show an effect of prior predictiveness on visual selection during the attentional blink. This is somewhat surprising given the
consistent findings showing a benefit in selection for predictive information (e.g., Livesey et al., 2009; Raymond & O’Brien, 2009), as well as work showing facilitated target detection for significant stimuli (e.g., Anderson, 2005; Anderson & Phelps, 2001; Jackson & Raymond, 2006; Shapiro, Caldwell, & Sorenson, 1997). As mentioned earlier, the skeletal AB task presents a straightforward test of the temporal resolution of the sustained use of limited capacity resources once target processing has been initiated. However, the key difference between this procedure and more standard versions of the task is the presence of distractors, which increase demands on selective processing. Indeed, it appears that while distractors appearing before the onset of T1 are inhibited (Dux & Harris, 2007; Dux, Coltheart, & Harris, 2006; Harris et al., 2010; Olivers & Watson, 2006), once effortful processing has been prompted on the basis of an initial target, not only is less attention available for T2, but distractor inhibition is attenuated (Dux & Harris, 2007; Dux & Marios, 2008). This suggests that in full stream versions of the task, visual competition between targets and distractors is a critical component of the observed deficit.

One possibility is that the hypothesised change in selection with predictive utility may only be evident when selection is in fact most crucial, that is, in the face of increased competition. Given a biased competition view of attention (e.g., Desimone & Duncan, 1995), selection is most critically involved during the relative competition between objects, as opposed to attention merely resulting in an absolute form of signal enhancement. If predictiveness is biasing the way that cues compete, then a skeletal design may not be as sensitive to the proposed changes in selection. Although masks consisting of noise provide some competition, a full stream of object distractors would provide increased interference by way of semantic and object based perceptual features. To address this issue, Experiment 3 made use of a full stream AB design where the effect of manipulating target as well as distractor predictiveness
could be examined. While the question still remains as to why the results here might diverge from those of Raymond and O’Brien (2009), this will be considered in the General Discussion in synthesis with subsequent experiments.

2.3. Experiment 3

Experiment 3 was carried out in order to examine whether variations in detection according to predictiveness could be observed in the AB by using a procedure in which competition is present. In the current design, all items in each stream were equally familiar, consisting of all cues encountered in the learning task. Specific components of the stream were controlled. The prior predictiveness of T1 and T2, as well as the critical distractors immediately flanking each target, was manipulated across multiple lags in a fully crossed design. If visual competition is biased in favour of predictive items, then allowing a comparison between predictive targets and equally familiarised non-predictive targets should provide a strong manipulation in which a difference can emerge.

Further, by manipulating the predictiveness of critical distractors there is the opportunity to directly influence the extent to which distractors interfere with target identification. The role of distractors in the AB has been a theoretically important one, and therefore controlling their predictiveness may be essential in isolating an effect of predictiveness on visual selection within the AB. Semantically related distractors can prime the subsequent identification of T2 (Harris & Little, 2010; Maki, Frigen, & Paulsen, 1997), as well as produce interference if considered as conceptually unrelated (Dux & Coltheart, 2005). Given that there is evidence to show that distractors immediately following T1 undergo attentive processing (Visser, Bischof,
& Di Lollo, 1999), this suggests that these items influence how attention is distributed across time during target processing.

Demonstrations of distractor repetition effects (DRE, e.g., Drew & Shapiro, 2006; Dux et al., 2006; Dux & Harris, 2007) highlight more specifically the role that distractors play in selection during RSVP. For example, when the distractors immediately flanking T1 are identical, and drawn from a different category to that of T1, T2 detection improves (Dux et al., 2006). Dux et al. (2006) suggested that this manipulation should allow for a reduced AB due to the more efficient processing of T1. This is because the distractor immediately following T1, that is the T1 + 1 distractor, should be inhibited both featurally, given a refractory period of the features encountered at the T1 – 1 distractor, as well as conceptually, as a result of the categorical difference between targets and distractors. Reduced T1 + 1 processing should greatly reduce the ability of this distractor to mask subsequent items, thus allowing more resources for T2 processing.

Dux and Harris (2007) showed that when the same manipulation is applied to T2, such that the distractors immediately before and after T2 are identical and categorically distinct from the target, there is an increase in T2 detection relative to conditions in which distractors are not repeated, but only when T2 is at lag 2. They argue that this selective T2 DRE provides some suggestion as to what may be happening to distractor processing during RSVP. Prior to the detection of T1, the availability of cognitive control facilitates distractor suppression. Once T1 is detected, that control is lost and one consequence of this is that distractor suppression fails during the duration of the blink. However, when T2 is presented at lag 2, the T2 – 1 item is also the T1 + 1 item. The T1 + 1 item undergoes attentive processing (so-called lag-1 sparing), and therefore, can be effectively inhibited. So repeating that distractor helps subsequent target selection. This inhibition fails when the distractor
preceding T2 occurs at subsequent short lags, and no difference between repeated distractor and non-repeated distractor conditions is seen\(^2\).

At a general level, this suggests that when distractors occur within the period of increased stimulus interference due to a loss of cognitive control, their salience influences the outcome of that competitive process. This means that if predictiveness changes the selection priority of stimuli, one should be able to observe an indirect effect on target processing by manipulating the prior predictiveness of these critical distractors.

2.3.1. Method

**Participants and apparatus**

Thirty-two first year psychology students enrolled at the University of Sydney participated in this experiment in exchange for partial course credit (21 female, mean age = 20.6). Apparatus remained the same as prior experiments.

**Stimuli**

Stimuli comprised the set of 16 images employed in Experiment 1. O1 and O2 were again randomly allocated for each participant from those employed in Experiment 1. Outcome presentation parameters as well as stimulus counterbalancing proceeded according to previous experiments.

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\(^2\) It is worth noting that this account makes the prediction that the DRE should indeed be observed at long lags once cognitive control has been regained. While this was not observed in Dux and Harris (2007), it is in fact quite difficult to demonstrate distractor effects at long lags, because of ceiling performance. For some evidence of distractor inhibition effects at these time points, see Harris, Benito, and Dux (2010).
Procedure

Learning phase. The learning phase was identical to that of Experiment 2.

RSVP phase. Immediately following the learning task, participants completed the RSVP phase. They were informed that on every trial they would be viewing a variety of objects that the alien was eating displayed rapidly at fixation. They were told that on every trial two of these items would be displayed in red and that they were required to report the identity of the two red items. Table 2.2 shows the design of the RSVP trial types for this phase.

Table 2.2
Trial types for Experiment 3.

<table>
<thead>
<tr>
<th>Trial Type</th>
<th>T1</th>
<th>T2</th>
<th>Critical Distractors</th>
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<td>1</td>
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<td>8</td>
<td>NP</td>
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</tr>
</tbody>
</table>

Note. Each trial type was presented at lag 1, lag 2, lag 5, and lag 9. P denotes items that were predictive in Phase I, and NP denotes items that were non-predictive in Phase I.

Each trial began with a fixation cross shown for 500 ms. This was immediately followed by the RSVP sequence consisting of the full set of 16 images. Four independent variables were manipulated in a $4 \times 2 \times 2 \times 2$ within subjects design.
with lag (lag 1, 2, 5, and 9), T1 predictiveness (predictive vs. non-predictive), T2 predictiveness (predictive vs. non-predictive), and the predictiveness of critical distractors (predictive vs. non-predictive) as factors. Thus, within each trial the identity of T1, T2, as well as the critical distractors was controlled. The remainder of the RSVP stream consisted of the remaining images in random order. As items were never repeated within a stream, the same item could never appear in more than one condition in any given trial. A total of 256 trials were completed, providing 8 trials per condition.

**Lag.** There were four lags separating T1 and T2. Thus, T2 could appear immediately following T1 (lag 1), following 1 intervening distractor (lag 2), following 4 intervening distractors (lag 5), or following 8 intervening distractors (lag 9). Each item in the stream was presented for 58 ms followed by a blank inter-stimulus interval (ISI) of 35ms, resulting in a SOA of 93 ms. Thus the second target could appear within 93, 186, 465, or 837 ms of T1.

**T1.** T1 consisted of either a predictive or non-predictive item. Each item appeared at T1 16 times across all trials, and was never repeated in the same condition more than once. T1 could appear at serial positions 3, 4, 5, or 6 within the stream. Each serial position was employed an equal number of times throughout the experiment.

**T2.** Similarly, T2 consisted of either a predictive or non-predictive item. Each item was shown as T2 an equal number of times across trials, appearing 16 times in total. Items did not appear in the same condition more than once.

**Critical distractors.** The predictiveness of the critical distractors was also manipulated such that these were either predictive or non-predictive cues. Critical distractors were defined as the distractors immediately flanking both targets, equating to 4 distinct critical distractors on each trial. To clarify, the distractors immediately
preceding and immediately following each target were controlled and were all either predictive or non-predictive on each trial. For lag 1 trials, the critical distractors comprised the 2 distractors immediately preceding T1 and the 2 distractors immediately following T2. In the lag 2 condition, these comprised the 2 distractors immediately preceding T1, the distractor separating T1 and T2, as well as the distractor immediately following T2. The allocation of each item as a critical distractor was equated across trials. Note that given the fully crossed nature of the design this means that predictive and non-predictive critical distractors can flank both predictive and non-predictive targets and thus provide no information as to whether the upcoming target will be a predictive or non-predictive item.

2.3.2. Results

Given a large number of conditions in Experiments 3 – 5, the results reported below are restricted to the most theoretically important analyses as well as any significant and marginal findings.

Exclusions. Three participants were excluded on the basis of the learning criterion, and three participants were excluded on the basis of the T1 criterion. All excluded participants were replaced.

Learning. Accuracy increased steadily across blocks in Phase I, as is shown in Figure 2.8. A one-way repeated measures ANOVA revealed a main effect of Block on accuracy, $F(4, 132) = 67.66, p < .001, \eta^2_p = .67$. 
Figure 2.8. Prediction accuracy for the learning phase across blocks, averaged across compounds, for Experiment 3. Error bars represent SEM.

**RSVP**

**T1.** T1 accuracy was averaged within each condition and scores were analysed by way of a 4 (Lag: 1, 2, 5, and 9) × 2 (T1 predictiveness: predictive vs. non-predictive) × 2 (T2 predictiveness: predictive vs. non-predictive) × 2 (critical distractor predictiveness: predictive vs. non-predictive) repeated measure ANOVA. This revealed a significant Lag × T2 predictiveness × Critical distractor predictiveness interaction, $F(3, 93) = 3.04, p = .034, \eta^2_p = .09$. There was little further indication that T1 detection varied across conditions as the main effects of lag, target predictiveness, and critical distractor predictiveness, as well their interactions did not reach significance, largest $F = 2.32, p = .09, \eta^2_p = .07$.

In order to investigate the three-way interaction, T1 accuracy was collapsed across the conditions in which T1 predictiveness varied, and analysed at each lag. Thus the T2 predictiveness × Critical distractor predictiveness interaction was examined at each lag. These data are shown in Figure 2.9. At lag 1, there was some indication that the influence of T2 predictiveness on T1 accuracy varied according to
whether the critical distractors were predictive or non-predictive, however the T2 predictiveness × critical distractor predictiveness interaction failed to reach a conventional level of significance, $F(1, 31) = 3.79, p = .061, \eta^2_p = .11$. There was no significant main effect of T2 predictiveness, and no main effect of critical distractor predictiveness, all $F$s < 1. The main effects of T2 predictiveness and critical distractor predictiveness, as well as their interaction, also failed to reach significance at subsequent lags, largest $F = 2.90, p = .10, \eta^2_p = .08$.

Figure 2.9. T1 accuracy averaged over conditions in which T1 identity varied. Accuracy is shown for conditions in which T2 as well as the critical distractors were predictive or non-predictive, at lag 1, 2, 5 and 9. Error bars represent the within-subjects standard error of the mean (Cousineau, 2005).
T2. T2 identification was again measured conditional upon the correct identification of T1 (T2|T1). Thus, the analysis of T2 accuracy only takes into account trials on which T1 has been identified correctly. Scores were subjected to repeated measures ANOVA with Lag (lag 1, 2, 5, and 9), T1 predictiveness (predictive vs. non-predictive), T2 predictiveness (predictive vs. non-predictive), and Critical distractor predictiveness (predictive vs. non-predictive) as factors. The presence of an attentional blink was confirmed by a significant effect of Lag on T2 detection, $F(3, 93) = 132.07, p < .001, \eta^2_p = .81$. There was also a significant main effect of Distractor predictiveness, such that T2 detection was better when targets were immediately flanked by predictive distractors, $F(1, 31) = 5.54, p = .025, \eta^2_p = .15$. However there was also a significant Lag $\times$ T1 predictiveness $\times$ Distractor predictiveness interaction, $F(3, 93) = 3.11, p = .042, \eta^2_p = .09$. None of the remaining main effects or interaction effects were significant, largest $F = 2.82, p = .10, \eta^2_p = .08$.

To detail the three-way interaction, scores were averaged across T2 predictiveness in order to test the T1 predictiveness $\times$ Distractor predictiveness interaction at each lag. This is shown in Figure 2.10, along with the mean accuracy for the main effect of distractor predictiveness. There were no significant main effects, and no significant interaction at lag 1, all $Fs < 1$, or at lag 2, largest $F = 2.03, p = .16, \eta^2_p = .06$, or at lag 5, all $Fs < 1$. The analysis at lag 9 revealed a significant T1 predictiveness $\times$ distractor predictiveness interaction, $F(1, 31) = 4.54, p = .041, \eta^2_p = .13$, but no main effect of distractor predictiveness, $F(1, 31) = 1.74, p = .18, \eta^2_p = .05$, and no main effect of T1 predictiveness, $F < 1$.

Simple effects analysis revealed that at lag 9, when T1 was predictive, T2 detection did not vary according to Distractor predictiveness, $F < 1$. When T1 was non-predictive, performance was slightly better when distractors were predictive,
however this failed to reach a conventional level of significance, $F(1, 31) = 3.83, p = .059, \eta^2_p = .11$. T2 detection according to T1 and distractor identity across lags is shown in Figure 2.10. The mean for predictive and non-predictive distractor conditions is also shown on the figure.

![Graph showing T2 conditional accuracy](image)

**Figure 2.10.** Conditional T2 accuracy averaged across conditions in which T2 identity varied. Thus, accuracy is shown for predictive and non-predictive T1 and critical distractor conditions across lags. Crosses represent the average overall accuracy for when distractors were predictive (black) and when distractors were non-predictive (grey). Error bars represent the within-subject standard error of the mean (Cousineau, 2005).
2.3.3. Discussion

Once again, there was little evidence that the prior predictiveness of targets influenced selection priority during the AB. For performance at T1 as well as T2, there was no difference in the ability of participants to identify targets according to whether they were predictive or non-predictive in a prior learning task.

On the other hand, there was some indication that predictiveness might influence target selection indirectly, via the level of distractor processing. Overall, T2 detection was better when targets were flanked by predictive distractors. This result is an interesting one in the absence of any initial effects of target predictiveness on target identification. Previous findings of facilitated selection for predictive targets (e.g., Livesey et al., 2009) suggest a benefit in the attentional resources dedicated to the processing of predictive items. Given that manipulations of distractor salience designed to decrease the processing of distractors facilitate target detection (Dux & Harris, 2007), one would anticipate increased interference from predictive distractors, and therefore reduced T2 selection.

One possibility is that predictive distractors are facilitating the allocation of attentional resources by maintaining a controlled state of selection once T1 has been detected. Numerous studies (e.g., Di Lollo, Kawahara, Ghorashi, & Enns, 2005; Nieuwenstein & Potter, 2006; Olivers, van der Stigchel, Hulleman, 2007) have reported an attenuation of the AB deficit in paradigms making use of the consecutive presentation of multiple targets, suggesting that a period of sustained consolidation can be generated under certain conditions. If predictive items have gained salience it may be that they behave more like targets and induce such a “spreading of sparing” effect. This appears unlikely for several reasons. First, this explanation would anticipate that the distractor effect would appear primarily at short lags. There was little evidence for this. Further, Livesey and Harris (2011) found little evidence of this
sparing effect for Snodgrass and Vanderwart (1980) images, suggesting that the effect may be isolated to alphanumerical stimuli. Finally, such an explanation is at odds with evidence showing that salient distractors in fact induce a deficit for subsequent targets, similar to that observed in the AB (Most, Chun, Widders, & Zald, 2005; Smith et al., 2006).

An alternative possibility is that predictive distractors decrease in salience as a result of increased familiarity. In related paradigms, it is well established that selection favours novel stimuli. Said another way, familiar items lose selection priority over novel items (Horstmann & Ansorge, 2006; Johnston & Schwarting, 1997; Neo & Chua, 2006). There is evidence that such effects are related to response selection under some circumstances. Visual information selected more frequently in one context as predictive of an outcome will interfere less as distracting information in a subsequent task (Anderson, Laurent, & Yantis, 2012). Given the increased selection of predictive items over non-predictive items in the learning task, as well as previous findings showing increased time spent looking at these cues (Le Pelley, Beesley, & Griffiths, 2011), it is possible that these familiarity effects are contributing towards the reduced competition of predictive stimuli as distractors, thereby enhancing target detection.

Regardless of how distractor salience influences target detection, any explanation would need to further take into account the fact that changes in selection appear to be occurring exclusively at the level of distractor predictiveness. This point is an important one, and given the relevance to subsequent experiments will be considered further in the General Discussion. However, it should be noted that the effect of distractor predictiveness on T2 detection varied as a function of lag and T1 identity. Similarly, while overall distractors did not influence T1 accuracy, there was some indication of a distractor effect that varied according to T2 identity and lag.
Unfortunately these interactions did not provide any interpretable indication as to the relationship between target predictiveness, distractor predictiveness, and lag. Thus the overall distractor effect should be interpreted with caution prior to a replication of the effect. With this in mind, Experiment 4 was designed to replicate the presence of a distractor effect while extending the design to include a manipulation of familiarity during RSVP.

2.4. Experiment 4

The aim of Experiment 4 was to establish an effect of distractor predictiveness on target selection in the AB in a procedure that includes a manipulation of familiarity. As highlighted above, stimulus novelty is a potent source of selection bias in tasks of visual selection. By controlling familiarity as an explicit factor, the effect of learning and familiarity can be more effectively teased apart. Again, the first phase of the experiment comprised the initial learning task. This was followed by the RSVP task requiring participants to detect two targets during each trial. In Experiment 3, predictive and non-predictive stimuli were intermixed such that each condition comprised equally exposed items. In Experiment 4, predictive and non-predictive cues appeared in separate trials intermixed with novel stimuli. As such, two separate stimulus sets were created that could appear in any given trial. Stimulus Set Predictive (Set P) consisted of the predictive items as well as an equal number of novel objects. Stimulus Set Non-predictive (Set NP) consisted of the non-predictive stimuli and an equal number of an alternative set of novel objects. Within each stimulus set, target and distractor identity was controlled in a fully crossed design. In Set P, for example, T1 could be predictive or novel, whereas in Set NP, T1 could be non-predictive or novel.
This means that within each stimulus set it is in fact familiarity that is manipulated, and observing an influence of predictiveness relies on differences in the effect of familiarity across stimulus sets. That is, in one stimulus set the familiar components are predictive, and in the remaining set the familiar components are non-predictive. If there is an influence of predictiveness this would suggest that the difference between familiar and novel items will depend on whether those familiar items are predictive or non-predictive. If the familiarity of the targets is influencing selection priority, then an overall deficit for familiar items relative to novel items should be observed. However, if predictive distractors are preferentially losing that competitive priority, then predictive distractor conditions should result in facilitated target detection relative to novel distractor conditions. In contrast, in Set NP one would expect less of a difference between non-predictive and novel distractor conditions.

2.4.1. Method

Participants and apparatus

Forty-eight first year undergraduate psychology students enrolled at the University of Sydney participated in this experiment in exchange for partial course credit. The apparatus remained the same as previous experiments.

Stimuli

The images employed during the learning phase for Experiment 4 were identical to those of previous experiments. In order to complete the required stimulus set of 32 images for the RSVP phase, the 16 additional images employed in Experiment 2 were again employed here. The identity and allocation of outcomes, as
well as the counterbalanced allocation of images to serve as cues A – H and S – Z, was done according to the procedure used in prior experiments.

Procedure

Learning phase. The learning phase was identical to that of the previous experiments.

RSVP phase. The instructions issued at the start of the RSVP phase were as per Experiment 3. Each RSVP stream consisted of 16 images. The full set of 32 images was divided into two stimulus sets of 16, the predictive stimulus set, and the non-predictive stimulus set. The predictive stimulus set consisted of the 8 predictive cues from the learning phase, as well as 8 randomly chosen images from the novel set. The 8 non-predictive cues from the learning phase, as well as the remaining 8 novel images comprised the non-predictive stimulus set. Half of all trials employed an RSVP stream consisting of items from the predictive stimulus set, and the remaining half of trials consisted of items from the non-predictive stimulus set.

For both stimulus sets, four independent variables were manipulated in a $4 \times 2 \times 2 \times 2$ within subjects design. This is depicted in Table 2.3. The factors in this design were lag (lag 1, 2, 5, and 9), T1 familiarity (novel vs. familiar), T2 familiarity (novel vs. familiar), and the nature of the critical distractors (novel vs. familiar). Given that these factors were manipulated within each stimulus set, the identity of familiar items depends on stimulus set. Thus, for the predictive stimulus set, the T1, T2, and distractor manipulations compare novel and predictive items. Similarly, for trials employing the non-predictive stimulus set, the T1, T2, and distractor manipulations compare novel items to those that were non-predictive. This means that within each trial the identity of T1, T2, as well as the critical distractors was controlled. The
remainder of the stream consisted of the remaining images within that stimulus set in random order. Four blocks of 64 trials were completed equating to 256 trials in total, and 4 trials per condition. Trials making use of the predictive stimulus set were intermixed with trials making use of the non-predictive stimulus set. There was no break in between blocks.

_Lag._ The same lags were used here as in Experiment 3. T2 could appear at lag 1, 2, 5 or 9. The timing of each item, and therefore the SOA between T1 and T2, was also identical to Experiment 3.

_T1._ In each trial, T1 was either novel or familiar. For predictive stimulus set trials, the familiar T1 consisted of a predictive cue, while for non-predictive stimulus set trials the familiar T1 was a non-predictive cue. Each image appeared an equal number of times as T1, and no more than once in the same condition across trials. T1 could appear at a serial position of 3, 4, 5, or 6 within the stream. Each of these positions was employed an equal number of times throughout the experiment.

_T2._ Similarly, T2 consisted of either a novel or familiar item. When trials consisted of Set P images, the familiar T2 was predictive, and when a stream consisted of Set NP images, the familiar T2 was non-predictive. Each image appeared as T2 an equal number of times and was never repeated in the same condition across trials. T1 and T2 pairings were never repeated across the experiment.

_Critical distractors._ Critical distractors were defined as the distractors immediately flanking both targets, as in Experiment 3. These were either novel or familiar. Familiar critical distractors were predictive in predictive set trial types, and non-predictive in non-predictive set trial types. The allocation of specific cues as critical distractors was approximately equated across trials.
Table 2.3. *RSVP trial types for Experiment 4.*

<table>
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<tr>
<th>Trial Type</th>
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<th>T2</th>
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<td>16</td>
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</table>

*Note.* Each trial type was presented at lag 1, lag 2, lag 5, and lag 9. P denotes items that were predictive in Phase I, and NP denotes items that were non-predictive in Phase I. The novel items in Set P and Set NP are separate sets of novel stimuli.
2.4.2. Results

Exclusions. 6 participants failed to reach the learning criterion, and 7 participants failed to reach the T1 criterion. These were replaced.

Learning. Accuracy during the initial acquisition of the discrimination was averaged across compounds and is shown in Figure 2.11. Learning increased steadily across blocks, as is shown by a significant one-way repeated measures ANOVA with Block as a factor, $F(4, 188) = 169.14, p < .001, \eta^2_p = .78$.

Figure 2.11. Prediction accuracy across training blocks for the learning phase of Experiment 4. Error bars show SEM.

RSVP

T1. Accuracy was analysed with repeated measures ANOVA with Set (Set P vs. Set NP), Lag (lag 1, 2, 5, and 9), T1 familiarity (novel vs. familiar), T2 familiarity (novel vs. familiar), and Distractor familiarity (novel vs. familiar) as factors. Thus,
overall, there are potential effects of lag, familiarity, and stimulus set (i.e.,
predictiveness). For clarity, these will be considered sequentially. Given that the key
hypotheses relate to the influence of learning, the effects of primary interest are
interactions involving stimulus set. To anticipate, effects of familiarity were observed
for target detection, and effects of predictiveness were observed at the level of the
distractor manipulation. Figure 2.12 depicts these effects across the four lags. For ease
of interpretation, they are again shown in Figure 2.13, averaged across lag.

**Effect of lag.** Overall, T1 performance was not influenced by lag, $F(3, 141) = 
1.1, p = .35, \eta^2_p = .02$.

**Effects of familiarity.** Familiarity at the target and distractor level influenced
T1 performance. Accuracy was better when T1 was novel, $F(1, 47) = 23.65, p < .001,
\eta^2_p = .34$, and better when distractors were familiar, $F(1, 47) = 18.87, p < .001, \eta^2_p
= .29$. The influence of distractor familiarity differed according to lag, as shown by a
significant Lag $\times$ Distractor familiarity interaction, $F(3, 141) = 4.14, p = .008, \eta^2_p
= .08$.

To examine the interaction, accuracy was averaged according to distractor
familiarity and compared at each lag. This analysis suggests that the interaction is
driven by performance at lag 2, where distractor familiarity does not appear to
influence T1 detection. That is, there was no difference in accuracy according to
whether distractors were predictive or non-predictive at lag 2, $F < 1$, whereas T1
detection was better when distractors were familiar at remaining lags, namely lag 1,
$F(1, 47) = 12.7, p = .001, \eta^2_p = .21$, lag 5, $F(1, 47) = 14.13, p < .001, \eta^2_p = .23$, and lag
9, $F(1, 47) = 7.16, p = .01, \eta^2_p = .13$. While the T1 familiarity $\times$ T2 familiarity $\times$
distractor familiarity interaction approached significance, the effect did not meet
conventional standards of significance, $F(1, 47) = 3.68, p = .06, \eta^2_p = .07$. The
Figure 2.12. The effect of familiarity (Panel A) and the effect of predictiveness (Panel B) on T1 accuracy for Experiment 4. Panel A shows T1 accuracy averaged over T2 conditions across lags. Panel B shows T1 accuracy according to distractor familiarity and stimulus set. Error bars show within-subject standard error of the mean (Cousineau, 2005).
Figure 2.13. The effect of familiarity (Panel A) and the effect of predictiveness (Panel B) on T1 accuracy for Experiment 4 averaged across lags. Accuracy averaged across T2 identity is shown in Panel A. Panel B shows accuracy according to distractor familiarity and stimulus set. Error bars show within-subject standard error of the mean (Cousineau, 2005).
remaining main effects of familiarity, as well as their interactions were not significant, largest $F = 2.3, p = .083, \eta^2_p = .04$.

**Effects of predictiveness.** Overall, T1 detection was better in the stimulus set containing familiar items that were predictive, Set P, $F(1, 47) = 11.57, p = .001, \eta^2_p = .2$. The effect of distractor familiarity, whereby performance was better when distractors were familiar, varied according to stimulus set. That is, there was a significant Set (Set P vs. Set NP) $\times$ Distractor familiarity (novel vs. familiar) interaction, $F(1, 47) = 19.27, p < .001, \eta^2_p = .29$. A simple effects analysis investigating the interaction revealed that in Set P (when familiar items were predictive), there was no significant difference in T1 detection according to whether distractors were novel or familiar (predictive), $F<1$. However, in stimulus Set NP, T1 detection was significantly higher when distractors were familiar (non-predictive) compared to when they were novel, $F(1, 47) = 28.5, p < .001, \eta^2_p = .38$.

**T2.** Conditional T2 accuracy (T2|T1) was initially analysed with a 2 (Stimulus set: Set P vs. Set NP) $\times$ 4 (Lag: 1, 2, 5, and 9) $\times$ 2 (T1 familiarity: novel vs. familiar) $\times$ 2 (T2 familiarity: novel vs. familiar) $\times$ 2 (Distractor familiarity: novel vs. familiar) repeated measures ANOVA. As was observed in T1 accuracy, there were interactions demonstrating an effect of familiarity as well as predictiveness. The effect of familiarity (Panel A) as well as predictiveness (Panel B) is shown for all lags in Figure 2.14. It should be noted that novel conditions did not differ so are collapsed for graphical purposes. Figure 2.15 illustrates the effects averaged across lag.

**Effects of lag.** Overall, an attentional blink was observed as suggested by a significant effect of Lag on T2 detection, $F(3, 141) = 296.68, p < .001, \eta^2_p = .86$.

**Effects of familiarity.** Both target and distractor familiarity influenced T2 detection. Detection was better when T2 was novel, $F(1, 47) = 44.34, p < .001, \eta^2_p$
=.49, and better when distractors were familiar, \( F(1, 47) = 6.27, p = .016, \eta^2_p = .12 \).

However, the influence of distractor familiarity varied according to T1 familiarity, producing a T1 familiarity \( \times \) Distractor familiarity interaction, \( F(1, 47) = 4.45, p = .04, \eta^2_p = .09 \). Data were collapsed across remaining conditions in order to investigate the interaction. Simple effects analysis revealed that when T1 was familiar, performance was significantly better when distractors were also familiar, \( F(1, 47) = 4.49, p = .039, \eta^2_p = .09 \). When T1 was novel, performance did not vary according to whether distractors were familiar or novel, \( F < 1 \).

Effects of predictiveness. The benefit in T2 detection for conditions in which distractors were familiar relied on whether the stimulus set was Set P or Set NP. That is, there was a significant stimulus set (Set P vs. Set NP) \( \times \) distractor familiarity (novel vs. familiar) interaction, \( F(1, 47) = 4.20, p = .046, \eta^2_p = .08 \). In order to detail the interaction, data were collapsed across remaining conditions and subjected to a simple effects analysis. This revealed that in stimulus Set P, there was no difference in T2 detection according to whether distractors were novel or familiar (predictive), \( F < 1 \). However, in stimulus Set NP, T2 performance was better when distractors were familiar (non-predictive), \( F(1, 47) = 7.66, p = .008, \eta^2_p = .14 \).
Figure 2.14. The top panel shows the effect of T2 familiarity on target detection across lags. Overall, target detection was better for novel targets. There was no influence of prior predictiveness on the detection of familiar targets. Panel B shows the effect of predictiveness. Target detection was better when targets were flanked by non-predictive distractors. Error bars show within-subject standard error of the mean (Cousineau, 2005).
Figure 2.15. The top panel shows the effect of T2 familiarity for the stimulus set containing familiar items that were predictive and the stimulus set containing familiar items that were non-predictive averaged over lag. Overall, target detection was better for novel targets and there was no influence of prior predictiveness on the detection of familiar targets. Panel B shows the effect of predictiveness averaged across lag. Target detection was better when targets were flanked by non-predictive distractors. Error bars show within-subject standard error of the mean (Cousineau, 2005).
2.4.3. Discussion

The aim of this experiment was to replicate the distractor effect observed in Experiment 3 by making use of a design that also included a manipulation of novelty during RSVP. Overall, there was a robust effect of familiarity that played out differently across target and distractor conditions. That is, there was a benefit in detection for novel targets, and better target detection when distractors were familiar. In line with previous experiments, there was no evidence that the predictiveness of targets influenced target identification. While a distractor effect was observed, this was in the opposite direction to that seen in Experiment 3. The effect of familiarity did differ according to whether distractors were predictive or non-predictive, however this amounted to a benefit in target performance for targets flanked by non-predictive distractors.

Taken in isolation, this effect appears to suggest that non-predictive items are easier to inhibit as distractors compared to predictive stimuli. Similar effects have been reported previously whereby low value items are easier to discount as distractors compared to salient high value stimuli (Anderson et al., 2001; Della Libera & Chelazzi, 2009; Le Pelley et al., 2015). Certainly, this effect could also be interpreted in line with the idea that salient predictive distractors are causing more interference. In the absence of an appropriate baseline the direction in which stimuli are changing in selection priority remains unclear. For example, while an effect of distractor predictiveness was observed in both T1 and T2 data benefitting non-predictive distractor conditions overall, in T1 this effect was observed on the basis of reduced performance when novel distractors appeared in the same stream as non-predictive items. That is, predictive and non-predictive distractor conditions were equivalent and the change came from reduced detection when distractors were novel, and mixed with non-predictive items. In contrast, the effect in T2 arises from increased target
detection when distractors were non-predictive; predictive distractors and both novel
distractor conditions were equivalent. Thus, the inclusion of some indication of
baseline performance would facilitate interpretation of these results.

However, the fact remains that the effect observed here goes in the opposite
direction to that seen in Experiment 3. Thus, so far, when predictive and non-
predictive cues are pitted directly against one another, predictive distractors cause less
interference. When these appear in separate RSVP streams amongst novel stimuli, it
seems that non-predictive distractors lose the ability to cause interference. With no a
priori reason as to why the addition of novelty should change the direction in which
predictiveness influences visual selection, interpreting these results would benefit
from being able to compare the trial types used in Experiment 3 and the trial types
used in Experiment 4 within the same experimental design. This was the aim of
Experiment 5.

2.5. Experiment 5

Following on from the seemingly conflicting results of Experiment 3 and
Experiment 4, the general aim of Experiment 5 was to further investigate the nature of
the distractor effect. Given that the overall level of familiarity of the items contained
in streams was quite different across Experiment 3 and Experiment 4, a design in
which these can be directly compared would serve to clarify the discrepancy of the
results. More specifically, it would be beneficial to confirm the direction of this effect
in a design that also allows for the direct comparison of trials comprising fully
familiarised items, as in Experiment 3, and trials comprising a combination of
familiarised and novel items, as in Experiment 4. This would provide a means of
exploring whether the overall level of familiarity within trials influences the
expression of the distractor effect. Additionally, trials were included that consisted of
novel items only. A novel only condition provides at least some indication of a
baseline level of target detection when predictiveness and familiarity are not
influencing performance.

2.5.1. Methods

Participants and apparatus

The participants in this experiment were 32 undergraduate psychology
students enrolled at the University of Sydney, who took part in the study in exchange
for partial course credit. The apparatus was identical to previous experiments.

Stimuli

The stimuli for Experiment 5 consisted of the 32 images employed in
Experiment 4. In Experiment 2 – Experiment 4, the same 16 images were
counterbalanced to serve as cues A – H and S – Z. Novel items were randomised from
the remaining stimuli. In this experiment, there were 32 counterbalancing conditions,
as both learning cues and novel stimuli were fully counterbalanced. Allergies were
randomly allocated to serve as outcomes O1 – O2.
Table 2.4  
*Design of Experiment 5.*

<table>
<thead>
<tr>
<th>Trial Type</th>
<th>Stimulus Set</th>
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*Note.* Each trial type appeared at lag 3 and lag 9. P denotes items that were predictive in learning, and NP denotes items that were non-predictive. Novel 1 and Novel 2 items were different sets of novel stimuli.
Procedure

Learning phase. The learning phase was the same as Experiment 2 – Experiment 4.

RSVP phase. Instructions, presentation parameters, as well as trial presentation remained identical to previous experiments. The design of Experiment 5 is shown in Table 2.4. Each of the total 256 trials (4 trials per condition) consisted of one of four stimulus sets. Each stimulus set was made up of two separate subsets of cues. These subsets were 8 predictive items (Set P), 8 non-predictive items (Set NP), 8 novel items (Set Novel 1), and another 8 novel items (Set Novel 2). To create the full stream, these were combined in the following manner: (a) Set P and Set Novel 1, (b) Set NP and Set Novel 2, (c) Set P and Set NP, (d) Set Novel 1 and Set Novel 2. Within each combination of stimuli, the identity of T1, T2, as well as the critical distractors was controlled in a crossed fashion.

Lag. Two lags separated the two targets in this design. T2 could appear at lag 3 or at lag 9. Each image appeared for 58 ms followed by a blank inter-stimulus interval of 35 ms. This means that T2 could appear within 279 or 837 ms of T1.

T1. Depending on stimulus set, T1 consisted of either a predictive, non-predictive, novel 1, or novel 2 item. T1 could appear at serial position 3, 4, 5, or 6 within the stream and these were used equally within each stimulus set.

T2. Similarly, T2 could be a predictive, non-predictive, novel 1, or novel 2 item. Items did not occur in the same condition twice.

Critical distractors. These were manipulated in the same way to previous experiments, and also consisted of either predictive, non-predictive, novel 1, or novel 2 items. Non-critical distractors were assigned in the same way as previous experiments.
2.5.2. Results

Exclusions. According to the exclusion criteria set out for previous experiments, 5 failed to reach an acceptable level of learning, and 7 failed to reach the criterion for T1 performance. These participants were replaced.

Learning. Accuracy was subjected to repeated measures ANOVA with Block (1 – 5) as a factor. This revealed that performance increased across blocks, \( F(4, 132) = 53.52, p < .001, \eta^2_p = .63 \), as is shown in Figure 2.16.

![Training accuracy for the learning phase of Experiment 5. Error bars show SEM.](image)

**Figure 2.16.** Training accuracy for the learning phase of Experiment 5. Error bars show SEM.

RSVP

Given that previous experiments in this thesis provide little evidence that the predictiveness of targets influences the selection of items in the AB, the primary conditions of interest here are ones that compare the effect of distractor identity. These are presented first. Given that target identity was crossed within each stimulus
set, and balanced across the experiment, the identity of T2 could not be predicted on the basis of T1 identity, or the identity of the distractors. Thus, the target analyses were restricted to confirming that any effect of familiarity did not vary according to predictiveness, as was observed in prior experiments.

**Effect of distractors.** The effect of distractor identity on both T1 and T2 identification is examined below.

**T1 accuracy.** First, in order to replicate the analysis of the distractor effect observed in Experiment 4, a 2 (Lag: 3 vs 9) × 2 (Set: Set P & N1 vs. Set NP & N2) × 2 (Distractor: novel vs. familiar) repeated measures ANOVA was conducted. This showed an effect of familiarity that did not rely on predictiveness, as shown in the upper panel of Figure 2.17. That is, there was a significant benefit in T1 detection when the critical distractors were familiar, $F(1, 31) = 16.73, p < .001, \eta^2_p = .35$. The remaining main effects as well as their interactions failed to reach significance, largest $F = 1.65, p = .21, \eta^2_p = .05$.

The effect of distractor was also investigated in the stimulus set that comprised only familiar items, that is, the P and NP cues. This analysed the trial types employed in Experiment 3. Repeated measures ANOVA with Lag (3 vs. 9) and Distractor (predictive vs. non-predictive) as factors revealed no significant main effects or interaction, largest $F = 1.50, p = .23, \eta^2_p = .05$. This effect is shown in Panel B of Figure 2.17.
Figure 2.17. The influence of distractor predictiveness on T1 accuracy for trials in which predictive and non-predictive items were intermixed with novel cues during RSVP for lag 3 and lag 9 (Panel A). Panel B shows T1 accuracy for trials in which predictive and non-predictive items were intermixed during the same RSVP streams. There was no influence of distractor predictiveness on T1 accuracy. Error bars show within-subject standard error (Cousineau, 2005).
The effects for conditions repeating those of Experiment 3 and Experiment 4 are illustrated in Figure 2.18. Following Experiment 4, conditional T2 accuracy was subjected to a 2 (Lag: 3 vs. 9) × 2 (Set: P & N1 vs. NP & N2) × 2 (Distractor: novel vs. familiar) repeated measures ANOVA. A significant main effect of Lag confirmed the presence of the AB, \( F(1, 31) = 195.6, p < .001, \eta^2_p = .86 \). Again, performance was better when distractors were familiar, \( F(1, 31) = 10.21, p = .003, \eta^2_p = .25 \), though this varied according to whether distractors were predictive or non-predictive, producing a significant Set × Distractor interaction, \( F(1, 31) = 4.68, p = .038, \eta^2_p = .13 \). Further, this interaction was different at lag 3 compared to lag 9, shown by a significant Lag × Set × Distractor interaction \( F(1, 31) = 4.71, p = .038, \eta^2_p = .13 \).

To detail the three-way interaction, the Set × Distractor interaction was examined at each lag. At lag 3, overall performance was better for familiar distractors, \( F(1, 31) = 6.49, p = .016, \eta^2_p = .17 \), though this varied according to Set, \( F(1, 31) = 8.2, p = .007, \eta^2_p = .21 \). Simple effects analysis confirmed that T2 accuracy did not vary between novel and predictive critical distractor conditions, \( F < 1 \), whereas performance was significantly better when distractors were non-predictive compared to when they were novel, \( F(1, 31) = 16.92, p < .001, \eta^2_p = .35 \). The influence of predictiveness was no longer evident at lag 9. Only the effect of distractor familiarity was significant, favouring familiar distractors, \( F(1, 31) = 6.12, p = .02, \eta^2_p = .17 \). Remaining main effects and interactions did not reach significance, largest \( F = 1.63, p = .21, \eta^2_p = .05 \).

To examine the results in the same manner as Experiment 3, repeated measures ANOVA with Lag (3 vs. 9) and Distractor (predictive vs. non-predictive) confirmed the AB with a significant main effect of Lag, \( F(1, 31) = 222.44, p < .001, \eta^2_p = .88 \). While performance was slightly better for non-predictive distractor
Figure 2.18. Panel A shows conditional T2 accuracy for distractor conditions in which familiar items and novel items were intermixed in the same RSVP stream. The influence of distractor predictiveness on T2 for trials in which predictive and non-predictive items were intermixed is shown in Panel B. Error bars represent within-subject standard error of the mean (Cousineau, 2005).
conditions, this did not reach statistical significance, $F(1, 31) = 2.98, p = .09, \eta^2_p = .08$. The interaction was not statistically significant, $F < 1$.

**Effect of T1.** The T1 analysis was restricted to the T1 identity manipulation. That is, T1 accuracy was analysed according to T1 identity within each set at each lag. Looking at the analysis for familiarity as per Experiment 4, a 2 (lag: 3 vs. 9) × 2 (stimulus set: P_N1 vs. NP_N2) × 2 (T1: novel vs. familiar) repeated measures ANOVA revealed a significant effect of T1 familiarity on T1 detection, benefitting novel targets, $F(1, 31) = 9.93, p = .004, \eta^2_p = .24$. Remaining main effects as well as their respective interactions failed to reach statistical significance, largest $F = 1.74, p = .20, \eta^2_p = .05$.

In order to analyse trials where predictive and non-predictive items were presented in the same stream, a 2 (Lag: 3 vs. 9) × 2 (T1: predictive vs. non-predictive) repeated measures ANOVA was used. This showed a marginal Lag × T1 interaction, $F(1, 31) = 4.13, p = .051, \eta^2_p = .18$, providing weak evidence that the effect of T1 predictiveness varied according to lag. The remaining main effects were not statistically significant, largest $F = 1.42, p = .24, \eta^2_p = .04$.

**Effects of T2.** Conditional T2 accuracy was pooled across T1 and distractor conditions so that T2 accuracy could be examined according to T2 identity only. These data were analysed by repeated measures ANOVA with Lag (3 vs. 9), Set (P_N1 vs. NP_N2), and T2 (novel vs. familiar) as factors. This showed a significant effect of lag, $F(1, 31) = 202.23, p < .001, \eta^2_p = .87$, but no remaining main effects or interactions, largest $F = 2.8, p = .10, \eta^2_p = .08$.

Performance was also examined within streams containing fully familiarised items. A 2 (Lag: 3 vs. 9) × 2 (T2: predictive vs. non-predictive) repeated measures
ANOVA revealed an effect of Lag, $F(1, 31) = 200.03, p < .001, \eta^2_p = .87$, but no further main effects or interactions, all $Fs < 1$.

**Novel baseline condition**

A secondary aim for including trials in which only novel items appeared was to provide an approximation of baseline performance against which the different distractor manipulations could be compared. This provides at least one source of evidence as to the direction of change in distractor processing. In order to reduce the number of comparisons, the critical distractor conditions were compared against novel streams for T2 detection only. Novel only conditions did not differ and were therefore collapsed. A difference score for the conditions of interest was calculated by subtracting this from predictive and non-predictive distractor conditions that contained mixed familiarity and fully familiarised trial types. This was done separately at each lag. These are shown in Figure 2.19. Paired-samples t-tests comparing each condition to baseline revealed that target detection was significantly above baseline at lag 3 for the non-predictive distractor condition when these cues were pitted against novel items in the same stream, $t(31) = 2.81, p = .009, \eta^2_p = .2$.

The trend at lag 9 was similar, $t(31) = 1.8, p = .08, \eta^2_p = .09$, though not statistically robust. No remaining conditions showed a significant difference from novel only performance, largest $t(31) = 1.67, p = .10, \eta^2_p = .08$. 
Figure 2.19. Difference scores for conditions in which critical distractors were predictive and non-predictive in RSVP streams consisting of either fully familiarised items or items that were novel and familiar intermixed within the same stream. Scores were calculated as a difference from conditions in which only novel stimuli were present. Error bars show within-subject SEM (Cousineau, 2005).

2.5.3. Discussion

The main purpose of this experiment was to provide a within-experiment comparison of the trial types that produced seemingly conflicting results across Experiment 3 and Experiment 4. The effect observed in Experiment 4 was replicated here. That is, facilitated target detection was seen when non-predictive distractors flanked targets compared to when targets where flanked by novel distractors. In contrast, the distractor effect seen in Experiment 3 (i.e., better target performance with predictive than non-predictive distractors) was not evident. Indeed, when streams consisted of fully familiarised items, there was actually a trend towards better target detection when distractors were non-predictive, at least relative to novel only
conditions. Thus, it appears that overall the reliable finding is a benefit in non-predictive distractor conditions when these items are pitted against novel cues in the same RSVP stream. These results will be considered further below.

2.6. General Discussion

The purpose of exploring learned predictiveness in combination with the attentional blink was to test the hypothesis that the bias reflects an automatic change in the selection priority of information. There was a fairly convincing failure to observe any influence of the predictive history of targets on visual selection. Across Experiment 2 – Experiment 5 the predictive history of target items had no bearing on the ability of participants to identify and report those stimuli. However, the prior predictiveness of stimuli did appear to influence target selection indirectly, at the level of distractor processing. While there was some discrepancy in the direction of this effect across experiments, the weight of evidence favours the conclusion that selection is facilitated when critical distractors are familiar, but non-predictive of a prior outcome.

In line with the aims of the study, this indeed provides a clear demonstration of the automaticity of changes in stimulus processing associated with predictive validity. Given that distractors were in no way useful for reporting the identity of the target, one would not expect to see the effects of predictiveness emerge exclusively in distractor conditions on the basis of controlled attention. This raises the question of how changes in distractor processing influence selection in the AB. It appears that such changes are associated with the non-predictive stimuli, such that selection priority of these distractors is altered in response to learning. When performance was compared against streams containing only novel items, the overall trend was that
detection in non-predictive distractor conditions was boosted above this approximation of baseline target identification.

One possibility is that learned predictiveness is facilitating the inhibition of task irrelevant information. This suggestion stems from the observation that changes in processing associated with predictiveness appear to be confined to the role played by distractors. In the design used here, targets are selected on the basis of a feature (colour), which is independent of predictiveness. In other words, prior predictiveness is task irrelevant during RSVP. According to the biased competition model of attention, a fundamental tenet of how attention operates relies on the mutual suppression of items competing for processing (Desimone & Duncan, 1995). Thus, targets and distractors are in a state of mutual inhibition until the system can resolve the point at which processing resources should be preferentially allocated. There is now much evidence showing that task set establishes a strong top-down bias influencing the outcome of this process (Chelazzi, Duncan, Miller, & Desimone, 1998; Downing, 2000; Han & Kim, 2009; Olivers, Meijer, & Theeuwes, 2006; Woodman & Luck, 2007). Thus, it may be that the top-down attentional set directed towards colour targets is sufficient to counteract any advantage that learnt biases might contribute towards competitive interactions. One could assume that in the absence of that potent source of control, information that is task irrelevant is free to influence competitive interactions for remaining items. If this is the case, it suggests that non-predictive distractors are more efficiently inhibited, reducing their ability to interfere with other stimuli.

It is interesting to note that related paradigms have shown dissociated effects of prior reward on target and distractor processing. Della Libera and Chelazzi (2009) first manipulated the value associated with target and distractor items in a visual selection task. Value could be high or low value monetary rewards for both targets
and distractors. In a subsequent, unrewarded test phase, all items appeared as targets and distractors. In their Experiment 1, for items appearing as targets at test, neither prior value or utility, that is, whether an item was previously a target or distractor, had an influence on performance. However, a robust effect was observed for distractor items. High value targets were subsequently harder to ignore as distractors, producing worse performance. In contrast, high value distractors were easier to ignore when again appearing as distractors and thus facilitated performance. Interestingly, by manipulating the nature of the test (Experiment 2) such that distractor suppression was less critical, they observed an influence of reward history on targets and not distractors, albeit as a less robust result statistically.

First, these findings provide another example in which the utility of ignoring an item transfers across tasks to bias attention for non-target items. That is, when top-down control is not directed towards an item, it is easier to discard that item if ignoring it in a past situation has facilitated learning or reward. Second, the finding that different test procedures produced diverging results suggests that one way to test the hypothesis outlined above, relating to why predictiveness effects are observed in distractor conditions only, would be to change the nature of the RSVP task. If the top-down bias towards colour is overriding any potential influence of predictiveness on stimulus competition, then changing the congruence between response selection in learning and RSVP may allow a direct effect of predictiveness on target identification to emerge.

Further, this issue relates to the question of why Raymond and O’Brien (2009) were able to find a clear effect of valence on target detection. Indeed, while our learning task investigated the influence of predictiveness on the AB as opposed to value associations per se, there is evidence to suggest that these two kinds of learning influence attention in similar ways (Le Pelley, Mitchell, & Johnson, 2013). What does
differ between the present experiments and Raymond and O’Brien’s study is the similarity of response selection across the learning and AB stages. In Raymond and O’Brien (2009), both the learning task and the AB response required face identification. In the procedure here, learning required object selection followed by selection based on colour. This suggests that an influence of learning on target detection may rely on a degree of congruence between the top-down requirements of the attentional task and the specific selection mechanisms engaged during prior learning.

A point worth noting is that the distractor effect observed here is most easily detected, if not isolated to, situations in which familiar items are pitted against novel cues. It appears that when predictive and non-predictive items compete within the same stream, the influence of predictiveness on distractor processing is less clear. One could argue that separating predictive and non-predictive items into separate streams allows for a cleaner comparison, given uncertainty as to the effect of predictiveness on activation and inhibition. If these processes are pitted against one another, an effect can be difficult to observe in the AB given a high degree of variability. One problem with this idea is that there was no evidence that predictive distractors differed from novel distractor conditions. In the absence of any such indication, it remains unclear whether predictive distractors are maintaining salience that is comparable to novel items, or whether there are changes in activation or inhibition to which the measures used here are not sensitive.

It is true that predictive and non-predictive items are in direct competition during learned predictiveness procedures in which the bias is consistently observed (e.g., Le Pelley & McLaren, 2003; Le Pelley et al., 2010; Le Pelley et al., 2011; Livesey et al., 2011). Unfortunately the role of novelty is yet to be systematically investigated in relation to learned predictiveness in more traditional two-phase
designs. While there is evidence that learning is still biased towards predictive items when these appear against novel items following the second stage of learning (Le Pelley, Suret, & Beesley, 2009), the question of how cue competition emerges during stage two when predictive and non-predictive items compete against novel cues at the outset remains open. This would provide a useful comparison to the results observed across conditions of mixed and consistent familiarity using the direct measure of attention used here. This provides the focus for experiments presented in Chapter 4.

One final methodological point relates to the number of comparisons required with the lengthy designs employed here. These far outnumber many AB experiments (e.g., Dux & Harris, 2007; Harris, Benito, & Dux, 2010; Livesey & Harris, 2011; Harris & Little, 2010; Maki, Frigen, & Paulson, 1997), and raise the possibility of a Type I error. Given that the benefit in target detection for non-predictive distractor conditions was replicated, overall this effect appears to be robust, if subtle. Nonetheless, it would be ideal to provide a replication making use of a design in which the number of conditions, and therefore the number of required statistical comparisons, is reduced.

In summary, this chapter provides evidence that at least one component of the learned predictiveness bias corresponds to an automatic change in stimulus selection. While effects of predictiveness on target selection could be interpreted as motivational, there is no incentive for participants to process distractors in the current task, suggesting that the influence of predictive history is influencing visual selection in a way that is independent of the intentions of the observer. Certainly, this does not suggest that automatic processes provide the sole basis for observing the bias. Indeed, many sources of evidence interact to ultimately direct attentional resources. Chapter 3 investigates how automaticity and controlled attention might interact during learned predictiveness.
In the previous chapter, the ability to detect cues as a function of their predictive history was measured under conditions in which the availability of controlled attention was disrupted. This provides a way of assessing automatic changes in the processing of stimuli. In this chapter, top-down attention is manipulated by issuing instructions about the causal structure of the task at the start of the second stage of learning. As highlighted in the introduction, this approach was introduced in the context of learned predictiveness by Mitchell et al. (2012), who instructed one group of participants (the continuity condition) that previously predictive cues would remain predictive, and the remaining group (the change condition) that previously predictive cues were no longer likely to be useful. The critical result was a complete reversal of the learned predictiveness effect in the change condition, that is, more was learnt about the relationship between previously non-predictive cues and their associated outcomes. Thus, learned predictiveness can come under complete top-down control, suggesting that inferred beliefs play a role in producing the bias.

Although the design of Mitchell et al.'s reversal experiment (2012) confirms that the effect of instructed attention is strong under certain conditions, it is not well-equipped to test whether automatic processes also contribute to the learned predictiveness bias. At test, Mitchell et al. (2012) used a learning score measure that combines cue-outcome recall and the extent to which that same cue is judged to be causal. The use of this measure in learned predictiveness experiments is certainly not uncommon, nor is the use of causal ratings in associative learning research more generally. One can make a defensible argument that the strength with which a cue is
associated with an outcome serves as an important source of evidence when making judgments about the causal relationship between them, especially when no further information is provided that might bear on this relationship. However, when a more compelling source of evidence, such as an explicit instruction, is present, there are strong reasons to question the link between the strength of learning and the strength of a causal judgment. Given that a set of cues was explicitly emphasized as important in each condition, it is not surprising that participants responded accordingly, providing higher causal ratings for cues instructed as likely to be causal. This might be viewed as nothing more than demand characteristics, or as a genuine form of rational causal attribution that does not necessarily reflect the strength of learning. For example, in the change condition, learning might still be weaker for W, a previously non-predictive cue. Thus, at test, the association between W and the outcome with which it was paired, O3 for example, would be weak. However, given the nature of the instruction, that is, that W is likely to be causal, participants might provide a higher rating in order to reflect the requirements of the task. By the same logic, a previously predictive cue such as A might be given a very low causal rating even if the participant remembers its associated outcome very well, because they have been instructed that the cue probably does not cause the effect.

Certainly, it is unsurprising that explicit instruction about causation affects causal reasoning. However, given the introduction of this instruction, one would assume the relationship between associative strength and causal inference to change. Le Pelley et al. (2013) reported a finding in which training and instruction showed opposing influences, such that attentional bias towards cues with a predictive history of signalling a high value outcome was observed. In contrast, under some situations instructions issued following training produced a bias towards cues signalling low value outcomes. This suggests that instruction can affect causal learning, though
importantly in a way that is dissociable from prior training. Thus, associative history and instructed inference may operate as distinct bases of causal judgment. Given that the major theories that offer an explanation of the learned predictiveness effect (e.g. Mackintosh, 1975) are theories of associative learning and not causal reasoning, a different measurement approach is needed when instructional manipulations are used, one that assesses the strength of associative retrieval and the strength of causal judgment separately.

The aim of the present set of experiments was to test whether these sources of bias could be distinguished within learned predictiveness in order to further gauge the relative contribution of automatic and controlled processes in producing the effect. To this end, instructional manipulations of learned predictiveness were explored in which cue-outcome recall and causal attribution were assessed separately at test. Thus, the test phase consisted of two components across all experiments. Cues were presented individually and rated on both a memory and causal inference question. The memory question probed the extent to which participants could accurately pair a given cue with its associated outcome, while the causal rating tested the extent to which a cue was believed to cause an allergic reaction, independent of the knowledge of the identity of that reaction. Given that instructional manipulations were administered throughout the study, one might expect a measure of causal inference to reflect that manipulation. That is, if you tell a participant that a specific food is likely to cause an allergic reaction, then their rating on a causal scale should reflect that instruction.

However, according to interpretations of learned predictiveness that rely on changes in processing according to associative strength, such as that offered by the Mackintosh (1975) model, the benefit for previously predictive cues in Phase II relies on the ability of those cues to become associated with specific outcomes. The recall measure, therefore, should provide an indication of that association. If a dissociation
between these measures can be demonstrated, such that a residual bias from Phase I training can be observed in recall despite a direct correspondence between instruction and causal ratings, this would implicate automatic attentional processes in producing the learned predictiveness bias. Such measures have been used successfully in related causal learning paradigms examining the blocking effect (e.g., Mitchell, Lovibond, & Gan, 2005; Mitchell, Lovibond, Minard, & Lavis, 2006), but have not previously been applied to learned predictiveness.

Experiment 6 attempted to replicate the finding by Mitchell et al. (2012) making use of the same instructional manipulation, albeit with a different cover scenario. To anticipate, a complete reversal was not observed, instead the results showed no difference across both test ratings according to predictiveness in the change condition. Thus learned predictiveness was abolished instead of reversed. Subsequent experiments introduced an orthogonal manipulation between Phase I predictiveness and instruction. If automatic biases are evident then one might expect to see differences in recall between previously predictive and non-predictive cues within the same instructional condition, despite causal ratings reflecting the instructional manipulation more directly.

3.1. Experiment 6

The aim of Experiment 6 was to replicate the instructed reversal of learned predictiveness reported by Mitchell et al. (2012). Participants completed the allergist causal learning task (Le Pelley & McLaren, 2003) according to the learned predictiveness training structure outlined in Table 3.1. In this task, participants were asked to observe the allergies of a fictitious patient in order to predict which foods were causing various allergic reactions. At the start of Phase II, participants were told
that they would be observing a new patient, suffering from different allergies. Further, one group of participants, those in the continuity condition, were told that it was likely that both patients were allergic to the same foods. Those in the change condition were instructed that the two patients likely suffered from allergies to different foods. In line with the findings of Mitchell et al. (2012), we anticipated that learning would be sensitive to the instructions issued at the start of Phase II. However, given the modifications to the test phase whereby associative memory and causal judgment were assessed independently at test, a different pattern of responding across these measures was expected. If the instructional manipulation indeed serves to control the extent to which participants reason about the causal nature of specific cues, then one would expect to see this inference reflected in the causal ratings. This measure, therefore, should show a complete reversal of learned predictiveness according to instruction. On the other hand, accuracy in the recall measure relies more specifically on the ability to identify the outcome with which a cue was paired. While this should still be sensitive to the instructions given at the start of Phase II, demonstrating an overall benefit in recall for cues instructed as causal, an automatic bias may be evident in better memory for cue-outcome relationships for previously predictive cues (A – D) compared to previously non-predictive cues (W – Z).

3.1.1. Method

Participants and apparatus

Forty-eight first year psychology students from the University of Sydney (27 female, mean age = 19) were tested individually for Experiment 6 in exchange for partial course credit. The experiment was conducted on Apple Mac Mini computers
attached to a 17-in. CRT monitor, running software programmed in PsychToolbox for Matlab (Brainard, 1997; Pelli, 1997).

**Stimuli**

Eight photographic pictures of food items, consisting of: coffee, fish, lemon, cheese, eggs, garlic, bread, and peanuts, were selected as stimuli in the experiment. These were randomly allocated for each participant to serve as predictive (A – D) and non-predictive (W – Z) cues. All cues measured $6.9^\circ \times 6.9^\circ$ of visual angle at a viewing distance of approximately 57 cm and were presented in pairs in the upper half of the screen separated by $9.5^\circ$. Four allergic reactions were randomly allocated to serve as the outcomes (O1 – O4). These were: headache, nausea, rash, and fever. Outcomes appeared in text format in the lower half of the screen.

**Procedure**

After being randomly allocated to either the continuity or change conditions, participants were informed that the task required them to take the role of an allergist in order to discover the allergens of a fictitious patient. They were told that on every trial they would observe two foods that the patient, Mr. X, had eaten. On being shown the foods, participants were required to predict which of two allergic reactions would occur. Each self-paced selection was immediately followed by feedback for the duration of 1 second stating whether the prediction was correct or incorrect, as well as providing the actual allergic reaction experienced.

Phase 1 consisted of the eight trial types shown in Table 1. Each of these was presented twice in each of the eight blocks of trials. Within each block, the order of trials was randomized, and the left and right position of the cues was counterbalanced.
At the start of Phase II, participants were told that they now had a new patient, Miss Y, and as before would be required to learn about which foods were causing which allergic reactions. They were then issued with one of the following sets of instructions:

Mr. X and Miss. Y [are/are not] allergic to the same foods. Therefore, it is highly [likely/unlikely] that the foods that controlled which reaction Mr. X suffered in the last phase will also influence which reactions Miss. Y suffers in this phase.

The instructions in italics differentiate between the two conditions, such that those in the continuity group were told that the two patients shared the same allergens, while those in the change group were told that the patients were allergic to different foods. Participants completed eight blocks of trials, with each block consisting of two of the four component discriminations shown in Table 3.1. Again, the order of trials was randomized and the location of cues counterbalanced.

Table 3.1
A basic learned predictiveness design (e.g., Le Pelley & McLaren, 2003).

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
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</thead>
<tbody>
<tr>
<td>AW – O1</td>
<td>AY – O3</td>
<td>AC</td>
</tr>
<tr>
<td>AX – O1</td>
<td>BZ – O4</td>
<td>WY</td>
</tr>
<tr>
<td>BW – O2</td>
<td>CW – O3</td>
<td>BD</td>
</tr>
<tr>
<td>BX – O2</td>
<td>DX – O4</td>
<td>XZ</td>
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<tr>
<td>CY – O2</td>
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</tr>
<tr>
<td>CZ – O2</td>
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<tr>
<td>DY – O1</td>
<td></td>
<td></td>
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<tr>
<td>DZ – O1</td>
<td></td>
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</tbody>
</table>

Note. Letters (A – D and W – Z) refer to individual food cues. O1 – O4 refer to four outcomes.
A test phase was administered immediately following Phase II. All cues were presented individually and in randomized order throughout this phase. Participants were first issued with the following set of instructions emphasizing the difference between the recall and causal ratings:

Every food that Miss Y ate (during the second phase of the experiment) was only ever followed by one type of allergic reaction. However, this does not necessarily mean that the food caused the allergic reaction…. Indicate which allergic reaction followed after the food was eaten by Miss Y. This is a bit like a memory test to see how well you recall which foods and which reactions went together…. [Then] indicate to what degree you think this food caused the allergic reaction in Miss Y.

On each trial, participants were first required to indicate whether the cue had been paired with outcome 3 or outcome 4. This was done by making a rating on a linear analogue scale, labeled “Definitely goes with [outcome 3]” on the left anchor, and “Definitely goes with [outcome 4]” on the right anchor. The midpoint of the scale was made explicit with the label “No idea”. Once this rating had been made, another scale appeared asking participants to rate whether that cue was causal. This scale was labeled “Definitely does not cause the reaction” on the left, and “Definitely does cause the reaction” on the right. Each rating scale yielded a value out of 100.

Finally, a manipulation check was included to ensure participants had encoded the instructions at the start of Phase II. Participants were presented with both sets of instructions and required to report which of those applied to their patient. There were no exclusions on the basis of this check, all participants having correctly indicated the set of instructions corresponding to the condition they had completed.
3.1.2. Results

Given that the critical predictions throughout this paper rely on sufficient acquisition of the initial component discriminations, an additional exclusion criterion was adopted whereby participants who failed to achieve 60% accuracy across the final quarter of the first phase were excluded from further analysis. This is similar with previous learned predictiveness protocols (e.g., Le Pelley & McLaren, 2003) and was applied to all three experiments. No participants were excluded on the basis of this criterion in Experiment 6.

Phase I. In order to assess initial acquisition, the accuracy of predictions was averaged across the eight compound trial types for each block. Participant accuracy increased steadily across training. A mixed-measures analysis of variance (ANOVA) with block (1 – 8) and condition (continuity vs. change) as factors revealed a significant main effect of block, $F(7, 322) = 65.37, p < .001, \eta_p^2 = .59$, but no significant effect of condition, and no block × group interaction, $Fs < 1$, providing no evidence of initial group differences. Phase I and Phase II learning curves are shown in Figure 3.1.

Phase II. Again, prediction accuracy was collapsed across trial types and increased steadily for both groups across Phase II. A mixed-measures ANOVA with training block (1 – 8) and group (continuity vs. change) as factors showed a significant effect of block, $F(7, 322) = 81.48, p < .001, \eta_p^2 = .64$. Accuracy for the change group was slightly better than for the continuity group, though this difference failed to reach conventional levels of significance, $F(1, 46) = 3.94, p = .053, \eta_p^2 = .08$, and there was no significant block × group interaction, $F(7, 322) = 1.88, p = .07, \eta_p^2 = .04$. 
Figure 3.1. Mean accuracy during training for Phase I (Panel A) and Phase II (Panel B) for the continuity and change conditions in Experiment 6. Error bars indicate SEM.

Memory ratings. For each cue, the memory rating was recoded as a score out of 100, where 100 reflects the most confident possible choice of the correct outcome, and 0 reflects the most confident possible choice of the wrong outcome. Thus 50 on this scale is representative of chance. Scores were averaged according to whether they were predictive (A – D) or non-predictive (W – Z) in Phase I. These are shown for the continuity and change conditions in the upper panel of Figure 3.2.

Scores were subjected to a mixed-measures ANOVA with group (continuity vs. change) and predictiveness (predictive vs. non-predictive) as factors. There was no main effect of group, $F < 1$, and the main effect of predictiveness failed to reach
Figure 3.2. Memory scores (Panel A) and Causal ratings (Panel B) for the continuity and change conditions for previously predictive and previously non-predictive cues in Experiment 6. Those in the continuity condition were instructed that previously predictive cues were likely to be relevant, while those in the change condition were instructed that previously non-predictive cues were likely to be relevant. Error bars represent standard error of the mean difference between predictive and non-predictive cues. The dotted line in Panel A represents chance.
conventional significance, $F(1, 46) = 3.49, p = .07, \eta^2_p = .07$, despite a slight benefit in memory for predictive cues. However, as suggested by the figure, this resulted from a significant group × predictiveness interaction, $F(1, 46) = 8.79, p = .004, \eta^2_p = .16$. This was explored using simple effects analysis, which revealed that memory scores for predictive cues were higher than non-predictive cues in the continuity condition, $F(1, 23) = 11.51, p = .002, \eta^2_p = .33$. The scores for the predictive and non-predictive cues did not differ significantly in the change condition, $F < 1$.

*Causal ratings.* Causal ratings were averaged according to Phase I predictiveness and are shown in the lower panel of Figure 3.2 for the continuity and change conditions. A mixed-measures ANOVA with group (continuity vs. change) and predictiveness (predictive vs. non-predictive) as factors showed a significant effect of predictiveness, $F(1, 46) = 6.22, p = .016, \eta^2_p = .12$, whereby predictive cues were given significantly higher causal ratings overall, as well as a significant group × predictiveness interaction, $F(1, 46) = 14.96, p < .001, \eta^2_p = .25$. The main effect of group did not reach significance, $F < 1$. The simple effects analysis investigating the interaction revealed that the pattern of causal ratings mirrored that of the memory ratings. That is, the difference in causal ratings between predictive and non-predictive cues was significant in the continuity condition, $F(1, 23) = 16.56, p < .001, \eta^2_p = .42$. This difference was not statistically significant in the change condition, $F(1, 23) = 1.21, p = .28, \eta^2_p = .05$.

3.1.3. Discussion

Experiment 6 provides a partial replication of Mitchell et al. (2012). Overall, a clear effect of instruction on learned predictiveness was observed on both associative
memory and causal ratings. In the continuity condition, recall was better for cues instructed as important, that is, previously predictive cues, compared to non-predictive cues. This was also observed in the causal ratings, whereby predictive cues were rated as more likely to be causal compared to non-predictive cues. However, learned predictiveness was abolished rather than reversed in the critical change condition. That is, there was no difference in recall between previously predictive and previously non-predictive cues, and no difference in the extent to which these cues were considered as causal of an allergic reaction when participants were told that non-predictive cues were informative for the second phase.

These results further validate the influence of voluntary processes on learned predictiveness. However, they provide an important extension to those of Mitchell et al. (2012) by demonstrating that the instructed reversal changes the strength of associative memory as well as the extent to which cues are judged as causal. A fairly significant caveat, however, is that our reversal was incomplete in the change condition. On the basis of the current design, this lack of complete reversal may be attributable to several factors. One possibility is that the instructional manipulation increases difficulty in the change condition. If more is learnt about the predictive cues in Phase I, these may still be needed for confirming the identity of cues that are important in Phase II. In order to know which cue is the allergen on any given trial, participants in this condition may use a strategy in which the known allergen from Phase I is identified and excluded. This is an additional process that is not necessary in the continuity condition. However, the trend towards higher accuracy in the change condition compared to the continuity condition in Phase II would argue against this interpretation. Alternatively, the results in the change condition might reflect competition between opposing inferential and automatic processes. If both of these processes are in operation, then an automatic attentional bias towards cues A – D
conflicts with the instructed explicit inference favouring cues W – Z. Although these two explanations are not necessarily mutually exclusive, the question remains as to why they might be evident here and not in the results of Mitchell et al. (2012).

It is worth noting that this discrepancy arises from a different pattern of results in the change condition across the two experiments. In the change condition of Mitchell et al. (2012), learning was better for previously non-predictive cues compared to previously predictive cues. In our results, there was no evidence for differences in learning across these two cue types. Given our null result in the critical change condition, one potentially informative analysis is a Bayes Factor (BF) calculation indicating whether the null hypothesis (no difference between predictive and non-predictive cues) is more likely than the alternative hypotheses given the data. Employing a method suggested by Rouder, Speckman, Sun, Morey and Iverson (2009), a BF was calculated for the t-test comparing cue types in our change condition. As Rouder et al. suggest, the JZS prior was used that assumes a Cauchy distribution of effect sizes for the alternative hypothesis (see Rouder et al., 2009 for further detail). Odds of 3 to 1 in favour of the alternative (BF = 0.33) or 3 to 1 in favour of the null (BF = 3) are widely considered to constitute moderate evidence in favour of one hypothesis over the other. Our analysis yielded a BF of 4.7, suggesting the null hypothesis is 4.7 times more likely than the alternative, providing moderate evidence favouring the conclusion that no instructed reversal of the learned predictiveness effect occurred.

Further, there was no differentiation between recall and causal ratings. This is somewhat surprising in light of related causal learning research showing that causal judgments and prediction judgments are sensitive to different kinds of information about the relationship between a cue and an outcome (Vadillo & Matute, 2007; Vadillo, Miller, & Matute, 2005). However, while this suggests that different
judgments at test are sensitive to different kinds of information about the relationship between a cue and an outcome, there are some important differences between these previous protocols and the one used here. For example, the prediction judgment employed by Vadillo et al. (2005) requires participants to predict the likelihood that an outcome will occur given a cue. While this may rely on recall to some degree, it requires a judgment regarding probability of a future event. This is distinct from our recall measure which requires a judgment about the prior co-occurrence of a cue and an outcome, independent of what might happen if the cue were presented again in the future.

Given the introduction of an explicit instruction about causality, whether a dissociation between our measure of recall and causal attribution is anticipated by an inferential account of learned predictiveness, such as that favored by Mitchell et al. (2012), is unclear. While a more detailed discussion of the limitations of such an explanation will be examined in more detail in the General Discussion of this chapter, given the absence of a complete reversal in either measure, it seems unlikely that learning is completely under the control of inferential reasoning. In order to assess stimulus associability independently of causal reasoning, a clear instruction is needed that separates knowledge of causality from Phase I bias. Since Experiment 6 established that a reversal instruction had a significant effect on the memory for cue-outcome pairings, Experiment 7 sought more definitive evidence of an automatic effect of Phase 1 predictive validity, that is, an effect that cannot be reasonably attributed to the instruction itself. The reversal design is not well-equipped to test this possibility because, as is evident in Experiment 6, even when resistance to reversal is observed it might be attributed to several mitigating factors, such as the reversal instruction just being inherently more complex.
3.2. Experiment 7

Experiment 7 was designed to further tease apart the involvement of inferential and automatic processes. This was achieved by introducing an orthogonal manipulation between Phase I predictiveness and instruction, the design of which is shown in Table 3.2. The first phase of training, in which participants learnt about the allergies of an initial patient, was identical to that of Experiment 6. Again, instructions about the causal status of foods as allergens for a new patient were issued before the start of the second phase. In Experiment 6 participants were either told that the same cues were likely to be relevant for the new patient, or that different cues were likely to be important, thus making use of a general instruction that relied on Phase I learning. In contrast, in Experiment 7 all participants were told that the new patient was allergic to a list of four foods, the names of which were made explicit. Thus, for example, they were told that Miss Y is only allergic to fish, coffee, lemon, and cheese. The critical manipulation here is that two of those foods were predictive in the first phase, corresponding to cues A and C, while the remaining two were non-predictive cues from Phase I, corresponding to cues X and Z. This means that in Experiment 7 there were four cues known to be causal, and four cues known to be non-causes. Of the known causes, two were predictive in Phase I (A and C), while two were non-predictive (X and Z). Of the cues now known to be safe, two were predictive in Phase I (B and D), and two were non-predictive in Phase I (W and Y). This orthogonal design therefore creates the condition in which an unambiguous instructional manipulation is present without removing the opportunity to observe an automatic influence of Phase I training, if indeed it is present.
Table 3.2

*Design of Experiment 7.*

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>AW – O1</td>
<td>AY – O3</td>
<td>A</td>
</tr>
<tr>
<td>AX – O1</td>
<td>BZ – O4</td>
<td>B</td>
</tr>
<tr>
<td>BW – O2</td>
<td>CW – O5</td>
<td>C</td>
</tr>
<tr>
<td>BX – O2</td>
<td>DX – O6</td>
<td>D</td>
</tr>
<tr>
<td>CY – O2</td>
<td></td>
<td>W</td>
</tr>
<tr>
<td>CZ – O2</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>DY – O1</td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>DZ – O1</td>
<td></td>
<td>Z</td>
</tr>
</tbody>
</table>

*Note.* Letters indicate individual cues. Underlined letters indicate cues instructed as informative for Phase II. O1 – O6 refer to the six outcomes.

If, as suggested by the findings of Experiment 6, controlled inferential processes are in operation, then a clear influence of instruction should be observed whereby causal ratings should reflect the instructions issued at the start of Phase II. Thus, by providing the exact identity of the allergens, participants should be able to accurately identify causal and non-causal cues on test. Again, it was anticipated that the memory ratings would show distinct results from those of the causal ratings. Given the explicit nature of the manipulation, recall should be better, overall, for cues instructed as causal. However, if an automatic attentional bias favouring predictive cues is also present, then a difference should be observed between instructed cues according to whether they were predictive (A and C) or non-predictive (X and Z) in the first phase. Given the advantage conferred by predictive utility, this predicts better recall of cue-outcome relationships for A and C relative to X and Z. Similarly, a bias would be expected in favour of previously predictive cues for cues known to be non-causal. Thus one might expect to observe better recall for B and D relative to W and
Y. This result, despite the introduction of knowledge equating the causality of predictive and non-predictive cues, would provide good evidence for an automatic residual bias favouring previously predictive information.

3.2.1. Method

*Participants and apparatus*

Twenty-six University of Sydney first year students (20 female, mean age = 19) participated in Experiment 7 for partial course credit. Apparatus remained as per Experiment 6.

*Stimuli*

Stimuli remained identical to those employed in Experiment 6 with the exception of the introduction of two additional allergic reactions in order to account for additional outcomes included within the design. These were coughing and sweating.

*Procedure*

Phase I training and instructions remained the same as in Experiment 6. Following Phase I, participants were told that they were now observing the allergies of a new patient. Further, they were issued with an instruction explicitly stating which foods were allergens for the new patient. That is, they were shown the names of four foods, corresponding to cues A, C, X, and Z and were informed that they would need to learn which of these corresponded to the various reactions that the patient was experiencing. Participants completed two blocks, each block consisting of two of the four trial types shown in Table 2. This change in procedure from Experiment 6, which
employed longer Phase II training, was motivated by an attempt to avoid ceiling performance in memory, given the small number of cues and the explicit nature of the instructional manipulation. On each trial, participants were now required to predict which of four allergic reactions would occur. By employing four outcomes this ensures that previously predictive known causes A and C were paired with different outcomes, as were previously non-predictive known causes, Z and X.

For each trial of the memory test, the four outcomes were displayed on screen as distinct alternatives beneath an individual cue. Participants were required to indicate which of these the cue had been paired with. Once that judgment had been completed, a rating scale appeared asking them to rate how confident they were in their response. The left anchor was labeled “Not at all confident”, and the right anchor labeled “Very confident”. This was followed by the appearance of the causal rating scale, which was identical to that used in Experiment 6.

Finally, the manipulation check required participants to report the instructed allergens of the second patient. Participants were excluded if they failed to correctly report all four allergens. Five participants were excluded on the basis of this check, as well as two participants who failed to reach the Phase I learning criterion, leaving 19 participants in the analysis. Remaining details of the method were as per Experiment 6.

3.2.2. Results

Phase I. In line with Experiment 6, prediction accuracy was averaged across the eight component discriminations and again increased steadily across training, as shown by Figure 3.3. A repeated-measures ANOVA showed a significant main effect of block on accuracy, $F(7, 126) = 26.35, p < .001, \eta_p^2 = .59$. 
Figure 3.3. Panel A shows mean accuracy for Phase I training for Experiment 7. Panel B shows accuracy for Phase II for compounds with an instructed component that was previously predictive (congruent), and an instructed component that was previously non-predictive (incongruent). Each block represents two presentations of the compound trials shown in Table 3.2. Error bars indicate standard error of the mean.

Phase II. Accuracy for Phase II was averaged across compounds according to whether it contained an instructed component that was previously predictive (i.e. congruent: AY/CW) or an instructed component that was previously non-predictive
(i.e. incongruent: BZ/DX). This is shown in Figure 3.3. A repeated-measures ANOVA with block (1–2) and compound (congruent vs. incongruent) showed a significant effect of block on accuracy, $F(1, 18) = 39.29, p < .001, \eta^2_p = .69$, and a main effect of compound, $F(1, 18) = 7.25, p = .015, \eta^2_p = .29$, such that accuracy was significantly higher for congruent compounds. The block $\times$ compound interaction failed to reach significance, $F < 1$.

Memory ratings. Accuracy for cue-outcome pairings was averaged according to whether cues were predictive or non-predictive in the first phase. This is shown for cues instructed as causal and those known to be non-causal in Figure 3.4. One advantage of having four outcomes at test is that differences in accuracy are potentially easier to detect, allowing use of outcome accuracy as a measure (without conflating accuracy and confidence, as is the case with most learning scores in this literature). These were analysed by means of a predictiveness (predictive vs. non-predictive) $\times$ instruction (causal vs. non-causal) repeated-measures ANOVA. There was a significant main effect of instruction, $F(1, 18) = 18.28, p < .001, \eta^2_p = .5$. While there was no main effect of predictiveness, $F < 1$, predictiveness and instruction showed a significant interaction $F(1, 18) = 10.6, p = .004, \eta^2_p = .37$, such that accuracy was higher for predictive than for non-predictive cues instructed as causal, $F(1, 18) = 5.7, p = .028, \eta^2_p = .24$, while for known non causes accuracy for non-predictive cues was higher relative to predictive cues, $F(1, 18) = 6.4, p = .02, \eta^2_p = .26$, as revealed by simple effects analysis.\(^3\)

\(^3\) For consistency with the other experiments, it is worth noting that when the same analysis was conducted on a measure that combined recall accuracy with confidence scores, it showed a similar pattern of results, that is, a robust interaction between Phase I predictiveness and instruction.
Figure 3.4. Accuracy for cue-outcome pairings (Panel A) and causal ratings (Panel B) averaged according to predictiveness, for known causes and known non-causes for Experiment 7. Error bars represent standard error of the mean difference between predictive and non-predictive cues. The dotted line in Panel A represents chance.
Causal ratings. Again, causal ratings were averaged according to Phase I predictiveness and instruction, as shown in Figure 3.4. A repeated-measures ANOVA with predictiveness (predictive vs. non-predictive) and instruction (causal vs. non-causal) as factors showed a significant effect of instruction, $F(1, 18) = 22.03, p < .001, \eta^2_p = .55$. Cues instructed as causal were given higher causal ratings at test. There was no main effect of predictiveness, and no instruction $\times$ predictiveness interaction, $F$s $< 1$.

3.2.3. Discussion

The causal inference and cued recall tests in Experiment 7 clearly diverge. Causal ratings closely followed the instructions issued at the start of Phase II: Regardless of the predictive status of cues in the first phase, cues instructed as allergens were attributed as causal at test, while those known to be safe were given low causal ratings. Recall of cue-outcome pairings, however, showed differences according to predictiveness within each of the instructional conditions. Consistent with predictions, the learned predictiveness effect was still evident amongst cues known to be allergenic. That is, more was learned about the previously predictive cues compared to previously non-predictive cues, despite the explicit knowledge that both sets of cues were allergens.

Surprisingly, the opposite pattern emerged for cues that were known non-causes, whereby recall was better for cues that were non-predictive in Phase I. This reversal raises the question of how Phase I training influences further learning under conditions of instructional manipulation. While the result for known causes suggests a role for automatic bias, this does not appear to combine with inferential reasoning in an additive manner to direct learning.
One limitation for providing a coherent account of the observed reversal is an asymmetry in outcome equivalence for predictive and non-predictive components across the two phases. For example, given that predictive cues A and C were paired with distinct outcomes during Phase I, O1 and O2 respectively, one way in which learning about the cue-outcome relationships may have been facilitated for these cues in Phase II is if participants equate O1 with O3, and O2 with O5, that is, the outcomes with which A and C are subsequently paired. A more detailed analysis of the acquisition results will be considered in the General Discussion, but it is worth noting that acquisition was indeed better for compounds in which outcome equivalence might facilitate learning (i.e., AY & CW). However, given that these are also the compounds in which the instructed component was previously predictive, there is no way to distinguish the effects of outcome equivalence from Phase I predictiveness on learning. If the results observed in Experiment 7 can be replicated under conditions in which no outcome equivalence is present for predictive cues across the two phases of learning, this would provide clearer evidence for an interaction between automatic and inferential processes in learned predictiveness under conditions of instructional manipulation.

3.3. Experiment 8

In Experiment 8 an extended design was employed, closely following that of Experiment 7. This is shown in Table 3.3. As per previous experiments, the initial phase of training followed the learned predictiveness procedure, though it employed additional cues that served to double the number of Phase I trial types. Again, at the start of Phase II, participants were informed which cues would be allergic for the new patient. This instruction was issued at the category level whereby it was made
explicit that the new patient was allergic to (and only allergic to) a specific category of foods. Therefore, all food cues in this experiment came from one of two categories. Half of the cues, those corresponding to A – D as well as W – Z, belonged to one category that was instructed as allergenic. The remaining cues, those corresponding to E – H and S – V, belonged to the “safe” category, thus each compound consisted of one component from either category. Given that half of the cues in each category were predictive in Phase I, and the remaining half non-predictive, this manipulation creates the same conditions as those in Experiment 7. If the results observed in Experiment 7 are robust, then recall for previously predictive cues should be better than non-predictive cues in the instructed category. For the category known to be safe, the reverse is expected whereby recall should be better for non-predictive compared to predictive cues. This measure should no longer be sensitive to differences in outcome equivalence across the two phases of learning, which are negated in the extended design. For example, cues A and D are predictive of O1 during the first phase. These same cues are equally likely to predict O3 and O4 respectively in Phase II. Thus any strategy employed by participants to equate outcomes across training phases would yield incorrect predictions on half of the trials. Causal ratings are again expected to reflect Phase II instructions, showing high causal attribution to the category of foods instructed as allergenic, and low ratings for foods in the category known to be safe.
3.3.1 Method

Participants and apparatus

Twenty-seven first year students enrolled at the University of Sydney participated in the experiment (17 female, mean age = 20). Apparatus was the same as previous experiments.

Stimuli

Food stimuli for this experiment were drawn from the two categories of “fruit and vegetables”, and “animal products such as meat, poultry, and dairy”. The eight fruit and vegetable category items consisted of: lemon, apple, avocado, peas, banana, mushroom, strawberries, and broccoli. Items from the meat and animal products category included: fish, milk, eggs, steak, cheese, bacon, chicken, and yoghurt. The four outcomes, as well as remaining details of the presentation parameters, were as per Experiment 6.

Procedure

The procedure for the initial phase of training was identical to that of the previous two experiments, though with an additional number of trial types in each block given the extended design. Following this, participants were again informed that they would be observing a new patient. They were told that this patient was only allergic to a specific category of food, corresponding to either fruit and vegetables, or animal products such as meat, poultry, and dairy. The eight compounds in this phase appeared twice per block, with participants completing two blocks each. The allocation of categories as allergens was counterbalanced across participants.
Aside from the additional cues presented at test, corresponding to each of the 16 cues included in the design, the structure of the test phase was identical to that of Experiment 6. This was followed by a manipulation check asking participants to report the category of food that the second patient was allergic to. There were no exclusions on the basis of this check, as all participants correctly reported the allergenic category. Three participants were excluded on the basis of the Phase I learning criterion, leaving twenty-four participants in the final analysis.

Table 3.3

*Design of Experiment 8.*

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>AS – O1</td>
<td>AU – O3</td>
<td>A</td>
</tr>
<tr>
<td>AT – O1</td>
<td>BV – O4</td>
<td>B</td>
</tr>
<tr>
<td>BS – O2</td>
<td>CS – O3</td>
<td>C</td>
</tr>
<tr>
<td>BT – O2</td>
<td>DT – O4</td>
<td>E</td>
</tr>
<tr>
<td>CU – O2</td>
<td>EY – O3</td>
<td>F</td>
</tr>
<tr>
<td>CV – O2</td>
<td>FZ – O4</td>
<td>G</td>
</tr>
<tr>
<td>DU – O1</td>
<td>GW – O3</td>
<td>H</td>
</tr>
<tr>
<td>DV – O1</td>
<td>HX – O4</td>
<td>S</td>
</tr>
<tr>
<td>EW – O1</td>
<td></td>
<td>T</td>
</tr>
<tr>
<td>EX – O1</td>
<td></td>
<td>U</td>
</tr>
<tr>
<td>FW – O2</td>
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<td>FX – O2</td>
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<td>W</td>
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<td>GZ – O2</td>
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<td>Y</td>
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<tr>
<td>HY – O1</td>
<td></td>
<td>Z</td>
</tr>
<tr>
<td>HZ – O1</td>
<td></td>
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</tr>
</tbody>
</table>

*Note.* Letters refer to individual food cues. Underlined letters indicate cues instructed as causal for Phase II. O1 – O4 refer to the four outcomes in this experiment.
3.3.2 Results

Phase I. Initial acquisition proceeded as expected, with a repeated-measures ANOVA showing a significant effect of block, $F(7, 161) = 50.57, p < .01, \eta^2_p = .69$.

Phase II. Figure 3.5 shows accuracy for Phase I and Phase II, averaged across compounds according to whether they contained an instructed component that was previously predictive (congruent) or previously non-predictive (incongruent). A repeated-measures ANOVA with block (1 – 2) and compound (congruent vs. incongruent) showed a significant effect of block, $F(1, 23) = 29.3, p < .001, \eta^2_p = .56$. Acquisition for congruent compounds was slightly better than incongruent compounds, though this difference did not reach a conventional level of significance, $F(1, 23) = 3.42, p = .07, \eta^2_p = .13$, and there was no significant block × compound interaction, $F < 1$. 
Figure 3.5. Panel A shows mean accuracy for Phase I training for Experiment 8. Panel B shows accuracy for Phase II for compounds with an instructed component that was previously predictive (congruent), and an instructed component that was previously non-predictive (incongruent). Each block represents two presentations of the compound trials shown in Table 3. Error bars represent SEM.

Memory test. Memory scores for each cue were calculated as per Experiment 6 and averaged according to whether they were predictive (A – H) or non-predictive (S – Z)
in the first phase. These are shown in Figure 3.6. for cues instructed as causal, and those known to be non-causal. Scores were analyzed by way of a repeated-measures ANOVA with predictiveness (predictive vs. non-predictive) and instruction (causal vs. non-causal) as factors. This revealed a main effect of predictiveness, $F(1, 23) = 4.81$, $p = .039$, $\eta^2_p = .17$, a main effect of instruction, $F(1, 23) = 32.62$, $p < .001$, $\eta^2_p = .59$, as well as a significant predictiveness $\times$ instruction interaction, $F(1, 23) = 9.16$, $p = .006$, $\eta^2_p = .29$. A simple effects analysis investigating the interaction revealed that for instructed causes, memory scores were significantly higher for previously predictive compared to previously non-predictive cues, $F(1, 23) = 8.36$, $p = .008$, $\eta^2_p = .27$. For known non-causes, the benefit for non-predictive cues was marginally higher compared to predictive cues, showing a similar, though less robust, trend to that observed in Experiment 7, $F(1, 23) = 3.55$, $p = .07$, $\eta^2_p = .13$.

Causal ratings. Causal ratings, shown in Figure 3.6, were similarly analysed by repeated-measures ANOVA, showing a significant main effect of predictiveness, $F(1, 23) = 5.27$, $p = .03$, $\eta^2_p = .19$, as well as a main effect of instruction, $F(1, 23) = 64.52$, $p < .001$, $\eta^2_p = .74$. The predictiveness $\times$ instruction interaction did not reach significance, $F(1, 23) = 1.11$, $p = .30$, $\eta^2_p = .05$. 
Figure 3.6. Memory scores (Panel A) and causal ratings (Panel B) averaged according to predictiveness, for known causes and known non-causes for Experiment 8. Error bars represent standard error of the mean difference between predictive and non-predictive cues. The dotted line in Panel A represents chance.
3.3.3 Discussion

Overall, the results of Experiment 8 provide a replication of those seen in Experiment 7, under conditions in which facilitation through outcome equivalence is impossible. For cues instructed as causal, better retention of the specific cue-outcome relationships was observed for predictive compared to non-predictive cues. The difference between predictive and non-predictive cues in the safe category did not reach conventional levels of statistical significance by a two-tailed test ($p = .07$).

Nevertheless, the ordinal pattern of means was the same as Experiment 7 and, given the robust interaction between predictiveness and instruction, it is very clear that prior predictiveness does not have the same effect on learning about known non-causes as it does on learning about known causes. Again, causal ratings showed little evidence of an interaction between Phase I training and instruction, closely reflecting the instructional manipulation. Further, acquisition followed a similar, though less statistically robust ($p = .07$), pattern to that observed in Experiment 7, such that learning was better for compounds that contained an instructed component that was previously predictive.

This pattern of results suggests a reliable persistence of the influence of Phase I training in learned predictiveness over and above the influence of instructional manipulations. Although making use of a categorical instruction appears to have improved memorability of the instruction following Phase II, this may have allowed for differences in generalization between cues across Phase I and Phase II. As cues from the same category are likely to be more similar to one another compared to cues from the alternative category, the associability of an item from Phase I might generalize more readily to items of the same category in Phase II. However, this is highly unlikely to have a confounding influence on the results. Across both stages of learning, each compound consisted of one component from either category. However,
each category consisted of cues that were predictive in Phase I, and cues that were non-predictive in Phase I. Take for example the instructed components A and Y, from compounds AU and EY respectively. Both A and Y are taken from the same category, yet one was predictive in Phase I, that is A, and one was non-predictive in Phase I, that is Y. If there was greater generalization between members of the same category, this would affect both A and Y. This means that any potential generalization of associability within a category is equated for predictive and non-predictive components.

3.4 General Discussion

Three experiments investigated the effect of instructional manipulations on associative memory and causal reasoning in learned predictiveness. In all experiments, the instructional manipulation clearly influenced recall of cue-outcome associations. Overall, this was also the case for causal ratings. While these closely followed the pattern of results observed for cue-outcome recall in Experiment 6, causal judgments in Experiments 7 and 8 diverged from our measure of associative memory. In line with the findings of Mitchell et al. (2012), Experiment 6 confirmed that reversal instructions influence the learned predictiveness bias, and provided an important extension by demonstrating that this influence is not isolated to causal reasoning, but also includes associative memory. In the continuity condition, both recall and causal attribution were higher for predictive cues compared to non-predictive cues. However, the reversal of the learned predictiveness effect in the change condition was incomplete as no difference between predictive and non-predictive cues was observed across both measures. It is unclear why the instructed reversal of learned predictiveness was not found here while Mitchell et al. (2012) showed strong
evidence for a reversal. One difference between the two protocols is the conceptual scenario employed. In the study of Mitchell et al. (2012), fictitious seeds, acting as the predictive and non-predictive cues are cross-pollinated in order to grow various shapes of tree, the outcomes. This scenario potentially favours a more categorical inferential process. Given the nature of the causal relationship between seeds and trees, that is, that only one seed will grow a specific tree, this aspect of the design raises the possibility that a complete reversal was facilitated based on conceptual aspects of the scenario in addition to the manipulation of interest. Specifically, if each outcome is most likely attributable to only one of the compound components during Phase II and not the other, this means that at test, ratings are more likely to reflect a mutually exclusive causal structure across those same components. However, whether this conceptual component would be sufficient to strengthen the magnitude of the reversal remains an empirical question.

Subsequent experiments provided clear evidence of an automatic bias in Phase II recall according to Phase I training. Making use of an orthogonal manipulation between Phase I predictiveness and instructions issued at the item (Experiment 7), and categorical (Experiment 8) level, a robust benefit in recall for previously predictive compared to previously non-predictive cues was observed for cues known to be allergenic. Surprisingly, this reversed for known non-causes as recall was higher for non-predictive cues. This reversal raises the question of how Phase I training influences further learning under conditions of instructional manipulation. While the result for known causes suggests a role for automatic bias, this does not appear to combine with inferential reasoning in an additive manner to direct learning.

One explanation for this result is that instead of directing attention in a rigid fashion, predictive utility enhances cognitive control. That is, previously predictive cues are both easier to attend and ignore, depending on task requirements. According
to this explanation, learning is facilitated for predictive known causes and suppressed for predictive cues known to be non-causal.

An alternative explanation can be made on the assumption that differences in congruence between instruction and predictive history is crucial for the rate of learning about the Phase II compounds. In both Experiments 7 and 8, some Phase II compounds can be seen to possess congruence between instruction and Phase I predictive utility. For example, in Experiment 7, for compounds AY and CW, predictive cues in Phase I are instructed as causal for Phase II and non-predictive cues in Phase I are instructed as non-causes in Phase II and thus remain irrelevant. In contrast, a switch in the utility of the cues occurs for the Phase II compounds BZ and DX in which cues that are non-predictive in Phase I are instructed as causal in Phase II, and cues that were predictive in Phase I are known to subsequently be non-causal. The incongruence between Phases of the utility of the cues in the latter set of compounds may produce a cost to learning about all stimuli present on those trials.

Likewise, according to this explanation, when the predictiveness of the cues from Phase I and the instructions about causation in Phase II are congruent, learning about all presented cues is achieved relatively easily. This raises the possibility that less is learned in general about Phase II compounds in which participants have to attend to the previously non-predictive cue and ignore the previously predictive cue.

The rate of learning in Phase II for congruent trial types appeared to be somewhat higher than for the incongruent trials in both Experiments 7 and 8. Prediction accuracy was higher for congruent trials in Experiment 7 and trended in the same direction in Experiment 8. This result is consistent with there being interference to the general rate of learning on incongruent trials. However, it is worth noting that this result is also amenable to an explanation based on a change in cognitive control. If previously predictive cues afford greater cognitive control then each would serve as
a highly attended and therefore associable cue on congruent trials or an efficiently ignored cue on incongruent trials. If cognitive control of the previously non-predictive cues was poorer, and thus did not compensate fully for the attention or suppression of the predictive cue, then net performance would remain higher on congruent trials than on incongruent trials.

Finally, a third alternative, based on the formation of within-compound associations during Phase II, might explain the observed interaction between Phase I training and instruction. During Phase II, there were compounds in which the instructed component was predictive in Phase I, such as AY, and compounds in which the instructed component was non-predictive in Phase I, such as BZ. If Phase I predictiveness increases the strength of the association for instructed components, then the predictive, instructed cue A would be expected to form a strong association with O3 on trials in which AY is present. In contrast, the non-predictive instructed component Z would be expected to form a weaker association with O4 on trials in which BZ is present. The formation of within-compound associations between A and Y therefore predicts that learning about Y is benefitted indirectly by virtue of a Y-A-O3 chain. Alternatively, the association between B and Z predicts that learning about B receives less benefit by virtue of the B-Z-O4 chain. This leads to the prediction that learning for A should be greater than learning for Z, but also that learning for B should be less than learning for Y, which is the pattern of results observed. Indeed, evidence consistent with the formation of within-compound associations during causal learning has previously been reported (Dickinson & Burke, 1996). While retrieval-based associative models can largely explain these effects without appealing to the presence of within-compound associations (e.g., Le Pelley & McLaren, 2001), whether these are necessary in explaining the present data will depend on further defining the nature of the interaction.
Regardless of why this interaction between predictive history and instruction occurs, an interesting feature of the results is that the outcome recall measures clearly produced a different set of results to the causal ratings across both experiments. The causal ratings closely followed the instructions issued at the start of Phase II.

Theorists who claim a link between associative learning and causal inference (e.g., McLaren, Green, & Mackintosh, 1994) usually assume that the strength with which a cue retrieves an associated outcome serves as one potential source of evidence on which a causal judgment might be made. This does not preclude the possibility that causal judgments might be made on the basis of alternative sources of evidence, such as the product of explicit inferences, if the individual is given sufficient motivation to do so. Direct instructions do exactly this. Importantly, our results demonstrate that despite the instructions having a profound effect on causal ratings, and a strong effect on memory-based judgments, there was still clear evidence that Phase I learning impacted on associative memory in a way that is not explained by the instruction. It should be noted that there was also some evidence for an influence of predictiveness on causal attribution in Experiment 8. This suggests that causal judgments, though reflecting explicit inference, may nonetheless be influenced by the strength of associations in some situations.

One important point to consider here, however, relates to the predictions generated by an inferential account of associative learning. In their investigation of memory and causal reasoning in the context of blocking, Mitchell et al. (2006) have argued that an inferential account predicts a dissociation between measures of associative memory and causal reasoning. In the case of blocking, a novel (blocked) cue appears alongside a cue previously established as causal. An inferential account makes the assumption that the relationship between the blocked cue and the outcome with which it is paired is indeed encoded. The memory of that relationship then serves
as a means to judge that same cue as non-causal. Thus, memory ratings for blocked cues should be comparable to cues previously established as causal. On the other hand, causal ratings for blocked cues would be low, while causal ratings for previously causal cues should be high. If this line of reasoning is extended to a more traditional demonstration of learned predictiveness, a strong inferential position might predict no evidence of learned predictiveness in associative memory, rather observing the bias in causal attribution. That is, one might expect to observe no difference in associative memory between predictive and non-predictive cues, while causal attribution would be high for predictive cues and low for non-predictive cues.

However, this line of reasoning becomes less clear when an instruction is introduced into the procedure. Given that the instructions are issued at the start of Phase II, participants have access to the explicit inference regarding causality while they are engaged in learning, and therefore have little reason to encode information about cues known to be non-causal. For example, if participants know that A is causal and that Y is non-causal, when encountering these cues during training there is little motivation to remember the relationship between Y and the outcome with which it is paired. Thus, whether an inferential account would predict the same dissociation when attention is purposefully biased via explicit instruction is unclear. This raises the question of whether an inferential account of associative learning is specified in enough detail in order to generate clear predictions in situations where automatic biases may be interacting with higher order inferences.

Certainly, it remains unclear as to whether these are best thought of as distinct ways in which information is processed, or whether automatic associations form the underlying structure from which inferences emerge. In either case, once an inference is present it is unlikely to exhibit the same properties as a simple association. The fact that the effects of instruction and predictive history are dissociable but seemingly
interactive seems to support this. Given that measures of causal learning were seemingly more sensitive to instruction than measures of associative memory, this raises the question of whether different kinds of learning are equivalent in their sensitivity to inferential processes. It may be that learning about causal value is under greater control of inferential processing. Whether instructions would manipulate predictive learning for example, independently of causal value, remains to be seen.

Overall, the present findings are consistent with an increasing collection of results from related paradigms demonstrating that predictiveness influences stimulus selection in tasks that are thought to reflect non-strategic processes. For example, it has been shown that previously predictive cues facilitate learning of subsequent spatial motor response sequences (Beesley & Le Pelley, 2010), capture spatial attention (Le Pelley, Vadillo, & Luque, 2013), and attenuate the attentional blink (Livesey, Harris, & Harris, 2009). While this provides evidence for an automatic attentional bias, it should be noted that our observed reversal in recall does not conform to the proposed relationship between associability and predictive history. Accordingly, there are a number of studies suggesting that the learned predictiveness effect does not operate via the competitive associative algorithms of attentional change described by Mackintosh (1975; Le Pelley, 2004; Pearce & Mackintosh, 2010). For instance, Le Pelley et al. (2010b) found that competition between cues in compound was not necessary for learned predictiveness to occur, and Livesey et al. (2011) found no evidence that direct (i.e. within-trial) comparison between predictive and non-predictive cues affected the magnitude of learned predictiveness. The current study demonstrates another way in which the automatic allocation of attention appears to behave differently from model predictions. Although there appears to be a relatively automatic influence of the predictive history of the cues, that influence only matches the predictions of associative learning theories for cues that are deliberately
attended.

So far, the interpretation has assumed that associability influences the strength of learning, such that cues with high $\alpha$ following Phase I have a direct benefit in the formation of subsequent associations. However, Mackintosh (1975) did raise the possibility that associability may influence performance as well as learning. Indeed, some models describe cue competition effects largely in terms of performance effects on test rather than acquisition deficits (Stout & Miller, 2007). Accordingly, Le Pelley, Suret, and Beesley (2009) have noted that a performance-based explanation of learned predictiveness would allow for equivalent gains in associative strength for predictive and non-predictive cues across Phase II. The observed bias is therefore a function of increased responding to cues with high $\alpha$ at test, that is, those that were predictive in Phase I. Indeed, there is some evidence to suggest that predictiveness impacts performance as well as learning (Le Pelley et al., 2009). Given that evidence of differences in acquisition was found in Experiments 2 and 3, it seems unlikely that our results would be amenable to explanations of learned predictiveness that rely exclusively on performance at test to explain differences in learning scores. However, it is possible that the effects reported here reflect a combination of changes in performance as well as learning.

In conclusion, it would appear that automatic biases in learning persist under conditions of explicit instructional manipulation of the learned predictiveness effect. Further, these results suggest a distinct effect of associative memory and causal reasoning in producing the bias. However, these processes do not appear to influence learning in an additive manner. Rather, it seems that reasoning and associative memory combine in ways that are not directly anticipated on the basis of attentional models of associative learning (e.g., Mackintosh, 1975). As stated at the end of
Chapter 2, a useful comparison for the effects observed when selection was measured during the AB in combination with manipulations of novelty would be an understanding of how learned predictiveness proceeds in combination with novelty under more traditional procedures demonstrating the effect. This was the aim of Chapter 4, which also allows a test of various explanations offered for the effects observed above.
Chapter 4: Learned predictiveness and novelty

In Chapter 2, the influence of predictiveness on stimulus selection during the attentional blink was assessed, both when predictive and non-predictive items were in direct competition with one another (Experiment 2 – Experiment 3, and Experiment 5), as well as when predictive and non-predictive cues were independently contrasted with novel items (Experiment 4 – Experiment 5). Chapter 3 investigated the nature of the direct competition between predictive and non-predictive cues under conditions where controlled attention was manipulated via instructions. This chapter extends the findings reported in Chapter 3, to include manipulations of familiarity in which predictive and non-predictive stimuli compete against novel items when volitional attention is manipulated. Thus, the question of interest in this study is how novelty influences the expression of learned predictiveness when instructions are issued about the causal nature of the cues. This provides a useful comparison of the effects of novelty under the various manipulations of cognitive control employed thus far.

While the effect of novelty on learned predictiveness has yet to be systematically investigated, there is some indication as to how predictiveness may operate in situations where predictive and non-predictive components appear separately during training. For example, Le Pelley, Turnbull, Reimers, and Knipe (2010) demonstrated that the benefit for previously predictive cues holds when that prior predictiveness is established for individual cues via single cue – outcome associations. Thus the benefit in learning for predictive cues emerges even when predictive and non-predictive components are not directly competing on a single learning trial. Similarly, Livesey et al. (2011) showed that even when participants are learning about the relationship between compound trials and an outcome, the direct comparison of predictive and non-predictive components within a trial is not
necessary to produce the effect. Rather, there is little evidence that the relative predictiveness of cues provides any additional contribution towards the bias beyond the effects of the absolute predictiveness of a single component. This evidence suggests that changes in stimulus selection during learned predictiveness operate at the level of individual cues, such that subsequent cue competition in favour of predictive components does not rely on the direct within-trial comparison of predictive and non-predictive components.

In line with this, in their Experiment 4, Le Pelley, Suret, and Beesley (2009) investigated a learned predictiveness task in which the second stage of learning incorporated two different sets of associations, experienced sequentially. First, participants completed traditional trial types comprising a combination of previously predictive and previously non-predictive cues. Following the acquisition of these cue–outcome pairings, new compounds were introduced, without any obvious break in training, that continued to predict the same outcomes, within the same context. Both predictive and non-predictive cues were paired with novel stimuli. Thus, predictive cue A was paired with novel cue a to form the compound Aa, and non-predictive cue W was paired with the novel cue w to create the compound Ww. When examining the learning for novel cues, they observed poorer learning for novel cues appearing in compound with predictive cues, such as cue a, compared to novel cues appearing alongside non-predictive cues, such as cue w. That is, predictive cues were more likely than non-predictive cues to block learning about the relationship between the novel cue and an already predicted outcome.

Thus, the increased selection priority of predictive cues appears to hold against novel items, at least under conditions in which novelty does little to signal the appearance of new outcomes. This provides an interesting contrast to demonstrations in which attention is automatically directed towards novel stimuli during tasks in
which the influence of learning is less explicit. For example, in visual search, when overall familiarity is manipulated across trials, novel stimuli automatically capture attention amongst familiar cues (Johnston, Hawley, Plewe, Elliot, & DeWitt, 1990; Johnston & Schwarting, 1997; Neo & Chua, 2006). If items are pre-exposed in a separate task, faster reaction times are observed for novel targets amongst familiar distractors (Kaplan & Lubow, 2001; Lubow & Kaplan, 1997). Similarly, the introduction of novel distractors appears to interfere with performance (Lubow & Kaplan, 1997).

Such studies manipulate novelty in a manner that is separate from, or incidental to, the intentions of the observer. That is, the task is always to search for and respond as quickly as possible to a specific target. Any influence of novelty, whether at the level of target or distractor, therefore appears unlikely to emerge from any intention to direct attention towards or away from novel items. However, optimising the allocation of attentional resources may rely on some degree of flexibility in responding to novelty, such that the extent to which novel items compete for processing resources depends on the context in which they are encountered. When controlled attention is manipulated, task instructions can influence the selection of novelty. Chong et al. (2008) differentially emphasised the importance of target detection versus exploratory visual search in a task that required a response to a target appearing amongst a small number of novel items. They observed decreased attentional responses to novel items under conditions in which target detection was highlighted, suggesting that task instructions can influence the extent to which novelty directs selection.

As a whole, these data suggest that while attention appears to be biased towards novelty in a fairly automatic fashion, the influence of top-down, volitional attention can modulate the expression of that bias. What is unclear is how learning in
particular influences this process, when familiar items have received equivalent pre-exposure but differ in prior predictiveness. The present chapter starts by investigating how learned predictiveness proceeds under conditions in which novel items are paired with predictive and non-predictive components at the start of Phase II. Subsequent experiments observe how learning proceeds for those same compounds when instructional manipulations are introduced.

4.1. Experiment 9

Experiment 9 was designed to examine the expression of learned predictiveness when predictive and non-predictive cues compete against novel items under conditions that mimic traditional demonstrations of the bias, that is, in the absence of instructions that explicitly state the identity of the causal components in Phase II. This provides a useful comparison of how learned predictiveness emerges in combination with novelty under traditional procedures, and how it emerges in combination with novelty when measured via the AB (Chapter 2). A secondary aim for introducing novelty is to test the predictions set out in Chapter 3 as they relate to the various explanations offered for the interaction between predictiveness and instruction. This will be addressed in Experiment 10. However, as a necessary precursor, in this study, the design of which is shown in Table 4.1, one group of participants, Group Standard, completed the standard two-stage learned predictiveness task. For the remaining group, Group Novel, predictive and non-predictive cues from Phase I were each paired with a novel component such that each compound consisted of one familiar cue and one novel cue. Given the findings of Le Pelley et al. (2009), it was anticipated that the benefit in learning for predictive cues
would be preserved when these appeared alongside novel cues during Phase II. Thus, a bias towards predictive over non-predictive cues is expected in both conditions.

4.1.1. Methods

*Participants and apparatus*

Fifty-six undergraduate psychology students (37 female, mean age 19.5) enrolled at the University of Sydney participated in the experiment in exchange for partial course credit. The apparatus was the same as for previous experiments.

*Stimuli*

Stimuli consisted of 16 photographic images of food items, including coffee, fish, lemon, olive oil, banana, apple, cheese, milk, eggs, garlic, bread, pasta, peanuts, avocado, steak, and mushrooms. These were randomly allocated to serve as the cues shown in Table 4.1. All images measured 6.9° × 6.9° of visual angle at a viewing distance of approximately 57 cm and were shown in pairs in the upper half of the screen separated by 9.5°. Four allergic reactions were chosen to serve as outcomes O1 – O4. These were randomly allocated and consisted of headache, nausea, rash, and fever.

*Procedure*

Participants were randomly allocated to Group Standard or Group Novel. The instructions at the start of Phase I and presentation parameters were identical to those in Chapter 3. Phase I consisted of the trial types shown in Table 4.1. These were identical for both groups and were presented twice in each of the eight blocks comprising this stage of learning. The order of trials was randomised and the left and
right position of the cues was counterbalanced within blocks. Following Phase I participants were told that they would now be observing a new patient with different allergic reactions and that they would be required to discover which foods were causing which allergic reaction based on their observations. For those in Group Novel, predictive cues A – D now appeared alongside novel cues a – d, whereas non-predictive cues W – Z appeared alongside novel cues w – z, as is shown in Table 4.1. For Group Standard, trial types consisted of traditional Phase II learned predictiveness compounds, that is, compounds comprising predictive and non-predictive cues in novel combinations. In addition, they responded to compounds consisting of the novel cues a – d as well as w – z (see Table 4.1). Participants completed four blocks of trials. Each compound appeared twice per block, with the left and right position of the cues counterbalanced.

Immediately following the second training phase, each cue was tested individually, in random order. Participants were instructed that they would be observing the foods that the second patient had eaten and would be required to judge how likely it would be that a specific food caused each of the allergic reactions. On each trial, the cue was presented in the upper half of the screen, with two analogue rating scales appearing below it. Each rating scale was titled, *How likely is it that [O3 / O4] will follow given that Miss Y ate this food?* The left anchor was labelled *Definitely WILL NOT occur*, and the right anchor was labelled, *Definitely WILL occur*. Participants were required to make a selection on each scale before moving on to the next trial, which was self paced. Each rating scale yielded a score out of 100.
Table 4.1  
*Design of Experiment 9*

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Group Standard</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AW – O1</td>
<td>AY – O3</td>
<td></td>
</tr>
<tr>
<td>AX – O1</td>
<td>BZ – O4</td>
<td></td>
</tr>
<tr>
<td>BW – O2</td>
<td>CX – O3</td>
<td></td>
</tr>
<tr>
<td>BX – O2</td>
<td>DW – O4</td>
<td>All cues individually</td>
</tr>
<tr>
<td>CY – O2</td>
<td>ay – O3</td>
<td></td>
</tr>
<tr>
<td>CZ – O2</td>
<td>bz – O4</td>
<td></td>
</tr>
<tr>
<td>DY – O1</td>
<td>cx – O3</td>
<td></td>
</tr>
<tr>
<td>DZ – O2</td>
<td>dw – O4</td>
<td></td>
</tr>
<tr>
<td><strong>Group Novel</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AW – O1</td>
<td>Aa – O3</td>
<td></td>
</tr>
<tr>
<td>AX – O1</td>
<td>Bb – O4</td>
<td></td>
</tr>
<tr>
<td>BW – O2</td>
<td>Cc – O3</td>
<td></td>
</tr>
<tr>
<td>BX – O2</td>
<td>Dd – O4</td>
<td>All cues individually</td>
</tr>
<tr>
<td>CY – O2</td>
<td>Ww – O3</td>
<td></td>
</tr>
<tr>
<td>CZ – O2</td>
<td>Xx – O4</td>
<td></td>
</tr>
<tr>
<td>DY – O1</td>
<td>Yy – O3</td>
<td></td>
</tr>
<tr>
<td>DZ – O2</td>
<td>Zz – O4</td>
<td></td>
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</tbody>
</table>

*Note.* Letters represent food cues. Lowercase letters denote food cues that are novel at the beginning of Phase II. O1 – O4 refer to the four outcomes employed during the experiment.
4.1.2. Results

**Exclusions.** Participants were excluded if they failed to reach 60% accuracy during the last quarter of the first phase. Four participants failed to reach this criterion and were excluded.

**Phase I.** Prediction accuracy was averaged across compounds for each block. This increased steadily for both groups during Phase I, as shown in Figure 4.1. Scores were analysed by way of a mixed measures ANOVA with Block (1–8) and Condition (novel vs. standard) as factors. This revealed a significant effect of Block, $F(7, 350) = 81.97, p < .001, \eta^2_p = .62$, but no main effect of Condition and no Block $\times$ Condition interaction, all $Fs < 1$, showing no evidence of initial group differences.

![Figure 4.1](image-url)

*Figure 4.1.* Accuracy for Phase I averaged across compounds for Group Standard and Group Novel. Error bars show SEM.
Phase II. Accuracy for Phase II learning was analysed separately for each group and is shown in Figure 4.2. Panel A of the figure shows training accuracy for Group Standard. For this group, accuracy was averaged according to whether compounds consisted of familiar items, that is, one predictive and one non-predictive item, or whether compounds consisted of novel items, which appeared in separate trials. A 4 (Block: 1 – 4) × 2 (Familiarity: novel vs. familiar) repeated measures ANOVA showed that accuracy increased steadily across blocks, producing a main effect of Block, $F(3, 78) = 30.20, p < .001, \eta^2_p = .54$. Overall learning was better for novel compounds, $F(3, 78) = 37.65, p < .001, \eta^2_p = .6$, and there was no significant Block × Familiarity interaction, $F(3, 78) = 1.12, p = .35, \eta^2_p = .04$.

For Group Novel, each compound consisted of one novel component, and one familiar component that was either predictive or non-predictive in Phase I. Thus, accuracy was averaged according to whether the familiar component in a compound was predictive or non-predictive. This is illustrated in Panel B of Figure 4.2. A repeated measures ANOVA with Block (1 – 4) and Compound (predictive vs. non-predictive) as factors showed a significant effect of Block, $F(3, 72) = 60.19, p < .001, \eta^2_p = .71$, but no main effect of Compound and no Block × Compound interaction, all $Fs < 1$. 

Figure 4.2.  Phase II accuracy for Experiment 9. Panel A shows accuracy for Group Standard across training blocks during Phase II for compounds consisting of familiar items and compounds consisting of novel items. Panel B shows accuracy for Group Novel averaged according to whether a compound contained a familiar item that was predictive or non-predictive in Phase I. Error bars show SEM.
Test. In order to assess the extent to which individual cues were associated with outcomes at test, a learning score was calculated for each cue by subtracting the rating for the outcome that was not predicted on the basis of that cue from the rating for the outcome that was predicted on the basis of the cue. This variable was transformed to reflect a score out of 100, ranging from 0 to 100, with 50 representing chance. These scores were averaged for predictive and non-predictive cues, as well as novel cues a–d and w–z. These are shown separately for Group Standard and Group Novel in Figure 4.3.

First, in order to examine the presence of learned predictiveness across groups, predictive cues were compared to non-predictive cues for each group separately using paired-samples t-tests. This confirmed the traditionally observed benefit in learning about previously predictive cues in Group Standard (i.e., where predictive and non-predictive items appeared in the same compound in Phase II), \( t(26) = 2.83, p = .009, \eta^2_p = .24 \). This was absent in Group Novel (i.e., where predictive and non-predictive items appeared on separate trials alongside a novel cue), \( t(24) = .26, p = .79, \eta^2_p = .003 \).

A 2 (Familiarity: novel vs. familiar) × 2 (Group: standard vs. novel) mixed measures ANOVA showed that novel cues were learnt about more effectively than familiar cues in both groups, as shown by a significant main effect of Familiarity, \( F(1, 50) = 27.72, p < .001, \eta^2_p = .36 \), that did not vary by group, \( F(1, 50) = 1.40, p = .24, \eta^2_p = .03 \). The main effect of group also failed to reach significance, \( F(1, 50) = 2.40, p = .12, \eta^2_p = .05 \). Finally, there was no significant difference between novel cues a–d and w–z in both groups, as shown by mixed-measures ANOVA with Cue (ad vs. wz) and Group (standard vs. novel) as factors. This produced no significant effects, largest \( F(1, 50) = 1.44, p = .24, \eta^2_p = .03 \).
Figure 4.3. Learning scores for Group Standard and Group Novel for Experiment 9. Scores were averaged across predictive and non-predictive cues from Phase I, as well as novel cues a – d and w – z respectively. Error bars show SEM.

4.1.3. Discussion

Despite observing a robust learned predictiveness effect under conditions employing traditional trial types, Experiment 9 found no evidence of the learned predictiveness bias that held for individual cues when these appeared with novel stimuli at the start of Phase II. Rather, under these conditions, learning was preferentially directed towards novel items.

This is somewhat surprising in light of the results reported by Le Pelley et al. (2009), which show a residual bias towards learning about predictive cues when these appear in compound with novel stimuli following traditional Phase II pairings. One
difference between this design and theirs is that in Le Pelley et al. (2009) novel cues did little to signal the presence of any new outcome or context because they were introduced once Phase II training was already underway. In the design used here, novel cues appeared alongside previously predictive and non-predictive items at the outset of Phase II. This suggests that once a bias towards learning about predictive cues in Phase II has been established, such as in Le Pelley et al. (2009), this is robust against the subsequent introduction of novelty. In contrast, when predictive and non-predictive items appear alongside novel cues at the outset of the new learning context, as they did here, their predictive history no longer influences learning.

Several theorists claim that multiple sources of evidence are integrated in order to judge the causal relationship between co-occurring events, (e.g., McLaren, Green, & Mackintosh, 1994; McLaren et al., 2014). This suggests that there are several possibilities regarding the content of information that is transferred between the two stages of learning in a learned predictiveness procedure. For example, one thing that participants learn in the first phase is that the patient is only ever allergic to one food presented on any given trial. This is necessary for successfully learning the causal structure of this stage given the design. If this factor transfers to subsequent phases, this means that at the start of Phase II, participants in Group Novel are faced with a novel cue appearing alongside a familiar cue that has been associated with a prior alternative outcome, or a familiar cue that is non-predictive of any specific outcome. If only one of these components is assumed to be potentially causal of a new outcome, one could reasonably argue that this creates a situation in which novel cues more readily become the focus of new learning.

This could reflect automatic associative processes whereby in the absence of interference from prior cue – outcome associations, novel stimuli are learnt about more easily. Alternatively, it could arise from an explicit assumption on the part of
the subjects that novel cues are more informative about new outcomes, in line with
the arguments of Mitchell, de Houwer, & Lovibond (2009) and Mitchell et al. (2012).
It should be noted that this strategy does not necessarily reflect a rational inference,
given that there is no reason to think that any relationship experienced in the first
phase is useful for learning the allergies of a distinct person. By this same logic, one
could argue that the presence of learned predictiveness is not logical either. Thus, the
challenge is in disentangling any number of assumptions that might exist in a situation
of causal ambiguity.

The important point is that in the absence of explicit knowledge about
causality, causal ambiguity can be resolved in a number of ways. It appears that
novelty provides a strong source of evidence during this process in a way that
overrides any prior influence of predictiveness. It is interesting to note that the lack of
learned predictiveness in Group Novel appears to be driven by a rise in learning for
non-predictive cues as opposed to a drop in learning for the predictive cues. This
suggests that the introduction of novelty is influencing the way in which
predictiveness affects subsequent learning as opposed to generating a deficit in
learning for familiar cues overall. One could argue that this could be explained by
appealing to within-compound associations. If the association between the novel cue
w and the outcome is strong, at test this may boost responding to the familiar, non-
predictive, cue W given its within-compound association with w. However, to
anticipate, the validity of this explanation appears to break down in the context of
subsequent findings. This issue is discussed in further detail in the General Discussion
of this chapter.

Based on the issues raised above, Experiment 10 attempts to reduce the extent
to which novel cues completely override a bias towards predictive stimuli via causal
certainty in the form of instructions. This may allow a clearer test of the relationship between novelty and predictive history.

4.2. Experiment 10

This experiment, the design of which is shown in Table 4.2, employs a variant of the orthogonal manipulation between instruction and Phase I predictiveness used in Experiment 7 and Experiment 8. Following Phase I, participants were allocated to one of two groups, each learning about a different set of cues. One group, the Positive Transfer Group, saw only predictive cues A – D each paired with a novel item, consisting of cues a – d. They were explicitly informed that the new patient was allergic to four foods, and were provided with the names of those foods. The instructed causes corresponded to two previously predictive cues, A and C, as well as two novel cues, b and d. The second group, the Negative Transfer Group, saw only compounds consisting of the non-predictive cues W – Z each paired with a novel stimulus, w – z. Participants in this group were told that the allergens were cues W and Z, as well as cues x and y. Thus, for both groups, each compound for Phase II contains one instructed cause, and one item known to be safe.

Thus, the current design assesses the competition between familiar and novel cues when familiar items are predictive or non-predictive in Phase I under two instructional conditions. That is, there are known causes that are predictive and novel (i.e., in the Positive Transfer Group), and known causes that are non-predictive and novel (i.e., in the Negative Transfer Group). There are cues known to be safe that are predictive and novel (i.e., in the Positive Transfer Group), and cues known to be safe that are non-predictive and novel (i.e., in the Negative Transfer Group). It was suggested above that the introduction of instructions might diminish the ability of
salient novel cues to override a bias associated with predictive history for familiar cues, allowing a more sensitive measure of residual predictiveness effects. If this were confirmed, then one would anticipate that for known causes, associative memory would be better for predictive compared to non-predictive items. In line with the results observed in Chapter 3, this is predicted to reverse for cues known to be non-causal whereby better recall is shown for non-predictive cues compared to predictive cues.

Table 4.2.
Design of Experiment 10

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Groups</strong></td>
<td><strong>Positive Transfer Group</strong></td>
<td></td>
</tr>
<tr>
<td>AW – O1</td>
<td>Aa – O3</td>
<td></td>
</tr>
<tr>
<td>AX – O1</td>
<td>Bb – O4</td>
<td>A – D and a – d</td>
</tr>
<tr>
<td>BW – O2</td>
<td>Cc – O5</td>
<td>individually</td>
</tr>
<tr>
<td>BX – O2</td>
<td>Dd – O6</td>
<td></td>
</tr>
<tr>
<td>CY – O2</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Negative Transfer Group</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CZ – O2</td>
<td>Ww – O3</td>
<td></td>
</tr>
<tr>
<td>DY – O1</td>
<td>Xx – O4</td>
<td>W – Z and w – z</td>
</tr>
<tr>
<td>DZ – O2</td>
<td>Yy – O5</td>
<td>individually</td>
</tr>
<tr>
<td></td>
<td>Zz – O6</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Letters refer to individual food cues. Bold underlined letters indicate cues instructed as causal for Phase II for the two separate groups. O1 – O6 indicate the six different outcomes.
The predictions for the recall of novel cues across the two instructional conditions are less clear, as this may rely on the mechanisms that produce the interaction between instruction and predictiveness seen in Chapter 3. One factor relates to the congruence between instructions and Phase I predictiveness. Predictive cues instructed as causal, as well as non-predictive cues instructed as safe retain congruent roles across Phase I and Phase II. Alternatively, non-predictive cues instructed as causal, as well as predictive cues instructed as non-causes have incongruent roles across phases. Thus, interference on trials with incongruent stimuli may retard learning for these compounds more generally. Another possibility is that predictiveness enhances cognitive control. According to this explanation, predictive cues are easier to learn about when relevant, and easier to suppress when irrelevant.

These mechanisms give rise to two different scenarios for how learning will proceed for novel stimuli. For clarity, a schematic representation of these is presented in Figure 4.4. As is shown in Panel A of the figure, if the interaction reflects the influence of cognitive control, then recall should be better for novel causes appearing with predictive cues known to be safe, as these non-causes are easier to suppress as safe cues. This is relative to novel causes appearing with non-predictive safe cues. These safe cues would receive less of this “facilitated suppression”, such that learning for the novel cues with which they are paired is worse. By the same reasoning, for novel cues known to be safe, recall should be worse for items that are paired with predictive causes, as learning is more easily directed towards these instructed components. Recall for novel safe cues appearing with non-predictive causes would be worse, as learning is less easily facilitated by non-predictive causes.
Figure 4.4. Predictions relating to the pattern of results expected for novel causes and novel non-causes appearing in compound with predictive and non-predictive components. Panel A outlines the predictions relating to the mechanism of cognitive control, and Panel B shows the expected results if congruence is affecting performance.

The congruence scenario is shown in Panel B of the figure. If the reversal seen in Chapter 3 is the result of interference stemming from differences in congruence, then novel causes appearing alongside predictive safe cues, as in compound Bb, should be worse than novel causes appearing alongside non-predictive safe cues, as in compound Xx. For novel cues drawn from the safe category, those appearing in compound with predictive causes, as in compound Aa, should show better recall than those appearing alongside non-predictive known causes, as in compound Ww. This is because learning should be better overall for compounds Aa and Xx, as there is no conflict from Phase I present for these trials. On the other hand, learning would be generally retarded for compounds such as Bb and Ww, as the roles of familiar cues are incongruent across the two stages of learning. Thus, this design allows a test of the interaction observed in Chapter 3 as well as investigating the role of novelty in the volitional control of attention.
4.2.1. Method

Participants and apparatus

Sixty first-year psychology students (25 female, mean age = 19.5) enrolled at
the University of Sydney participated in Experiment 10 in exchange for course credit.
The apparatus and testing conditions were identical to Experiment 9.

Stimuli

Stimuli in this experiment comprised 16 photographic images of food. These
consisted of: coffee, fish, lemon, cheese, eggs, garlic, bread, peanuts, olive oil,
bananas, apples, milk, pasta, avocado, beef, and mushrooms. Two additional
outcomes were added to those used in Experiment 9, these were coughing and
sweating. The presentation parameters of all stimuli were also identical to those used
in Experiment 9.

Procedure

Participants were randomly allocated to the Positive Transfer or the Negative
Transfer conditions. For both groups, initial training was identical to previous
experiments, consisting of the trial types shown in Table 4.2. Upon completion of the
first training phase, all participants were told that they would now be required to
observe the allergies of a new patient. They were issued with explicit instructions
providing the name of four foods that the new patient was allergic to, and were
informed that they would be required to learn which of the allergens was causing
various allergic reactions in the patient. For those in the Positive Transfer group, those
four foods corresponded to cues A, D, b, and c. Alternatively, those in the Negative
Transfer condition were instructed that foods corresponding to cue W, Y, x, and z were allergens. Two blocks were completed comprising the trial types shown in Table 4.2. On each trial, participants were now required to make a prediction as to which of four allergic reactions would occur. Remaining parameters were the same as those used in Experiment 9.

Immediately following training, the test phase commenced in which all cues were tested individually on both a memory and causal question. Beneath the food cue for that trial, the four outcomes were presented in text form and participants were required to indicate which of these had been paired with the cue. Following this judgment, a scale appeared asking them to indicate how confident they were in that response by means of a rating scale labelled not at all confident on the left anchor and very confident on the right anchor. This was followed by the appearance of the causal rating scale. This was an identical rating scale with a title asking whether the food was causal of the allergic reaction. The left anchor was labelled, definitely DOES NOT cause a reaction, and the right anchor was labelled, definitely DOES cause a reaction. This yielded a score out of 100.

Finally, a manipulation check required participants to name the food items instructed as allergens for the second patient. Participants were excluded if they failed to correctly report the identity of all four allergens. Three participants were excluded on the basis of this criterion, as well as eight participants who failed to reach the Phase I learning criterion. These participants were replaced in order to maintain an equal number of participants in each condition.
4.2.2. Results

**Phase I.** Prediction accuracy was averaged across compounds for each block, and is shown in Panel A of Figure 4.5. This increased steadily for both groups during Phase I. Scores were analysed by way of a mixed measures ANOVA with Block (1 – 8) as repeated measures and Condition (Positive Transfer vs. Negative Transfer) as the between subjects factor. This revealed a significant effect of Block, \( F(7, 406) = 105.77, p < .001, \eta^2_p = .65 \), but no main effect of Condition, and no Block × Condition interaction, all \( Fs < 1 \), showing no evidence of initial group differences.

**Phase II.** Accuracy during Phase II was averaged according to the nature of the component instructed as causal. This is shown in Panel B of Figure 4.5. There was little evidence that learning differed between groups during training. A 2 (Condition: Positive Transfer vs. Negative Transfer) × 2 (Block: 1 – 2) × 2 (Instruction: familiar cause vs. novel cause) mixed measures ANOVA revealed a significant effect of Block, \( F(1, 58) = 170.71, p < .001, \eta^2_p = .75 \), but no other significant main effects or interactions, largest \( F(1, 58) = 1.24, p = .27, \eta^2_p = .004 \).
Figure 4.5. Prediction accuracy across training blocks. Panel A shows acquisition for the Positive Transfer and Negative Transfer groups during Phase I. Panel B shows Phase II learning for both groups according to whether the instructed cause was familiar or novel. Error bars show SEM.
**Test phase**

**Memory ratings.** For each cue, accuracy for cue – outcome recall was averaged according to whether items were novel or familiar, and according to whether they were instructed as causal or non-causal. This is shown for the Positive Transfer Group (i.e., when familiar cues were predictive) and the Negative Transfer Group (i.e., when familiar cues were non-predictive) in Figure 4.6 (Panel A). Accuracy was analysed with a mixed measures ANOVA with Group (Positive Transfer vs. Negative Transfer), Instruction (causal vs. non-causal), and Familiarity (novel vs. familiar) as factors. This revealed that the instruction was indeed effective in influencing learning, as shown by a significant main effect of Instruction, $F(1, 58) = 73.88, p < .001, \eta^2_p = .56$, as well as a benefit in memory for novel cues $F(1, 58) = 22.46, p < .001, \eta^2_p = .28$.

There was also a significant Instruction $\times$ Familiarity interaction, $F(1, 58) = 6.02, p = .02, \eta^2_p = .09$, suggesting the benefit for novelty varied according to whether cues were instructed as causal or non-causal. The main effect of Group as well as remaining interaction effects did not reach significance, all $Fs < 1$.

Breaking down the interaction provided little evidence that the Instruction $\times$ Familiarity interaction was meaningful. The Group (Positive Transfer vs. Negative Transfer) $\times$ Familiarity (novel vs. familiar) mixed measures ANOVA was conducted separately according to instruction, that is, for known causes and then for known non-causes. For known causes, this showed significantly better accuracy for novel cues, $F(1, 58) = 6.10, p = .016, \eta^2_p = .10$. This did not vary according to group, Group $\times$ Familiarity interaction $F(1, 58) = 3.11, p = .08, \eta^2_p = .05$, and there were no significant group differences, $F < 1$. For non-causes, accuracy was also better for novel cues, $F(1, 58) = 15.90, p < .001, \eta^2_p = .22$, and there was no main effect of
Group, or Group × Familiarity interaction, all $F$s < 1. Thus, for both causes and non-causes, the main influence on recall was familiarity.

*Causal ratings.* Causal ratings for each cue were averaged according to the familiarity of the cues (novel vs. familiar) as well as the instructed status of the cue (cause vs. non-cause). These are shown for the Positive Transfer Group and the Negative Transfer Group in Panel B of Figure 4.6. Ratings were subjected to a 2 (Group: Positive Transfer vs. Negative Transfer) × 2 (Instruction: causal vs. non-causal) × 2 (Familiarity: novel vs. familiar) mixed measures ANOVA. This revealed that cues instructed as causal were indeed rated as significantly more likely to cause an outcome, $F(1, 58) = 155.16, p < .001, \eta^2_p = .73$. Novel cues also received higher causal attribution compared to familiar cues overall, $F(1, 58) = 7.25, p = .009, \eta^2_p = .11$. No other main effects or their corresponding interactions were significant, all $F$s < 1.

A fairly important caveat in interpreting these data should be mentioned. In both the memory ratings and causal attribution data there was at least one condition in which the groups had unequal variance, Levene’s test $p < .05$. This suggests that in fact non-parametric tests are more appropriate for the present data. However, such tests are not well suited to test the nature of the interaction across conditions that are of interest in this design. Thus, despite some evidence that familiarity is the main driver of differences in this experiment, this conclusion requires additional testing.
Figure 4.6. Accuracy of cue – outcome recall (A) and causal ratings (B) averaged according to familiarity and instructional condition, for the Positive Transfer Group and the Negative Transfer Group for Experiment 10. Familiar cues in the Positive Transfer Group are predictive cues from Phase I, and familiar cues in the Negative Transfer Group are non-predictive cues from Phase I. Error bars show SEM. The dotted line in Panel A shows chance performance in the recall test.
4.2.3. Discussion

It appears that novelty overrides any bias towards learning about cues with a history of prior predictiveness, even when the intentional nature of learning is more explicitly controlled. Learning was preferentially directed towards novel items, regardless of whether familiar cues were predictive or non-predictive. This was the case for cues known to be causal as well as cues known to be non-causal.

Interestingly, this pattern of results also emerged in the causal rating data, suggesting that even though participants explicitly knew that a cue was causal, they viewed novel stimuli as more likely to cause an allergy. Thus, causal attribution and associative memory are not well differentiated in this experiment. One could argue that it is unsurprising that cue – outcome associations proceed more rapidly for novel cues, given that they have no prior associations with a different prior outcome. However, if memory and causal assessments are conflated this raises the possibility that a common source of evidence is influencing both judgments.

There is reason to suggest that the data in this experiment might be problematic. First, performance is at ceiling for known causes. While the use of four outcomes should increase working memory load as well as provide a more sensitive measure of accuracy, the instructional manipulation may simply be too strong to allow hypothesised differences to emerge. Second, in both the memory data as well as the causal rating data, there appear to be differences in variance across groups for some conditions. Thus, any interpretation of the current data is limited given the violation of critical statistical assumptions. As such, Experiment 11 aims to replicate the conditions in Experiment 10 making use of an extended within-subjects procedure designed to increase task difficulty.
4.3. Experiment 11

Experiment 11 employed an extended within subjects design, shown in Table 4.3, creating the same conditions as Experiment 10. The initial training employed additional cues in order to double the number of Phase I compounds but was otherwise the same as previous experiments. Again, at the start of Phase II, participants were issued with instructions about the causal nature of the food cues for the second patient. Unlike in the previous experiment where individual cues were instructed as causal, here the instruction was issued at the level of food category. That is, participants were told that the new patient was allergic to (and only allergic to) a particular category of food consisting of either meat and animal products or fruit and vegetables. As such, half of the cues used in this experiment were taken from the meat and animal products category, and the remaining cues drawn exclusively from the fruit and vegetables category, and each compound consisted of one item from either category. The food cues corresponding to A – D, W – Z, e – h, and s – v all belonged to the same category, and this category was instructed as allergenic. The food cues corresponding to E – H, S – V, a – d, and w – z were drawn from the other category and were known to be non-causal.

This means that the cues known to be causal consisted of previously predictive cues, i.e., A – D, previously non-predictive cues, i.e., W – Z, novel cues appearing alongside previously predictive cues, i.e., e – h, and novel cues appearing alongside previously non-predictive cues, i.e., s – v. Similarly, cues known to be safe for the patient consisted of previously predictive cues, i.e., E – H, non-predictive cues from Phase I, i.e., S – V, novel cues appearing alongside predictive causes, i.e., a – d, and novel cues appearing alongside non-predictive causes, i.e., w – z. Given the extended
number of associations in Phase II this manipulation should serve to increase task difficulty and bring performance below ceiling, allowing a test of the predictions outlined in Experiment 10.

4.3.1. Method

Participants and apparatus

The sample for this experiment comprised thirty undergraduate students (20 female, mean age = 19.6) enrolled at the University of Sydney who participated in exchange for course credit. The apparatus was the same as that used in Experiment 10.

Stimuli

Stimuli consisted of 32 photographic images of food items, half of which were drawn from the food category “animal products such as meat, poultry, and dairy”, and the other half from “fruit and vegetables”. The sixteen meat and animal products category consisted of: butter, chicken, bacon, prawns, lamb, egg, duck, octopus, kangaroo, beef, fish, milk, yoghurt, cheese, lobster, and pork. Items from the fruit and vegetable category included: pineapple, pumpkin, cherries, peach, broccoli, tomato, corn, carrots, mango, strawberries, apple, banana, lemon, mushrooms, peas, and avocado. Items were randomly allocated to serve as cues within each category. The four outcomes consisted of fever, nausea, headache, and rash. The presentation parameters of the stimuli remained the same as Experiment 10.

Procedure

Aside from the increased number of trial types, the initial training phase was identical to that of Experiment 10. Following Phase I, participants were informed that
they would be observing the allergies of a new patient. They were told that the new patient was only allergic to a specific category of food, either to fruit and vegetables, or to meat and animal products. The allergenic category was counterbalanced across participants. The 16 trial types shown in Table 4.3 were presented twice per block, for the duration of two blocks in total. Note that compounds in Phase II always contained one allergenic and one safe item.

The test phase commenced immediately following the completion of Phase II. Each cue was presented individually on separate test trials in random order. On each trial, a rating scale assessing memory for specific cue – outcome pairings appeared beneath the food cue. This was rated on a linear analogue scale labelled, *definitely goes with* [Outcome 3] on the left, and *definitely goes with* [Outcome 4], on the right. The mid point of the scale was made explicit with the label *no idea*. This was different to the scale used in Experiment 10 as the number of outcomes in Phase II in this design differs. Once this rating had been completed, another scale appeared asking whether the current food cue caused the reaction. Similarly, this was a rating scale with *definitely DOES cause the reaction* on the left, and *definitely DOES NOT cause the reaction* on the right. Both rating scales yielded a score out of 100. A manipulation check was included whereby participants were presented with a question asking them to provide the category of food that their second patient was allergic to. There were no exclusions on the basis of this check, all participants having correctly provided the allergenic category.
Table 4.3.  
Design of Experiment II.

<table>
<thead>
<tr>
<th>Phase I</th>
<th>Phase II</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>AS – O1</td>
<td><strong>Aa</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>AT – O1</td>
<td><strong>Bb</strong> – O4</td>
<td></td>
</tr>
<tr>
<td>BS – O2</td>
<td><strong>Cc</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>BT – O2</td>
<td><strong>Dd</strong> – O4</td>
<td></td>
</tr>
<tr>
<td>CU – O2</td>
<td><strong>Ee</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>CV – O2</td>
<td><strong>Ff</strong> – O4</td>
<td></td>
</tr>
<tr>
<td>DU – O1</td>
<td><strong>Gg</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>DV – O1</td>
<td><strong>Hh</strong> – O4</td>
<td>All cues individually</td>
</tr>
<tr>
<td>EW – O1</td>
<td><strong>Ss</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>EX – O1</td>
<td><strong>Tt</strong> – O4</td>
<td></td>
</tr>
<tr>
<td>FW – O2</td>
<td><strong>Uu</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>FX – O2</td>
<td><strong>Vv</strong> – O4</td>
<td></td>
</tr>
<tr>
<td>GY – O2</td>
<td><strong>Ww</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>GZ – O2</td>
<td><strong>Xx</strong> – O4</td>
<td></td>
</tr>
<tr>
<td>HY – O1</td>
<td><strong>Yy</strong> – O3</td>
<td></td>
</tr>
<tr>
<td>HZ – O1</td>
<td><strong>Zz</strong> – O4</td>
<td></td>
</tr>
</tbody>
</table>

Note. Letters represent individual food cues during training. Bold underlined letters show cues instructed as causal for Phase II. All cues instructed as causal come from one food category, and the remaining food cues are drawn from an alternative category. O1 – O4 indicate the four different outcomes.
4.3.2. Results

*Phase I.* Prediction accuracy was averaged across the eight compound discriminations for Phase I and is shown across training blocks in Panel A of Figure 4.7. As is shown in the figure, accuracy increased steadily across training. This was confirmed in a repeated measures ANOVA with Block (1 – 8) as a factor, which showed a significant effect of block on accuracy, $F(7, 203) = 55.14, p < .001, \eta_p^2 = .66$.

*Phase II.* In order to assess acquisition during Phase II, accuracy was averaged according to the nature of the component instructed as causal. Panel B of Figure 4.7 shows this for compounds with a predictive causal component (Aa – Dd), a non-predictive causal component (Ww – Zz), a novel cause appearing alongside a predictive non-cause (Ee – Hh), and a novel cause appearing alongside a non-predictive non-cause (Ss – Vv). Accuracy was analysed with a 2 (Block: 1 – 2) \times 2 (Familiarity: novel vs. familiar) \times 2 (Compound: predictive compounds vs. non-predictive compounds) repeated measures ANOVA. This revealed a significant effect of Block, $F(1, 29) = 20.41, p < .001, \eta_p^2 = .41$. Overall, acquisition was slightly better for compounds containing of non-predictive components, but this was not significant, $F(1, 29) = 3.14, p = .08, \eta_p^2 = .10$. No other main effects or interactions were significant, largest $F(1, 29) = 2.78, p = .11, \eta_p^2 = .09$. 
Figure 4.7. Panel A shows prediction accuracy averaged across all training compounds for Phase I during Experiment 11. Phase II accuracy is shown in Panel B, for compounds with novel and familiar cues instructed as causal. Error bars represent SEM.
Test

Memory ratings. A memory score was calculated for each cue to reflect a score out of 100, where 100 represents the most confident choice of the correct outcome, and 0 the most confident choice of the incorrect outcome. A score of 50 therefore represents chance. Scores were averaged according to whether cues were familiar or novel, as well as whether novel items appeared in compound with previously predictive components (predictive compounds), or previously non-predictive components (non-predictive compounds) in Phase II. These are shown for the known causes and non-causes in Panel A of Figure 4.8.

Scores were analysed by repeated measures ANOVA with Instruction (causal vs. non-causal), Familiarity (novel vs. familiar), and Compound (predictive vs. non-predictive) as factors. This revealed an overall benefit in memory for cues instructed as causal, $F(1, 29) = 17.04, p < .001, \eta^2_p = .37$, as well as cues that were novel, $F(1, 29) = 13.91, p = .001, \eta^2_p = .32$. However, this varied according to whether compounds contained previously predictive or non-predictive items, as suggested by the significant Instruction $\times$ Familiarity $\times$ Compound interaction, $F(1, 29) = 7.1, p = .012, \eta^2_p = .2$. The Familiarity $\times$ Compound interaction approached significance, $F(1, 29) = 3.93, p = .057, \eta^2_p = .12$, but the remaining main effects as well as their interactions were not significant, largest $F(1, 29) = 2.65, p = .12, \eta^2_p = .08$.

In order to investigate the three-way interaction, the Familiarity $\times$ Compound interaction was assessed for causal and non-causal instructional conditions separately. For cues instructed as causal, there was superior memory for novel items, $F(1, 29) = 10.99, p = .002, \eta^2_p = .28$, but no main effect of Compound, and no Familiarity $\times$ Compound interaction, all $Fs < 1$. For cues known to be non-causal, memory for cue outcome pairings was also better for novel cues, $F(1, 29) = 5.06, p = .03, \eta^2_p = .15$. However this varied according to which compound cues were presented in, resulting
Figure 4.8. Memory ratings (A) and causal ratings (B) averaged according to familiarity for known causes and known non-causes for Experiment 11. Error bars show within-subjects standard error of the mean (Cousineau, 2005). The dotted line in Panel A shows chance performance in the recall test.
in a significant Familiarity × Compound interaction, $F(1, 29) = 9.61, p = .004, \eta^2_p = .25$. Simple effects analysis revealed that for familiar cues, memory was significantly better for predictive cues compared to non-predictive cues, $F(1, 29) = 4.33, p = .04, \eta^2_p = .13$. For novel cues, this pattern reversed with better memory for novel items appearing alongside non-predictive causes compared to novel items appearing alongside predictive causes, $F(1, 29) = 5.69, p = .02, \eta^2_p = .16$.

**Causal ratings.** As shown in Figure 4.8 (Panel B), causal ratings were averaged in the same way as memory scores. A 2 (Instruction: causal vs. non-causal) × 2 (Familiarity: novel vs. familiar) × 2 (Compound: predictive vs. non-predictive) repeated measures ANOVA showed a significant effect of Instruction, $F(1, 29) = 55.59, p < .001, \eta^2_p = .66$. No further main effects or interactions reached statistical significance, largest $F(1, 29) = 1.51, p = .23, \eta^2_p = .05$.

4.3.3. Discussion

The extended design was clearly effective in bringing recall performance below ceiling for cues instructed as causal. There was a clear influence of controlled attention on associative memory such that learning was superior for cues instructed as causal. Once again, novelty eradicated the learned predictiveness bias, at least for items explicitly known to be causal. However, differences did emerge for cues known to be non-causal, whereby a residual learned predictiveness effect was present for familiar cues. In contrast, better associative memory was seen for novel cues that appeared alongside non-predictive causes compared to novel cues that appeared in compound with predictive causes.

This pattern of results runs counter to what was reported in Chapter 3, where cues instructed as causal were resistant to complete voluntary control. The differences
for non-causes was the opposite of that seen in Experiment 7 and Experiment 8. Given that causal inference once again diverged from cue – outcome recall, this suggests that participants were indeed making their causal judgments on the basis of instruction alone in a way that did not appear to be influenced by associative memory. Thus, it appears that the introduction of novelty alters the way in which selection is biased by predictive history in a way that is different for known causes compared to known non-causes. This result is considered in more detail below.

4.4. General Discussion

In this chapter, three experiments examined the expression of learned predictiveness when predictive and non-predictive cues appeared in compound with novel items at the start of Phase II. In the absence of explicit knowledge about the causal nature of the cues, this eliminated the learned predictiveness bias (Experiment 9). Subsequent experiments controlled the allocation of voluntary attention by issuing instructions about the causal nature of the cues. Although the data in Experiment 10 proved problematic for statistical purposes, there was some consistency between this and Experiment 11. In both experiments, learned predictiveness was absent in the recall measure for known causes, suggesting that the introduction of novelty eliminates the bias, at least for cues that are the target of intentional learning. However, it also seems that voluntary attention alleviates the strong bias towards novelty, that is, overall participants are able to turn their attention away from novel cues known to be safe. In both Experiment 10 and Experiment 11, instruction influenced associative memory such that learning was better for familiar causes compared to the novel ‘safe’ cues with which they were paired.
In Experiment 11 there was some evidence that the predictive history of cues influences associative memory when learning is unintentional, that is, for cues known to be non-causal. This varied for familiar and novel cues such that learned predictiveness emerged when non-causes were familiar; better associative memory for predictive compared to non-predictive cues was observed. On the other hand, there was better learning for novel cues paired with non-predictive known causes compared to novel cues appearing in compound with predictive causes. This pattern of results is consistent with traditional assumptions about the relationship between attention and predictive history. While attentional models of associative learning (e.g., Kruschke, 2001; Mackintosh, 1975; Pearce & Mackintosh, 2010) do not generally allow for differential predictions relating to intentional versus unintentional learning conditions, the effect for familiar non-causes is consistent with the proposed benefit in selection for stimuli with prior predictive utility. Given an attentional advantage for predictive cues from the first phase of learning, selection favours these cues in subsequent contexts. This same principle suggests that novel non-causes appearing with predictive items lose out in the competitive process, more so than novel safe items paired with non-predictive causes.

It should be noted that while the reasoning outlined above conforms to the general idea that attention varies according to associative competition, additional assumptions would need to allow for the fact that such effects can emerge in incidental learning conditions when the remaining components in a given compound, that is, the known causes, are under complete control of volitional attention and therefore not sensitive to the same mechanisms. Of course, the interaction between inference and automaticity is a complicated one. This pattern of results was quite different to those observed in Chapter 3 when familiar cues appeared in direct competition with one another. One could argue that observing the effect of predictive
history in distractor, or incidental conditions exclusively provides a strong case for the
presence of automaticity, given that there is clear motivation to discard these items
during learning. However, by that same reasoning it is somewhat surprising that
residual predictiveness effects were preserved for intentional learning conditions in
Chapter 3. As the results presented here are clearly less consistent across the similar
manipulations applied in Experiment 10 and Experiment 11, compared to the
observations put forward in Chapter 3, further attempts at disentangling these
processes need to clarify the influence of novelty in changing the way in which
selection is biased by predictiveness.

A further motivation for using a design in which novelty was pitted against
predictive and non-predictive cues was to differentiate explanations of cognitive
control and congruence in producing the interaction between predictive history and
instruction in Chapter 3. Unfortunately the results from Experiment 10 and
Experiment 11 are not easily amenable to the predictions set out by either explanation.
First, both explanations anticipate that the reversal seen previously would replicate.
Sadly that reversal was absent here. Rather, in both experiments there was no
indication that predictive history influenced recall for instructed causes when
comparing predictive and non-predictive stimuli indirectly through their pairing with
novel cues.

Similarly, the two predictions rely on observing a difference for novel causes
as well as novel non-causes according to whether they appeared in compound with
predictive or non-predictive cues. Overall, there was no difference between novel
causes regardless of the nature of the remaining components. A difference for novel
non-causes did emerge in Experiment 11 that was consistent with the mechanism of
cognitive control. The prediction states that recall should be worse for novel non-
causes appearing with predictive causes compared to novel non-causes appearing with
non-predictive causes. This is because it should be easier to attend exclusively to predictive causes compared to non-predictive causes. While it is true that this was observed, if cognitive control was engaged by predictive history, then you would expect the influence of predictiveness to be robust against novelty and a difference to emerge for novel causes as a result of that. This was not the case, and it seems unlikely that cognitive control would operate exclusively at the level of incidental learning conditions.

It should be mentioned that a third possibility, the presence of within-compound associations, was raised as a potential source of the interaction found in Experiment 7 and Experiment 8. According to this explanation, if predictive history facilitates associative memory for cues instructed as causal, then previously non-predictive non-causes appearing with predictive causes would receive a boost in associative strength with the outcome via its within-compound association with the known cause. Given that cues from Phase I are paired with novel items at the outset of the second stage, this manipulation prevents any within-compound associations forming between the cues in which the interaction was observed, given that they no longer appear together, as they did in Chapter 3. An indirect argument might be made that since the interaction was absent when the involvement of the hypothesised within-compound associations was negated that it provides a plausible mechanism for producing the interaction.

However, in order for within-compound associations to provide a viable explanation of the interaction in Chapter 3, one would have to assume that in the second stage, the direct associations between instructed causes and outcomes are strong, and, on test, are not influenced by these second-order associations, whereas direct learning about non-causes is relatively weak. Thus, second-order associations support most of the variation in performance for non-causal cues on test. The results
from Experiment 10 and Experiment 11 speak against this hypothesis in two ways. First, if this was the case, one would expect higher recall for familiar non-causes compared to novel non-causes as these would be supported by stronger second-order associations: They are paired with novel causes. This was not seen. Second, in Experiment 11 one would expect novel non-causes paired with predictive causes to show better recall than novel non-causes paired with non-predictive causes. This is the opposite of what was observed. Thus the presence of within-compound associations does not provide a consistent explanation of the results across Chapter 3 and Chapter 4. Whether recourse to such explanations is necessary or sufficient remains unclear.

In summary, the introduction of novelty appears to alter the way in which new learning is biased by predictive history. This is the case under more traditional learning procedures as well as when voluntary attention is manipulated by way of instruction. Overall, novelty appears to override a bias towards learning about previously predictive cues. Voluntary attention seems to overcome the influence of novelty, directing learning towards familiar over novel items if they are known to be causal. Nevertheless, novel known causes elicited better recall than familiar known causes, and novel safe cues showed better recall than familiar safe cues, suggesting that the advantages for novel cues in stage two are not purely inferential in nature. While there is some evidence that predictiveness effects are present in incidental learning conditions, a finding consistent with the presence of automatic processes, the influence of novelty remains to be fully characterised.
Chapter 5: General Discussion

This thesis posed the problem that biases in learning that arise due to the predictive history of information can be characterised by a number of the processing changes associated with selective attention. The aim of this work was to investigate what these changes may be, and as such examined the expression of learned predictiveness under manipulations of automatic and controlled attention. By using cognitive measures of stimulus processing in combination with learning, the studies reported here complement an increasing body of evidence relating to the nature of the processing changes that emerge with learning, as well as highlighting how they function. In this chapter, findings are first summarised according to the two manipulations of interest, that is, measuring the processing of predictiveness during the AB as an index of automatic mechanisms, and issuing instructions about the causal nature of cues as a manipulation of controlled, inferential processes. This is followed by a discussion of how they relate to theories of learning and attention.

The attentional blink as an index of automaticity

Previous work (e.g., O’Brien & Raymond, 2012; Raymond & O’Brien, 2009) has introduced the use of stimuli with prior value associations in visual detection tasks such as the attentional blink. This was extended here to examine the effect of predictive history on target detection under conditions in which the availability of controlled attention is severely limited. This method provided evidence for the presence of an automatic change in selection due to learning. Predictive history influenced visual detection exclusively at the level of distractor processing, an effect that appears to stem from decreased interference from non-predictive distractors (Experiment 4 and Experiment 5). That is, when learned predictiveness was combined
with the AB, the only influence of predictiveness on detection was at the level of distractor predictiveness. There was no effect of target predictiveness on target detection. Here, a key feature of the attentional blink is that distractors interfere with target detection, suggesting that performance is unlikely to reflect any strategy in the way in which these items are attended. This means that distractor effects, such as the one observed here, appear to emerge outside of volitional control. In combination with previous findings showing an effect of prior learning on the ability of distractors to cause interference (Anderson, Laurent, & Yantis, 2011a, 2011b; Della Libera & Chelazzi, 2009; Le Pelley, Vadillo, & Luque, 2013), this finding suggests that learning can influence the properties of the bottom-up processing of a stimulus to the extent that its ability to compete for attention is affected. This is an idea further clarified in later stages of this chapter.

It is well established that novelty is a potent source of processing bias (e.g., Horstmann & Ansorge, 2006; Johnston & Schwarting, 1997; Lubow, Kaplan, Abramovich, Rudnick, & Laor, 2000; Lubow, Kaplan, & De la Casa, 2001; Neo & Chua, 2006). This was also observed here. Novel targets were easier to detect than familiar targets, regardless of the predictive history of those familiar items (Experiment 4 and Experiment 5). It is unlikely that the strong bias towards novel targets was overriding any direct influence of predictiveness on target detection, given that target effects were absent when only familiar items were present (Experiment 3 and Experiment 5). However, there was a more subtle indication that the overall novelty of the RSVP stream influenced the sensitivity of performance to predictiveness. Changes at the level of distractor processing associated with predictiveness were most easily detected, or potentially isolated to, conditions in which familiar items were competing with novel cues in the same stream, as observed across and within Experiment 4 and Experiment 5. This means that the indirect effect
of predictiveness on visual detection preferentially emerges when attention is engaged by novelty.

Instructions as an index of controlled attention

According to the explanation of learned predictiveness put forward by Mitchell et al. (2012), the inferential attentional bias responsible for the effect emerges as a result of beliefs developed across both phases of learning. The attentional blink procedure tested predictiveness effects immediately following the first phase of learning, providing evidence for a change in automatic selection that can be detected without the occurrence of the second stage of the learning scenario in which the critical inference is proposed to develop. Subsequent experiments examined selection following the initial stage of learning. Instructions about the causal structure of the task were employed in order to control the content of the inference, an approach first introduced by Mitchell et al. (2012). However, using orthogonal manipulations of instruction and predictive history produced conditions in which top-down and automatic biases were consistent (i.e., when predictive items were instructed as causal, and non-predictive items instructed as safe), as well as conflicting (i.e., when predictive items were instructed as safe, and non-predictive items instructed as causal). By including distinct measures of reasoning and associative memory processes, the procedure here potentially provides a more sensitive way of assessing the relative contribution of automatic and controlled selection.

This method provided two additional sources of evidence to suggest the presence of automatic selection. First, in Chapter 3, despite a robust influence of controlled attention on learning, there was still an effect of predictive history that was resistant to complete volitional control (Experiment 7 – Experiment 8). In particular,
associative memory was better for instructed targets that were predictive in prior learning. Thus, a selection bias towards predictive items was still evident in the presence of a strong top-down signal, that is, explicit knowledge. One could argue that while participants may have understood and remembered the instructions, this would not necessarily confirm that they were in fact using these instructions to direct their learning during the second stage. If they found adhering to the instructions too effortful, it is possible that they simply relied on what they had learnt earlier in a controlled manner. However, one aspect of the data presented here argues against this possibility. In Experiment 7 – Experiment 8 the effect of predictiveness reversed across known causes and known non-causes. If participants were relying on what they had learnt previously in an explicit controlled manner, you would see the same pattern of results across known causes and non-causes.

Second, predictive history still influenced associative memory when there was no reason to learn about or attend to cues. That is, there were residual effects of predictiveness for items known to be non-causal of an aversive outcome. The pattern of these ‘instructed distractor’ effects presented a complex picture across Chapter 3 and Chapter 4. When instructed causes failed to come under complete control (Chapter 3), associative memory for distractor items was biased towards non-predictive stimuli compared to predictive cues (Experiment 7 – Experiment 8). In Chapter 4, when instructed targets came under top-down control, more was learnt about predictive safe items over non-predictive safe stimuli. Novel distractor items also varied according to the predictive history of the causes with which they were paired. More was learnt about novel safe cues appearing with non-predictive causes compared to novel safe cues appearing in compound with predictive causes (Experiment 11).
An important factor differentiating the designs across these two sets of experiments is the presence of novelty. In the absence of instruction, learning was directed towards novelty in a way that eliminated any indication of an attentional bias towards stimuli with prior predictiveness (Experiment 9). This was also the case for items instructed as causal when top-down attention was controlled. For instructed targets, learning was better for novel over familiar target items, and familiar targets showed no evidence of attentional priority that varied with predictive history (Experiment 10 – Experiment 11). Thus, in a similar finding to that observed when top-down attention was restricted during the attentional blink, target selection favours novelty irrespective of the predictive history of familiar targets.

Summary

To summarise, an effect of predictiveness on target selection only emerged in Chapter 3 when top-down biases were engaged and familiar items were in direct competition with one another. In contrast, remaining studies showed a strong preference towards novel targets regardless of the predictive history of familiar target stimuli. Predictiveness effects emerged consistently in distractor conditions, both when top-down attention was limited during the AB (Chapter 2), and when it was controlled during instructional manipulations (Chapter 3 and Chapter 4). However, the direction of interference associated with predictiveness was not always in the same direction, and to some degree relied on the presence of novelty.

Theoretical questions

Based on the results reported here it seems logical to conclude that learned predictiveness reflects the operation of both automatic and controlled selection. How does this conclusion align with attentional theories of learning? In the context of the
inferential account of learning put forward by Mitchell et al. (2009), it should be noted that the existence of automatic processes is not denied, but instead isolated to recall mechanisms. Although the nature of how these interact with attention and performance is not well defined, one can pose the question of whether recall might account for the evidence of automaticity presented here. For example, if the explicit knowledge that non-predictive stimuli are not useful leads to inferior encoding, and if one assumes that items in working memory are tied to more long term encoding processes, then this might explain why non-predictive distractors compete less during the attentional blink. As discussed previously, the reasoning associated with this view becomes less clear when inferential processes are manipulated during learning, providing direct motivation for preferentially encoding some items over others. The fact that differences in associative memory were still observed at test under these conditions suggests that aspects of the data are less easily amenable to this role for automaticity. Given the tight coupling between learning, memory, and attention (e.g., Ballesteros, Reales, Garcia, Carrasco, 2006; Desimone & Duncan, 1995; Gazzaley & Nobre, 2012; Markant, Worden, & Amso, 2015), providing a theoretically clarified role for automaticity presents a challenge for this class of explanation.

Similarly, specific predictions about the interaction between higher-order and automatic attentional mechanisms are generally absent from the class of attentional models of associative learning that connect attention with an automatic gain in associative strength (e.g., Mackintosh, 1975). One might start by asking how such models might capture the evidence for automaticity observed in the absence of volitional control during the attentional blink, when changes in processing were observed immediately following stage 1. It appears that the exact nature of the change observed here is not fully anticipated by models such as the one put forward by Mackintosh (1975), which although generally predicting an increase in attention to
predictive items, remains largely silent as to the nature of the variation in processing that is expected on the basis of this change beyond an increased rate of learning. If one assumes that the starting value of $\alpha$ is low, then the Mackintosh model predicts that the attention paid to novel cues increases for progressively familiarised, predictive cues. Instead, the results here suggest that the processing of predictive items, at least at the level of distractors, was no different to novel salient items and it was instead the non-predictive components that were processed differently. In line with this, if one instead assumes that the starting value of $\alpha$ is high, then the model in fact predicts that the attention paid to novel cues is high and decreases for non-predictive cues. Importantly however, this was only the case for distractor conditions, raising the issue that the application of such models to the specific components of attentional tasks in which target and distractor conditions are more clearly delineated by task requirements can be challenging. In the attentional blink for example, although volitional control is limited via high temporal processing demands, top-down biases are still present for target items on the basis of task instructions. In the absence of an explicit assumption about how this top-down signal might override the automatic preference for predictive items at the target level, such a model would struggle to describe this pattern of results.

When more traditional measures of learning were employed, the automatic allocation of attention did not always conform to model predictions. In Chapter 3, the automatic resistance of predictive history to volitional control was consistent with model predictions only for items that formed the focus of deliberate attention. In that situation, the effects of automaticity and top-down bias were additive. However, across conditions the effect of automaticity and top-down signals was clearly interactive. Adding to the complexity of the problem, in Chapter 4 when novelty was introduced and the bias towards previously predictive target items was eliminated,
there was some indication of learned predictiveness for non-causal distractor items, that is, better associative memory for previously predictive compared to non-predictive items.

It should be noted that there are alternative theories about the direction of the relationship between automatic selection and learning. For example, the Pearce-Hall model (Pearce & Hall, 1980) takes as its foundation the idea that attention is most adaptively directed towards information for which the usefulness is unknown. This means that the attention devoted to novel stimuli is high in order to support rapid learning, and this attentional priority gradually decreases as cues become better predictors of specific events and responding to them becomes automatic. At a general level this model makes few sensible predictions regarding learned predictiveness, given that it assumes that the attention to all information present will change equally, so does not allow for differences between predictive and non-predictive items to emerge in the first phase. However, the spirit of the model does capture superior selection for novel stimuli, a result observed throughout this thesis. Further, there are findings in human learning that are consistent with a mechanism favouring the processing of information for which the outcome is unknown (e.g., Griffiths, Johnson, & Mitchell, 2011; Hogarth, Dickinson, Austin, Brown, & Duka, 2008; Trick, Hogarth, & Duka, 2011). This suggests that the role of learning in producing automatic changes in selection may be multiply determined.

There are certainly models that allow for selection to be preferentially directed towards useful predictors as well as towards stimuli for which the outcome is unknown (Le Pelley, 2004; Pearce & Mackintosh, 2010). Given the evidence discussed above, it seems reasonable to argue that both biases operate in concert in order to determine ultimate selection during learning. One could argue that traditional demonstrations of learned predictiveness are biased towards observing changes in
selection consistent with what would be expected on the basis of the Mackintosh (1975) model. In the first phase of learning the structure of the task necessitates that selection come under the control of predictive items. In the second phase, two familiarised items are presented in isolation on every trial, providing little choice or motivation to change a pattern of response. Different learning tasks that provide the opportunity to engage a wider variety of selection mechanisms may be sensitive to detecting differences in the direction of attentional change.

The nature of this issue mirrors a fundamental problem for cognition, that is, that we appear to be simultaneously biased towards processing novelty and familiarity. For example, Triesman (1992) highlighted this distinction in the observation that:

> by creating accumulated traces of past perceptual objects or events, the world molds our minds to recreate earlier experiences. At the same time, we retain an impressive capacity also to represent any new object that fails to find its match in our prior assembly of stored tokens. (p. 874)

One could argue that this paradox reflects some of the fundamental mechanisms inherent in a system of limited capacity optimising the processing of information. Desimone and Duncan (1995) suggest that familiarity can be thought of in terms of an object feature that influences attentional competition. While novel objects have an initial competitive advantage in acquiring attentional control, increased experience with a stimulus increases the amount of information incorporated into stable knowledge that serves the function of streamlining behavioural responses to that item. This reduces the strength of that signal, freeing up resources for the processing of subsequent novelty.
The description above highlights bottom-up, or automatic, biases in attentional control. According to the biased competition framework (Desimone & Duncan, 1995), bottom-up biases are not restricted to physical salience, such as high contrast or sudden onset, but are also derived from information available in long-term memory that may influence the initial processing of a stimulus. Importantly, this latter form of bottom-up bias is tied to the learned importance of an event. Desimone and Duncan relate this to examples of learned relevance breaking through perceptual noise, such as the classic cocktail party effect.

The theory does fall short of fully integrating an idea of how differences in learning correspond to variations in the mechanisms of bottom-up competition. As a result, some predictions regarding how these might interact with top-down bias are unclear. However, some general questions can be raised on the basis of the principles outlined above. In the interest of clarity, I first examine the situation in which only familiar items that vary in past predictiveness are present. If predictive items have undergone superior processing this means that they would have a bottom-up competitive advantage, given the automatic retrieval of information conferring a processing preference for these stimuli. At a general level this is consistent with what is observed in learned predictiveness under normal conditions. If a strong top-down bias is induced by way of an inferential manipulation, it stands to reason that this bottom-up preference would work in an additive manner with the top-down processing. This is consistent with our target effects observed in Chapter 3, though would require the added assumption that the strength of the top-down influence is not sufficient to completely override bottom-up processing.

It is less clear whether the results observed for instructed distractors are as easily amenable to the model. Consider classic findings showing that when a well-practiced, or ‘automatised’ target is subsequently a distractor, it interferes with
performance (Shiffrin & Schneider, 1977). This suggests that under some conditions
top-down selection bias can come into conflict with automatic bottom-up biases,
causing a detriment to performance. Thus a potential prediction is that due to conflict
between top-down and bottom-up signals for predictive distractors, they lose out in
terms of selection bias relative to items for which bottom-up and top-down signals are
congruent, that is, for non-predictive distractors.

How does novelty fit within these predictions? The finding that novelty
changed the way in which predictiveness effects emerged implies that this factor
modulates the competitive interactions between top-down and bottom-up signals. The
benefit in selection for novel targets is consistent with an additive relationship
between top-down signals and novelty in a manner that overrides any competition that
may arise from the bottom-up retrieval of information associated with that stimulus.
This suggests that the change in bottom-up processing with learning measured in this
thesis is relatively weak. This is perhaps unsurprising given that the training
employed here is far shorter than other demonstrations of automatised stimulus
processing with experience (e.g., Anderson et al., 2011a, 2011b, 2012; Le Pelley et al.,
2015; Shiffrin & Schneider, 1977).

Caveats

The discussion above draws comparisons from the results observed across two
distinct manipulations of attention in which learning is not equated. While this
allowed a test of automaticity at two critical points in learning, it does prompt some
qualifications in relation to the general theoretical issues raised thus far. It may be that
the kind of automatic process that is sensitive to measurement in the attentional blink
is quite distinct from that observed in measures of associative memory employed in
subsequent chapters. Indeed, I have highlighted above the argument that automatic
effects differ according to the nature of the information stored about specific stimuli. This raises the possibility that the automatic effects measured here should be considered as distinct from one another, such that the way in which they compete with top-down signals would be expected to show different properties. It would be informative to examine the attentional blink manipulation following the completion of the learned predictiveness procedure in order to examine whether the effects change. Similarly, a procedure in which automatic and volitional control can be engaged independently while equating learning would be informative as to the degree of specificity for which the current results should be interpreted.

Related to this issue is the observation that the attentional blink engages distinct performance from that generally involved in learned predictiveness tasks. Conversely, the kind of responses required in learned predictiveness diverge from demonstrations in which learning or frequency effects have been reported in the attentional blink (e.g., Crebolder, Jolicœur, & McIlwaine, 2002; Livesey et al., 2009; Mayberry, Livesey, & Dux, 2010). If the congruence between the performance engaged by the learning task and an attentional measure influences how that measure is sensitive to changes in selection due to learning, it may be that more ‘implicit response’ learning paradigms might produce quite different results in a measure such as the attentional blink.

The discussion above questions the extent to which attentional models of associative learning (e.g., Le Pelley, 2004; Mackintosh, 1975; Pearce & Hall, 1980; Pearce & Mackintosh, 2010) can be applied to findings in which changes in selection are indexed by direct measures of attention taken from the cognitive literature. One could argue that this comparison is not a directly relevant one, given that such models are explicitly formulated in order to explain changes in the rate of learning, a measure that is subsequently tied to attentive processing. Indeed, it seems that such models are
not equipped to handle results at the level of specificity discussed here. However, the fact still remains that such models make claims about the automatic nature of the change in attention with learning. Isolating the predictions of these models to this measure would appear to limit their applicability to theorising about attentive processes. A clearer outline of the relationship between changes in associability, or learning rate, and other attentive processes may provide some clarity in how these models would be applied to increasing work combining direct measures of attention with learning. Work in this arena is still in its infancy, such that key questions remain as to the kind of results that should inform extensions of such models.

Conclusions

This thesis explored variations in stimulus selection during learned predictiveness in order to gain a better understanding of how learning and attention co-ordinate behaviour. The results provide clear evidence for the presence of automatic processes, suggesting that both top-down and bottom-up signals contribute to the observation of learnt biases. However, these interact in complex ways. Under some circumstances, they appear to be additive, for example, when automatic signals for familiar targets are congruent with top-down biases at the object level and there is no competition from novel stimuli. Novelty appears to provide a salient source of stimulus selection, modulating the competitive interaction between learnt bottom-up signals and deliberate attention. For items that form the focus of top-down attention, novelty overrides any competitive advantage for the bottom-up signals associated with learning. However, these are present in situations when top-down attention is directed elsewhere, that is, for distractors. Clearly the ways in which these sources of processing bias interact are complex. Further work clarifying the boundaries of these
competitive interactions presents an exciting challenge both empirically and theoretically.
References


Krebs, R. M., Boehler, C. N., & Woldorff, M. G. (2010). The Influence Of Reward


Human Associative Learning. *Behavioral And Brain Sciences*, 32(02), 183–64.


Olivers, C. N. L., Meijer, F., & Theeuwes, J. (2006). Feature-Based Memory-Driven


*Psychological Research*, 71(2), 126–139.


