A WEIGHTED SUMMATION FRAMEWORK FOR CONJUNCTIVE PREDICTIONS

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Abstract

The mind readily learns predictive relationships in the environment where a cue predicts a specific outcome. This research examines a novel question: How does the mind spontaneously generate predictions when multiple cues associated with different outcomes are jointly presented. I propose a weighted summation framework to model human predictions: when encountering joint cues, the mind sums up the associated outcomes based on their respective probabilities. The conjunction that represents the overlap of the two outcomes would have the highest summed probability, and would be prioritized and consistently predicted. To examine the research question, Experiments 1-3 employed a spatial search paradigm. Participants were first exposed to cue-location associations where specific color (Experiments 1-2) or texture cues (Experiment 3) predicted target appearance in specific locations. Then, two cues jointly appeared either side-by-side (Experiments 1-2) or into a new object (Experiment 3), and the target appeared in all locations with equal frequency. Following the two cues, there would be locations consistent with both of them, making these locations the conjunctive locations. The results showed that search time was faster when the target appeared in the conjunctive location. In Experiments 4-6, an attention tracking paradigm was used to extend the findings in Experiment 1. The results showed that when two cues jointly appeared, participants tended to first check the conjunctive location for the target, suggesting they made conjunctive predictions. Experiments 7-9 aimed to further extend the previous findings. Specifically, Experiment 7 replicated previous results with a conceptual paradigm, where each cue was associated with a conceptual category of objects (e.g., red predicts large objects). Experiments 8-9 examined weighted subtraction, where participants were exposed to associations between a pair of joint cues and specific spatial locations, and made predictions when they encounter a single cue from the pair. Experiments 10-11 examined the
role of exposure in forming conjunctive predictions, where exposure was replaced with only explicit instructions (Experiment 10), or the strength of cue-outcome associations was reduced during exposure (Experiment 11). Overall, the results of the current research suggested that people tended to make conjunctive predictions when encountering joint cues, consistent with the weighted summation framework.
Lay Summary

We all know that raining follows a thunder, and emergency vehicles follow loud siren sounds. Such knowledge is common, and learning such relationships could be important for survival. On the other hand, learning and the resulting knowledge may guide our behaviors in novel scenarios. This research examines one of those scenarios, where people encounter the joint presentation of predictive cues for the first time.

This scenario is common, and people could encounter joint cues in the form of traffic signs, product labelling, and poster advertisement. To understand people’s behaviors, I measured research participants’ responses following joint cues. Through multiple experiments with diverse paradigms, I found that people made conjunctive predictions that represented the overlap of the outcomes predicted by the joint cues. These results contribute to the understanding of people’s behaviors in novel situations, and the findings are helpful to those who design signage and labelling for the general public.
Preface

Experiments in Chapter 3 were conducted at the Behavioral Sustainability Lab at the University of British Columbia. The experiments received approval from the UBC Behavioral Research Ethics Board (H13-02684). Experimental design, data collection, data analysis, and manuscript drafting were performed by me, Ru Qi Yu, under the supervision of Dr. Jiaying Zhao. A version of Chapter 3 was published in Psychonomic Bulletin & Review:


Data for Chapters 4 to 6 in the dissertation were collected online through UBC’s research participation system with approval from the UBC Behavioural Research Ethics Boards (H20-03741). Again, experimental design, data collection, data analysis, and manuscript drafting were performed by me, under the supervision of Dr. Jiaying Zhao. A version of Chapters 4 and 5 was accepted as a proceedings paper for the 43rd Annual Conference of the Cognitive Science Society:


Experiments in Chapter 6 along with some experiments from Chapters 4 and 5 have been written up and the manuscript is currently under review in a peer-reviewed journal.
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Chapter 1. Introduction and general overview

1.1 Research question and Overview of Chapter 1

The environment contains widespread regularities, where the presence of certain objects can reliably predict the occurrence of other objects or events. Learning these associations is highly important for the survival of an organism. For example, learning that certain smells predict poisonous food can save us from consuming harmful substances; and learning that thunders often predict heavy rains can save us time in finding a nearby shelter.

While the mechanisms involved in learning predictive relationships have been extensively examined in past research, a relatively under-investigated question is the effects of learning on people in future scenarios. Specifically, the current research aims to examine how the past knowledge of learned associations could guide human predictions when encountering the joint presentation of multiple predictive cues. This type of situation is common in daily lives. For example, when trying to find the apartment keys, I see both my wife and myself in the room. I have the knowledge that I tend to put them on tables and my wife tends to put them anywhere in the living room. So where should I check for the keys? The current research proposes a novel weighted summation framework to model human predictions in such scenarios, and the details of the framework are discussed in Chapter 2.

In Chapter 1, the relevant literature leading to the current research question is discussed. These studies form the foundation of the current research and together demonstrate that the research question is valid and valuable.

Specifically, the definition for predictive relationships is established first (section 1.2), and the significance of predictive relationships in daily lives is discussed (section 1.3). Then, the research paradigms employed to empirically examine the learning of predictive relationships are
thoroughly reviewed (section 1.4). Next, section 1.5 presents evidence showing that learning can interfere with future learning, with results in section 1.6 further demonstrating that learning is spontaneous and can persist for a long time without any instructions. These studies together point to one important reason why people learn: learning is not just a response to the current task, but a process to extract any regularities in anticipation of future scenarios. Such evidence would indicate how the current research question is novel (section 1.7) and well connected to the previous research in the general field of learning.

1.2. What are predictive relationships?

It is important to first establish a concrete definition for predictive relationships. Predictive relationships discussed in the current research are reliable associations between a predictor and the outcome, where the presence of a predictor reliably predicts the occurrence of the outcome. These predictive relationships do not necessarily entail causation. For example, while heavy rain typically follows thunder, thunder is not the cause of heavy rain. Rather, they are both the results of heavy clouds congregating in the sky (Williams, Cooke, & Wright, 1985). In human experiences, the critical difference between predictive relationships and causal relationships is that in a predictive relationship, we passively encounter the predictor, and then we observe the outcome. On the other hand, in a causal relationship, by initiating the cause, we can directly observe the outcome (Gopnik et al., 2004). In the real world, causal relationships can only be directly verified if we can act on the predictor and observe the outcome immediately afterward (e.g., Watson & Ramey, 1987). Therefore, causal relationships are computationally challenging and are often inferred (Ahn & Kalish, 2000; Cheng, 1997). Sometimes, causal inferences that people make are based on correlational evidence and can therefore be false.
Simply put, causal relationships are predictive, but predictive relationships are not always causal. The current research question is about human predictions when encountering the novel combination of predictors, therefore studies examining causal relationships are relevant. On the other hand, the current research does not directly examine whether and how do people make causal inferences given the predictive relationships presented to them.

1.3. The importance of predictive relationships

Why is important to study predictive relationships? Predictive relationships are widespread and often important to people’s daily lives. Knowledge of these relationships profoundly affects the way people behave. Some of these predictive relationships are common knowledge. Learning some of the common knowledge is critical for survival. For example, touching the power outlet can lead to deadly electrocution, and loud sirens indicate a fast-approaching vehicle that might not yield to pedestrians. Such knowledge can help people avoid deadly electrocution and car crashes. Nevertheless, some of the common knowledge is trivial, yet people know them simply because they are prevalent. For example, salt and pepper always occur with one another on the dining table. Such trivial knowledge affects human behaviors in more subtle ways. For example, people might grab bottles of salt and pepper together when their dish tastes too bland without even realizing doing so.

Other predictive relationships in our lives are very personal knowledge. Again, some of the personal knowledge can be important for survival. For example, certain food ingredients can lead to severe allergic reactions, and certain physical activities can worsen existing injuries. These ingredients and activities need to be avoided at all costs. Other personal knowledge can be quite trivial. For example, a certain number is associated with a few sad experiences, so people would tend to avoid using it.
1.4. What are the ways to empirically study predictive relationships?

The previous examples of common and personal knowledge show that people readily learn predictive relationships in daily lives, usually spontaneously without instructions from others. How do empirical studies study such learning in experimental settings?

1.4.1. Similarities in empirical studies

Empirical studies that examine learning share commonalities that would typically reduce the computational complexity of the to-be-learned predictive relationships to make learning feasible in a study session. First, in these empirical studies, outcomes typically directly follow the predictors without significant delays. Second, participants typically see a very limited number of possible predictors or possible outcomes at a given time point. Third, each to-be-learned predictive relationship is usually repeated with multiple exemplars.

1.4.2. Automatic learning of basic predictive relationships

Some predictive relationships are basic and can be automatically learned across many species. Two of such mechanisms are briefly discussed below. While not directly relevant to the current research question, they do illustrate the fundamental mechanisms of learning.

The first form of such learning is habituation. Specifically, certain stimuli in the environment predict a lack of meaningful consequences, therefore the neural and behavioral responses to these stimuli decrease after repeated exposure. Habituation is a learning process (Groves & Thompson, 1970; Thompson & Spencer, 1966) because it differs from simple sensory adaptation (where the activities of sensory neurons decrease as a result of repeated exposure to a stimulus) and sensory/motor fatigue (where the muscles responsible for generating responses get fatigued). Habituation can be observed in multiple species (e.g., Maschke et al., 2000; Rose &
Rankin, 2001). Habituation can be adaptive since it helps the organism to decrease the response level to non-threatening stimuli in order to save energy.

The second form of basic learning is classical conditioning. Specifically, when a neutral stimulus (e.g., a ringing bell) reliably precedes another stimulus that elicits reflexive behaviors (e.g., some food that would elicit salivation), an organism also learns to respond to the neutral stimulus in the same way (Pavlov, 1927). The neutral stimulus is often called the conditioned stimulus (CS), and the stimulus that elicits reflexive behaviors is often called the unconditioned stimulus (US). Classical conditioning can be adaptive because it allows the organism to generate responses faster, and it can also be observed in a wide array of species (e.g., Blass, Granch, & Steiner, 1984; Morrison et al., 1999; Pavlov, 1927; Wen et al., 1997).

The underlying neural mechanisms suggest that classical conditioning is more automatic than other forms of associative learning in humans (Thompson, 1990). Nevertheless, classical conditioning is relevant to these more complicated forms of human learning in two ways. First, classical conditioning depends on the reliable association between the US and the CS (i.e., the CS follows the US with high probabilities), rather than the mere frequency of associations (Recorla, 1966). This finding suggests that learning of predictive relationships hinges on the reliability between the predictor and the predicted outcome, and the mind is sensitive to probability rather than frequency. Second, classical conditioning can go through extinction if the US could no longer reliably predict the CS. Importantly, this extinction is an additional learning process to inhibit the knowledge of US-CS pairing, because the behavioral responses to the CS can automatically recover after extinction (Baum, 1988). This finding suggests that the knowledge of predictive relationships is flexible and can be updated with new information.
1.4.3. Explicit learning

In human research, the most straightforward way to study learning is to directly ask participants to find the predictive relationships in a set of stimuli presented to them. Typically, participants would be given written instructions explicitly telling them that there would be predictive relationships between A and B. For example in a study by Le Pelley and Mclaren (2003), participants were given the instructions that patient Mr. X is allergic to some foods. Participants then would learn how specific food combinations can cause the corresponding allergic reactions. Participants were then asked to rate on a scale of 0 to 10 for the strength of predictive associations between each food and each allergic reaction that Mr. X would develop. This paradigm is termed “learned predictiveness” by the authors.

Explicit learning paradigms have several advantages. First, participants are explicitly asked to observe the predictive relationships. As a result, any failure to learn the relationships likely does not result from problems with the instructions. Second, because participants are aware of the existence of predictive relationships, they can explicitly reason to find more complicated relationships. Third, participants’ reports of their knowledge after exposure tend to be relatively accurate. This is apparent because they are instructed to find such relationships.

On the other hand, there is an important disadvantage. Such paradigms cannot reflect learning in the real world. Specifically, participants in these studies are aware of the existence of predictive relationships. Such pre-existing knowledge would be mostly absent when people naively observe the external world. For example, when learning that a salt bottle always appears next to a pepper bottle on a dining table, most of us are not told to observe regularities on the table. Therefore, explicit paradigms cannot adequately simulate such learning experiences.
1.4.4. Learning through close interactions

Similar intentional learning paradigms are used in developmental studies that examine toddlers’ learning of predictive relationships. Nevertheless, the participating children typically are not directly told about the existence of predictive relationships. Instead, these predictive relationships are played out with real objects. In some tasks, the participants know that task performance must rely on finding such relationships. For example, in the learning task by Eimas (1996), participating children were asked to play a game with the experimenter. The children had to choose certain cards with the goal of finding a winning chip behind the cards. Cards of certain features (e.g., its shape) reliably predicted the existence of a winning chip. Alternatively, the task for the participating children can be actively observing the interactions between the predictors and outcomes (Gopnik & Sobel, 2000).

One important advantage of these paradigms is that they tend to better simulate real-world learning experiences. Specifically, participants attentively observe the interactions between the predictors and outcomes in actual objects to achieve better performance. As a result, participants’ behaviors in these tasks can directly reflect their knowledge. Another advantage of these paradigms is that participants’ attention is consistently drawn to the interactions between the predictors and outcomes, either because they are instructed to do so, or because they know that their performance could be greatly improved by finding the predictive relationships.

On the other hand, these paradigms are difficult to implement, and this is the main disadvantage. The usage of real objects and the active involvement of human experimenters mean that the study procedures cannot be automated. This would lower the efficiency of data collection and restrict the complexity of the predictive relationships in these experiments.
1.4.5. Implicit learning

In many other learning studies, participants are not made aware of the existence of regularities nor is their attention drawn to observing the predictors and outcomes. As a result, learning is implicit in these paradigms.

For example, in a contextual cueing task devised by Chun and Jiang (1998), participants were asked to find a target “T” among distractor “L”s in a display. Unbeknownst to the participants, the overall spatial configuration of the display predicted the target location. It was found that participants’ response time in target search became faster over time compared with the baseline, indicating their knowledge of the associations between the display configurations and the target locations. Importantly, participants were never aware of such associations. These effects can also be found in other spatial search paradigms. For example, participants could shift their attention to the location where the search target mostly appeared, without explicit awareness of the spatial distribution of target locations (Miller, 1988; Shaw & Shaw, 1988).

Implicit learning can even occur in non-cueing paradigms, where learning is completely unrelated to task performance. For example, in statistical learning, participants are able to learn regularities of reliable object co-occurrences that they passively encounter. The initial study on statistical learning examined infants’ ability to detect the co-occurrences of auditory sounds (Saffran et al., 1996). Specifically, there were 12 unique syllables in the auditory stream, and the syllables were divided into four triplets (i.e., syllables ABC, DEF, GHI, and JKL) such that the three syllables within a triplet always appeared one after another in a fixed temporal order. The order across the triplets was randomized in the speech stream (e.g., DEF JKL ABC GHI), and

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1 In this paper, statistical learning strictly refers to the learning of object co-occurrences, where objects either appear one after another in a fixed order or one next to another in a fixed spatial configuration.
there was no conspicuous auditory cue to indicate the boundaries between any two triplets. It was found that infants could discriminate a triplet against a sequence of three syllables that never appeared together in the speech stream (e.g., EJK) or even a triplet from a less frequent three-syllable sequence in the speech stream (e.g., an accidental sequence of BCJ, formed when triplet JKL followed triplet ABC). Statistical learning of regularities also occurs in other sensory domains. For example, infants could detect spatially co-occurring objects in visual arrays with multiple shapes presented at the same time (Fiser & Aslin, 2002; Kirkham et al., 2002), and adults could even detect statistical regularities from tactile input (Conway & Christiansen, 2005).

The advantage of implicit learning paradigms is that they could demonstrate the robustness of learning. Specifically, learning occurred without explicit task demands or deliberate observation, but merely as the result of passive exposure. The disadvantage of implicit paradigms is that learning is hard to quantify. Because participants would often fail to explicitly report the predictive relationships (e.g., Jiang, Swallow, & Rosenbaum, 2013; Turk-Brwone, Jungé, & Scholl, 2005), learning can only be indirectly measured. For example in statistical learning, to assess learning, participants are typically given the co-occurring objects and a set of other objects, and asked to judge which set of objects feel or seemed more “familiar” to them. This two-alternative forced-choice test often yields above-chance performance for a group of participants, but it is a poor indicator of individual differences in learning.

Moreover, implicit learning paradigms also limit the complexity of relationships that people can learn. For example, in statistical learning, participants can only implicitly learn the relationships between individual objects, but not higher-order structures of how different contexts could affect relationships of individual objects (Yim, Dennis, & Sloutsky, 2020).
1.5. The common effects of learning

The current research aims to examine how learning of predictive relationships can guide predictions in future scenarios. This question assumes that the knowledge of learning can affect behaviors in future scenarios. Nevertheless, these carefully crafted paradigms to empirically study learning raises the possibility that learning in these tasks is the result of task demands, thus learning likely cannot affect performances in the future.

However, despite the divergent methodologies used by explicit and implicit learning studies, some consistent findings emerged in learning literature: learning interferes with future learning, possibly by modulating attention.

1.5.1. Effects of explicit learning on attention

In explicit learning paradigms, participants’ overt attention can be selectively drawn to the reliable predictors. Specifically, Le Pelley, Beesley, and Griffiths (2011) used a similar paradigm to the Le Pelley and McLaren (2003) study, where participants were explicitly told that Mr. X would develop certain allergic reactions to certain foods. Participants’ eye gaze during the presentation of different foods was tracked, and it was found that the looking time on foods reliably predicting an allergic reaction was longer than the looking time on other foods.

Additionally, attention can also be selectively biased toward the predictive feature dimension (Rehder & Hoffman, 2005). This selective attention is not task-relevant. Specifically, when two cues appeared together, with one cue being previously predictive of the outcome in the preceding task and the other being never predictive, participants were faster to respond to the previously predictive cue (Le Pelly, Vadillo, & Luque, 2013).

In explicit learning studies, it was unclear whether the overt selective attention resulted from top-down control or implicit biases. Explicit instructions entail a top-down process to
modulate attention. On the other hand, participants could involuntarily develop a bias in attention fostered by their explicit knowledge (see Ellis, 2005 for a discussion).

1.5.2. Effects of implicit learning on attention

In implicit learning, there are several studies with a wide range of paradigms that have examined the effect of learning on attention. First, predictive relationships draw attention spatially. This is evident in spatial cueing paradigms, where learning is assessed through faster response time, which would be the proxy for spatial attention (Brockmole, Castelhano, & Henderson, 2006). Furthermore, learning can alter the spatial scale (local vs. global) of attention (Zhao & Luo, 2017) and learning of non-spatial regularities can also guide spatial attention. For example, in statistical learning, a study by Zhao, Al-Aidroos, and Turk-Brown (2013) found that the location containing regularities can draw attention spatially. Specifically, four streams of visual objects were presented in four different locations on the screen. One of the locations contained temporal statistical regularities and the other locations contained similar objects that appeared in a random order. Through a target search task, it was found that attention was spatially drawn to the location with regularities. Importantly, the location of statistical regularities was not relevant to the search task that the participants had to complete.

Evidence from implicit learning studies also showed that predictive relationships can increase the temporal span of attention for the predictors (Livesey, Harris, & Harris, 2009) using an attentional blink paradigm (Raymond, Shapiro, & Arnell, 1992). Additionally, attentional bias can be directed toward the perceptual features of the objects in a predictive relationship, even after the predictive relationship disappeared (Barakat, Seitz, & Shams, 2013).

These results together demonstrated that statistical learning leads to an increase in the temporal attentional span for predictive objects, and result in an implicit bias to preferentially
attend to the location, spatial scale, and perceptual features of regularities. The biases in attention often are task-irrelevant. It is important to note that the interactions between attentional biases and learning contain a lot more nuances, which are beyond the scope of the current research, but see Batterink and Paller (2017, 2019) for more detailed results and discussions.

1.5.3. Effects of learning on subsequent learning

While modulating attention, learning can further interfere with future learning. As discussed previously, attentional bias to the visual features of predictive cues persists even after the exposure to the predictive relationships (Le Pelley et al., 2013 for explicit learning and Barakat et al., 2013 for implicit learning). Similarly, spatial attention can be implicitly and persistently drawn to the locations with previous regularities even after the regularities have long disappeared (Jiang, Won, & Swallow, 2014; Yu & Zhao, 2015). One explanation for the persistent attentional bias is that such bias can lead to more efficient learning of similar regularities in the future. Indeed, when participants have explicitly learned that certain feature dimensions (e.g., shapes) are predictive of a task-relevant outcome, learning of future predictive relationships in that dimension would be efficient (e.g., Eckstrand & Wickens, 1954; House & Zeaman, 1962), and this effect can be explained by overt attention (Le Pelley et al., 2011).

On the other hand, results from implicit learning studies suggest that the attentional bias toward the visual features or the locations of the original regularities may serve to hinder or even block future learning of different regularities, rather than making future learning of similar regularities more efficient. The most direct evidence comes from Yu and Zhao (2015), where it was found that task-irrelevant spatial attention was persistently drawn to the location that previously contained regularities, even though regularities no longer appeared there while new regularities emerged somewhere else. This directly resulted in participants’ failure to learn the
new regularities in other locations. Similar findings are reported in auditory statistical learning (Gebhart, Newport, & Aslin, 2009), probability cueing paradigm (Jiang, Swallow, Rosenbaum, & Herzig, 2013), and contextual cueing (Jungé, Scholl, & Chun, 2007).

Taken together, these results offer several insights into the relationship between learning current regularities and future learning performances. First, learning the predictive relationships persistently draws attention to the visual features or spatial locations of the regularities in both explicit and implicit learning. Second, this persistent bias is not task-relevant and can make it difficult to learn future predictive relationships in other feature dimensions or spatial locations. Third, this difficulty is more pronounced with implicit learning. In explicit learning paradigms, learning different predictive relationships can still be possible (e.g., Le Pelly et al., 2011), likely because explicit awareness can lead to more flexible knowledge representations, making it possible to update the knowledge with new information (Mitchell et al., 2012). In implicit learning, current and future regularities have to be demarcated with clear boundaries (e.g., a long pause or a salient auditory signal) to enable successful future learning (Gebhart et al., 2009).

1.6. Learning is spontaneous

Studies in the previous section demonstrate that learning predictive relationships draws attention and interferes with subsequent learning. These learning effects often are not relevant to the current task demands, suggesting that learned knowledge might be persistently preserved in expectation of future scenarios where it can be applied.

Nevertheless, there is an alternative interpretation: persistent preservation of learned knowledge that blocks subsequent learning may be the by-product of optimizing the performance in the current task, rather than expecting similar regularities in the future. However, this is unlikely because learning can be completely spontaneous and harm performance in the current
task. For example, in the study by Zhao and Yu (2016), participants were asked to estimate the number of objects in visual arrays. Unbeknownst to the participants and unrelated to the estimation task, the visual arrays contained object pairs, where the two objects in a pair always appeared one next to another in a fixed spatial configuration. Participants reliably underestimated the number of objects in visual arrays containing such regularities. This finding demonstrates the spontaneous nature of such learning because not only is learning irrelevant to the estimation task, it even results in worse task performance.

1.6.1. Learned knowledge persists over time

Additionally, the implicitly acquired knowledge of predictive relationships can be preserved for a long time after learning. In probability cueing, the learned bias in spatial attention can persist for a day after initial learning (Jiang et al., 2013). Similarly in statistical learning, with a 5-minute exposure, participants can maintain the knowledge of the regularities one day after exposure (Kim et al., 2009), by discriminating co-occurring objects versus other object combinations (Arciuli & Simpson, 2012). Importantly, participants were not instructed to memorize or maintain such implicitly acquired knowledge.

These results together show that people actively find predictive relationships in the environment, regardless of whether the learning process benefits the task at hand. The knowledge of predictive relationships is maintained and consolidated over an extended period of time without awareness (Kim et al., 2009). These findings suggest one important reason for learning: people learn spontaneously in anticipation of a future scenario where the knowledge can be applied. Such evidence in learning of predictive relationships shows how past research is well connected to the current research question, which investigates how can past knowledge of predictive relationships guide predictions in novel scenarios.
1.7. How does learning affect judgments in novel scenarios?

1.7.1. Implicit learning and generalization to novel stimuli

In implicit learning, most studies do not directly examine how people apply previous knowledge when making future predictions. Instead, participants are given novel options and are asked to judge which option is consistent with the previously encountered ones (Reber, 1967). In some cases, the encountered stimuli contain complicated rules similar to the nested structures in human languages (e.g., Reber & Lewis, 1977; Howard & Ballas, 1980), in other studies, the encountered stimuli contain simple rules such as ABA (Marcus et al., 1999). When generalizing to novel stimuli, participants often feel like guessing (see Perruchet & Pacton, 2006 for a review), and further evidence suggests that this process operates mostly implicitly (Knowlton, Ramu, & Squire, 1992; Reber, 1989).

Similar findings also emerge in implicit statistical learning. In a study by Luo and Zhao (2018), it is found that when past knowledge contains transitive structures (i.e., A predicts B, and B predicts C), people would judge the pairing between A and C to be more familiar than A and D. Furthermore, when people observe changes in the predictor, the recall of the predicted object changes in the same way (Yu & Zhao, 2018b).

1.7.2. Decision making

While previous implicit learning studies have demonstrated that past knowledge can subtly affect future judgments, they fail to clearly reveal the predictions that people have in mind in future scenarios. One obvious way to directly assess predictions is to explicitly ask participants. Such paradigms are frequently used in decision-making studies. One prominent example is conjunction fallacy (Tversky & Kahneman, 1983). Specifically, participants were given written descriptions of a female character who was smart and progressive. Then two
options were given: 1. She is a bank teller, and 2. She is a bank teller and a feminist. Participants predicted which statement was more probable. It was found that the majority of participants chose the second statement, even though the second statement contained the conjunction of two predictions, while the first one only contained a single prediction. Objectively, the conjunction of two predictions could not be more probable than one of the predictions alone, so this tendency to choose the conjunction statement is termed as “conjunction fallacy”. While these findings are ground-breaking, there are a couple of drawbacks of using this decision-making paradigm.

First, all the task instructions in such paradigms are delivered verbally, so participants might have various interpretations of the same word. Indeed, this is one of the main criticisms of conjunction fallacy, where people’s interpretation of the word “probable” may vary from the intended meanings (Hertwig & Chase, 1998; Hertwig & Gigerenzer, 1999). Additionally, people might have different interpretations of the word “and” in the option “She is a bank teller and a feminist” (e.g., Dulany & Hilton, 1991). While these problems are partially ruled out in follow-up studies using a betting paradigm (Bonini, Tentori, & Osherson, 2004; Tentori, Bonini, & Osherson, 2004), the need for such follow-ups highlights the ambiguities in verbal instructions.

The second drawback is the constraints on people’s predictions. Participants are typically given a limited number of options. For example, participants are given only two options in Tversky and Kahneman (1983), and three options in a modified paradigm by Bonini et al. (2004). Alternatively, experimenters could assess participants’ predictions by rating on a scale of 1 to 10 (Alvarez, Ruble, & Bolger, 2001). While well-defined options reduce ambiguities, such constraints prevented the experimenters from observing spontaneous predictions. Therefore, participants in such decision-making paradigms were not making genuine predictions, rather, they were indeed making a decision from one of the prescribed options provided to them.
Chapter 2. The current research question and the proposed paradigm

The current research specifically examines how people make predictions when encountering the joint presentation of multiple predictive cues. The current research defines predictions as the outcome that is first acted upon following the cues. This definition is in line with most of the previous studies discussed in section 1.7, where participants are asked to choose the best option following the descriptions (e.g., Bonini et al. 2004; Tversky & Kahneman, 1983).

There are several advantages of employing joint cues as the novel scenario. The first advantage is that they can simulate the real-world environment, where predictors often appear jointly. Therefore, understanding how people would make predictions when seeing joint cues can have important practical implications. A previously discussed example is that when trying to find the apartment keys without remembering much about where I last saw them. I see both my wife and myself. I have the prior knowledge that I tend to put keys on tables and my wife tends to put keys in the living room. Where should I look for the keys? Knowing my search behaviors could help us better place the keys in the future.

The second advantage of using joint cues is that they can account for the possibility that people might have diverse predictions. Since the joint cues are novel, people might interpret the cues differently based on previous experiences. For example, when a right-turn sign and a speed-limit sign jointly appear, some people might think that both signs must be true simultaneously, thus expecting a narrow right-turn ahead. Some people might attend to the more personally relevant sign (e.g., the right-turn sign) and expect diverging paths ahead, thus would carefully check the navigation system before moving on. Some people might not care at all and would drive forward as per usual. Importantly, because the joint appearance of cues is novel, there would be no correct predictions, and the goal of the research is to observe and quantify the
diverse possible responses. To achieve this, participants should not be given a limited number of options from which to respond. This can be adequately designed with joint cues as the novel situation and spatial search as the task. Specifically, participants can be asked to find a target object from a display, and for each trial, the preceding cue would predict the general location of the target (e.g., a red cue predicts the target appearing on the top half of the display). Then, when two predictive cues both appear in a subsequent phase, participants are still asked to perform the same search task. Importantly, for each trial, participants can search anywhere on the screen for the target, and the response time for different target locations and participants’ movement patterns can be quantified to assess the type of predictions they had made.

Paradigms with joint cues have been previously used in associative learning studies examining the “blocking” effect. However, the blocking paradigm examines a fundamentally different question: how the presence of joint cues affects associative learning, rather than how learning affects future predictions when seeing joint predictive cues. Specifically, in the blocking paradigm, participants first learn A-outcome associations, then are presented with AB-outcome associations. It is found that participants cannot learn the B-outcome associations. These results are demonstrated both in animal conditioning studies (Kamin, 1969), and explicit human learning studies (e.g., Chapman & Robbins, 1990; Le Pelley, Oakeshott, & McLaren, 2005).

2.1. The weighted summation framework

To model and understand people’s predictions in novel scenarios, the current research has put forth a new theoretical framework of **weighted summation**. Again, predictions are defined as the first outcome that people act on.

When encountering multiple predictors simultaneously, there is a corresponding outcome associated with each predictor. For example, color A is associated with the top half of the
display, and color B is associated with the left half of the display. This means that color A (red) predicts the top-left quadrant 50% of the time and the top-right quadrant 50% of the time, and color B (blue) predicts the top-left quadrant 50% of the time and the bottom-left quadrant 50% of the time (Figure 2.1a).

![Diagram of original associations and weighted summation process]

**Figure 2.1. The weighted summation process.** a) An example of the original associations that people have learned. b) When two cues jointly appear, the probability distributions of the corresponding outcomes are summed. c) The summed distribution is weighted to form the new probability distribution for the joint cues.

Then in the framework, the sum of outcome probabilities is computed when the predictors jointly appear (Figure 2.1b). By summing the probability for each location, there would be a 100% chance for the top-left quadrant, and a 50% chance for the top-right and bottom-left quadrants (Figure 2.1b).
Then, to represent the summed probabilities as a realistic set of possible outcomes given the joint cues, a probability distribution with an overall chance of 100% needs to be obtained. Therefore, the chance for each quadrant would be multiplied by a weight of 0.5, resulting in a 50% chance for the top-left quadrant, and a 25% chance for the top-right and bottom-left quadrants. This is the weighted sum for the probability of each outcome subset after the joint predictors (Figure 2.1c).

In the final step, the framework postulates that people prioritize the outcome subset with the highest weighted sum (i.e., the conjunction of the associated outcomes) when they make predictions. Because predictions are defined as the first outcome to be acted on, the prioritized conjunction is consistently predicted. It is important to point out here that though predictions are based on the weighted sum of outcome probabilities, they reflect the first option that comes to people’s mind when encountering the joint cues. Thus predictions do not need to match the represented probability of each outcome subset. This point can be illustrated with the following example. When one kid hypothetically runs 50km/hour and another runs 25km/hour, almost all coaches will select the much faster kid to be on the sprinting team. Though the coaches’ decisions are based on the kids’ running speed, the number of coaches who choose the faster kid versus the slower kid is likely going to be 73 versus 2, rather than proportional to the kids’ running speed, which would be 50 versus 25.

Therefore, prioritizing the outcome subset with the highest probability effectively enlarges the frequency of that outcome in people’s predictions compared with that outcome’s represented probability. In the discussed example, the probability for the spatial conjunction (the top-left quadrant) is represented as 50% as a result of weighted summation. Because it is clearly more probable than any of the disjunctive locations (25%) after weighted summation, people
consistently prioritize the conjunctive location in predictions following the joint cues. Consequently, people consistently make conjunctive predictions in the majority of the trials, though they only represent the probability of the conjunction of outcomes as 50%. It is important to note that the current research is primarily interested in whether people would prioritize the conjunction of outcomes to make conjunctive predictions. Representing the probability of the outcomes as the weighted sum is not the ultimate goal of the research, though it is an important step in the framework to explain why people might make conjunctive predictions.

Conjunctive predictions based on the most probable outcome after the weighted summation process mean that the outcomes associated with each cue need to be simultaneously represented/integrated and are not independently represented. This is because without integrating the outcomes, it would not be possible to compute the weighted sum of these outcomes.

Although the weighted summation framework is novel in modeling the predictions that people make when encountering joint predictive cues, there are several lines of research that provided similar models in areas such as perceptual processing and explicit reasoning.

2.2. Evidence supporting the weighted summation framework

At the level of perceptual processing, previous studies on multi-cue integration have proposed similar models to the current weighted summation framework. First, the current framework is supported by a co-activation model of human response to multiple cues (Miller, 1982). Specifically, if two cues predict the same behavioral response (e.g., pressing a button after seeing either one of the two visual cues), their joint presentation would result in even faster responses. This faster response cannot be explained by simply taking the faster response to either one of the two cues, and can only be explained through an integration of the activation caused by the two cues. This integration is an accumulative process rather than an exponential synergistic
effect (Miller, 1986). The co-activation model suggests that the joint cues are integrated rather than independently processed. It can also explain why simultaneous contrasting cues can result in delayed responses (Login, 1980) in paradigms such as the Stroop task (Stroop, 1935).

Furthermore, perceptual experiences resulting from joint audio-visual cues such as the McGurk effect (McGurk & MacDonald, 1976) and the Ventriloquist effect (Alais & Burr, 2004) also demonstrate that unique experiences that are distinct from the input of individual sensory cues can arise as a result of multi-cue integration. Models that are similar to the current weighted summation framework have been proposed to account for the unique perceptual experiences arising from sensory integration (Alais & Burr, 2004; Peters, Zhang, & Shams 2018), where the probability of each associated cue is integrated to generate the unique perceptual experience resulting from sensory integration.

Admittedly, the current framework pertains to the way people represent the probability of the possible outcomes to inform predictions in a novel scenario, rather than an automatic perceptual experience directly resulting from the joint cues. Specifically, the joint cues in the current paradigm are associated with a location through past knowledge and are not directly associated with a direct behavioral response or an automatic perceptual experience. Consequently, the computations necessary for a weighted summation framework might involve a more explicit reasoning process.

The second line of research that provides support for the current framework is semantic processing. Specifically, results from past research have shown that the conjunction of conceptual constructs can create a new integrated representation. For example, when given a new phrase of “brown apple”, subjective ratings indicated that participants represented the new phrase as a different concept from the constituent concepts of “brown”, and “apple” (Smith &
Osherson, 1984). In other words, people typically think of brown apples rather than thinking of all the brown stuff or all the apples. This new representation can be rapidly generated without much effort (Springer & Murphy, 1992). Based on these findings, the joint predictive cues may be quickly integrated, and the conjunction of the associated outcomes can be quickly represented as the typical outcome of this new integrated pair of cues.

Lastly, at the level of explicit decision-making, evidence suggests that people tend to over-report the frequency of representative events, especially when they are asked to generate the events themselves (e.g., Tversky & Kahneman, 1974). In the current paradigm, the conjunction of the associated outcomes might be viewed as the representative outcome. Direct support for the current framework comes from the previously discussed conjunction fallacy studies. Those results suggest that people tend to favor an option that is the conjunction of two predictions that are both consistent with the given descriptions of a person, rather than any one of the two predictions (Tversky & Kahneman, 1983). Later results confirm that this is the result of people’s over-report in the chance of conjunction in their predictions (Bonini et al., 2004). This distortion in people’s predictions is consistent with the weighted summation framework, with the difference being that conjunction fallacy takes place during explicit decision making when given specific options to choose from.

It is important to note that when two predictors appear jointly, the conjunction of each predictor’s respective outcome is not necessarily the correct outcome. For example, natural oxygen (O₂) and hydrogen (H₂) are both gaseous. So when adding them together, it might be intuitive to think that a gaseous mixture of the two will emerge. However, in reality, mixing hydrogen and oxygen in a burning reaction will result in a completely new aqueous substance: water (H₂O, or hydrogen peroxide H₂O₂). Therefore, this weighted summation framework aims
to describe the predictions that people tend to make when encountering the novel combination of two known predictors, rather than the predictions that are actually true.

2.3. Alternative possibilities

There are three other possible ways that people can make predictions upon seeing the joint presentation of cues. In the first account, participants would selectively attend to one cue at a time. Participants would be perfectly faithful to the associations between the cues and the outcomes and would make no predictions beyond what they have previously learned. Specifically, in the spatial search paradigm, participants would process one cue at a time and search for the target in the locations predicted by that cue. If the target is not found in these locations, participants might then search for the target in other locations that are associated with the second cue. This account is partially supported by results from spatial cueing studies demonstrating that the bias in spatial attention to the high-probability locations can persist despite various changes in the spatial distribution of target appearances (Jiang, Swallow, & Rosenbaum, 2013).

In the second account, participants would attend to both cues, and they would represent all possible outcomes equally. That is, participants would make conjunctive and disjunctive predictions with equal frequency, which means that they would not be sensitive to the differences in summed probabilities between the conjunction and disjunction of outcomes. This account is possible because no previous evidence had directly shown that people could automatically sum up the probabilities of multiple outcomes.

In the third account, participants would view the joint presentation of previous predictive cues as an explicit sign to start a new learning session. In the new learning session, participants would expect new associations between the joint cues and the outcomes, and would not make
any predictions based on previous knowledge at all (e.g., Gebhart et al. 2009). In the search paradigm, this would mean that participants would check all locations equally for the target.

### 2.4. Propositions given the weighted summation framework

Several propositions for empirical studies can be devised where their results can be predicted by the weighted summation framework. These propositions allow us to examine the framework with quantifiable behaviors. I have laid out these propositions, and each proposition would be examined in the corresponding experiments:

1) When encountering the joint presentation of predictive cues, the conjunction of the predicted outcomes would be consistently prioritized according to the weighted summation framework. Therefore, in a search task, participants would expect the target to appear in the location that represents conjunction, and search time in this location would be faster. Experiments 1-3 in Chapter 3 examined this proposition.

2) If participants have prioritized the conjunction of outcomes and made conjunctive predictions, then they should choose the conjunctive outcome first in their search strategy. Experiments 4-6 in Chapter 4 examined this proposition with an attention tracking paradigm.

3) The weighted summation framework is generalizable and can be applied to the conjunction of abstract categories beyond spatial conjunctions. An example of that would be the conjunction of dogs and small animals being Chihuahuas. Experiment 7 in Chapter 5 examined this proposition.

4) If the outcome with the highest probability after weighted summation is consistently prioritized in predictions, then the most probable outcome after a weighted subtraction should also be prioritized. A simple illustration is provided below (Figure
2.2). Experiments 8 and 9 in Chapter 5 examined this proposition.

![Diagram of weighted subtraction]

**Figure 2.2. A graphical representation of weighted subtraction.** Specifically, two predictors together predict a specific outcome, and one of the two predictors alone predicts a subset of the outcome. When the other predictor is presented later, the probability of the associated outcomes may be subtracted, and the subtracted outcome which represents the difference between the two associated outcomes is now the most probable, and thus may be predicted.

5) In the weighted summation framework, conjunctive predictions are based on predictor-outcome associations. Then, exposure to the associations and the strength of these associations should modulate conjunctive predictions. Experiments 10 and 11 in Chapter 6 examined this proposition.
Chapter 3: Is it faster to find the conjunction of outcomes?

The current chapter examined proposition 1. As discussed before, to better observe participants’ spontaneous behaviors after encountering the joint predictive cues, the current chapter used a spatial search task, where target locations of the search task were predicted by the cues. If participants made conjunctive predictions as per the weighted summation framework, it would be faster for them to find target in the location consistent with a conjunctive prediction. It is important to note that faster response time is a measure of participants’ prioritizations in the predictions. Faster response time in certain locations would mean that participants expect to find the target in those locations first. This would indicate the nature of participants’ predictions. This response time measure could not directly gauge whether participants represented the probability of each outcome as the weighted sum of their previous associations with the cues.

3.1. Experiment 1: Response time measures

3.1.1. Participants

A total of 120 students (81 females, mean age=20.0 years, SD=2.3) from UBC participated in this experiment for course credit.

3.1.2. Stimuli

In this experiment, the cues were four colored dots (R/G/B): blue (0/0/255), red (255/0/0), yellow (255/255/0), and grey (192/192/192), each subtending 2.2° of visual angle. Each dot was followed by a search array that contained 16 objects appearing in four quadrants (Figure 3.1a). Each quadrant was an invisible 4×4 grid, with each cell subtending 1.7° of visual angle. There was a gap subtending 2.2° of visual angle between any two adjacent quadrants. Four
objects appeared in each quadrant, where no row or column in the grid could be empty. One object was the target (a rotated T) and the other 15 objects were L-shaped distractors.

3.1.3. Procedure

There were two phases in the experiment. Participants first completed the exposure phase where in each trial one colored dot appeared on the screen for 1000ms, followed by a 1000ms blank screen, and then a search array. The task was to find the target and indicate which direction it was pointing (left or right) by pressing a key as quickly and accurately as possible. Unbeknownst to the participants, the color of the dot predicted in which half of the array the target would appear. For example, after the blue dot, the target would always appear in the top half of the array (Figure 3.1a). The target appeared in a random cell within the quadrants, and the direction of the target was also random. The four color-location associations were determined randomly for each participant but remained fixed throughout exposure. Each color dot and its associated search array were presented 40 times during exposure, resulting in 160 trials presented in a random order. The search array appeared on the screen until response. The inter-trial interval was 1000ms.

After exposure, participants completed the prediction phase which was identical to exposure, except that now two color dots were presented simultaneously, followed by a search array where the target now appeared in each of the four quadrants with equal frequency (Figure 3.1a). In other words, the color dots were no longer predictive of target locations. The four color dots were combined into six unique color pairs. Each color pair was presented four times, resulting in 24 trials presented in a random order. The limited number of trials during the prediction phase was to minimize the degradation of the knowledge learned from the exposure phase, since the colors were no longer predictive of the target locations. The two dots in each
pair were presented either horizontally or vertically (randomly determined), with the order of the two colors (e.g., which one was on the left) counterbalanced.

Based on the color-location associations during exposure, there were three location types following each pair (Figure 3.1b): locations consistent with a conjunctive prediction, locations consistent with an exclusive disjunctive prediction, and impossible locations where the target would never appear based on exposure. For example, following the blue-red pair, the top left quadrant was a conjunctive location, the top right and bottom left quadrants were disjunctive locations, and the bottom right quadrant was an impossible location. Since the target now appeared in each of the four quadrants with equal frequency, faster response time in a given location would reveal the nature of the predictions formed by participants upon seeing the color pair. For example, faster response time in the conjunctive than disjunctive location would suggest that participants expected the target to appear in the conjunctive location, thus indicating a conjunctive prediction. However, if response time was identical in the conjunctive and disjunctive locations, this would suggest no expectation of the target appearing in the conjunctive location, which would indicate a lack of the conjunctive prediction.

To further examine whether such predictions required explicit knowledge of the color-location associations, half of the participants (N=60) were randomly assigned to the explicit condition where they were told about the color-location associations (i.e., where the target would appear following which color), and the other half of participants were in the implicit condition where they were told to only pay attention to the colored dots, and there was no mention of the existence of color-location associations. During the prediction phase, participants in both conditions were told that now they would see two colors, and their task was to find the target in the array as quickly and accurately as possible.
After the prediction phase, participants in the implicit condition also completed a knowledge test to probe their awareness of the color-location associations. Specifically, they were asked to choose in which half (top, bottom, left, or right) of the array the target would appear after seeing each color dot.

**Figure 3.1. Experiment 1 paradigm and results.** a) During exposure, participants saw a color dot first, then searched for the target (the rotated T) and judged its direction as quickly and accurately as possible. Each color dot predicted in which half of the search array the target would appear (indicated in gray). b) During prediction, there were six color pairs. Each pair was presented first, followed by a search array. The target now appeared in all four quadrants with equal frequency. There were three location types: locations consistent with a conjunctive prediction (C), locations consistent with an exclusive disjunctive
prediction (D), and impossible locations (I). For four color pairs, there were two disjunctive quadrants (2Q); for the other two pairs, there were four disjunctive quadrants (4Q). c) Response time (RT) in seconds (s) of visual search for each location type was graphed for the explicit condition where participants were told about the color-location associations, and the implicit condition where participants were not told about the associations (Error bars reflect ±1 SEM; **p<.01, ***p<.001).

3.1.4. Results and Discussion

Overall search accuracy was high (96% in the explicit condition and 95% in the implicit condition), so response time (RT) of correct trials in the prediction phase was analyzed to examine what kind of predictions participants made when they saw the color pair (Figure 3.1c). Search accuracy was high in all four types of locations and there was no reliable difference in accuracy across conditions and locations, suggesting no speed-accuracy tradeoff (see Figure 3.5A for a more detailed analysis on the search accuracy across experiments).

A 2 (condition: explicit vs. implicit; between-subjects) × 4 (location type: conjunctive, 2-quadrant disjunctive, 4-quadrant disjunctive, and impossible; within-subjects) mixed-design ANOVA revealed a significant main effect of location type \([F(3,354)=16.04, p<.001, \eta_p^2=0.12]\), but no main effect of condition \([F(1,118)=3.27, p=.07, \eta_p^2=0.03]\), or interaction \([F(3,354)=1.29, p=.28, \eta_p^2=0.01]\). Based on the post-hoc Tukey HSD test, there was no significant difference between the 2-quadrant and 4-quadrant disjunctive trials \([p’s>.63]\), so they were combined into a single group of disjunctive trials in this and all subsequent experiments. Then, we performed planned contrasts separately for the explicit and implicit conditions. For both conditions, RT was significantly faster when the target appeared in conjunctive locations than in disjunctive locations \([p’s<.01]\). RT was also faster when the target appeared in disjunctive locations than in impossible locations \([p’s<.01]\). This suggested that participants expected the target to appear in conjunctive locations more strongly than in disjunctive locations, thus indicating a conjunctive prediction, regardless of whether the knowledge about the color-location associations were explicitly told or implicitly learned. Moreover in the implicit condition, test accuracy was 51%
which was reliably above chance \([\text{chance} = 25\%, \ p < .001]\), indicating successful learning of the color-location associations. These results suggested that when two cues were presented simultaneously, participants made a conjunctive prediction of the outcome which was the overlap of the different outcomes associated with each cue.

3.2. Experiment 2: Equating the spatial scope

In Experiment 1, the spatial scope of the conjunctive location (one quadrant) was smaller than that for the disjunctive location (two or four quadrants), so the faster RT might be explained by the smaller area for visual search. This account was unlikely for two reasons. First, the conjunctive location was identical in scope to the impossible location, and yet RT was reliably faster in the conjunctive location. Second, there was no difference in RT between the 2-quadrant and the 4-quadrant disjunctive locations, suggesting that spatial scope had little impact on search RT. Despite this partial evidence, we aimed to equate the spatial scope of conjunctive and disjunctive locations in Experiment 2 to directly examine spatial scope had an impact.

3.2.1. Participants

A new group of 120 students (95 females, mean age=20.2 years, SD=1.9) from UBC participated for course credit.

3.2.2. Stimuli and Procedure

The stimuli and procedure were identical to those in Experiment 1, except for one important difference: during exposure, each color dot predicted that the target could appear in three of the four quadrants (Figure 3.2a). This meant that during the prediction phase, two quadrants would be consistent with a conjunctive prediction, and the other two would be
consistent with an exclusive disjunctive prediction, following a pair of color dots (Figure 3.2b). Thus, the spatial scope of the conjunctive and disjunctive quadrants was equated.

3.2.3. Results and Discussion

Again, search accuracy in the prediction phase was high (97% in the explicit condition and 97% in the implicit condition), and RT in correct trials was analyzed.

As in Experiment 1, we performed a two-way mixed-design ANOVA on the RTs of correct trials (Figure 3.2c). It revealed no main effect of condition \[F(1,118)=0.40, p=.53, \eta^2_p=0.00\], or location type \[F(1,118)=1.22, p=.27, \eta^2_p=0.01\], but a significant interaction between condition and location type \[F(1,118)=3.865, p<.05, \eta^2_p=0.03\]. In the explicit condition, RT was reliably faster when the target appeared in conjunctive locations than in disjunctive locations \[t(1,59)=2.03, p<.05, d=0.24\], but there was no significant difference in RT between the two locations in the implicit condition \[t(1,59)=0.66, p=.51, d=0.07\]. The lack of difference could be explained by a lack of learning of the color-location associations in the implicit condition, since the knowledge test accuracy was 31%, which was not reliably above chance \([\text{chance}=25\%, p=.11\)]. These results provided evidence supporting conjunctive predictions, but only when the color-location associations were learned explicitly. Due to poor learning in the implicit condition, it could not be concluded whether implicit learning of the associations could lead to conjunctive predictions. Taken together, these results meant that the findings in Experiment 1 were not solely driven by the smaller spatial scope for the conjunctive location than for the disjunctive location.
3.3. Experiment 3: Feature conjunction

In Experiments 1 and 2, the two colored dots were presented simultaneously during the prediction phase to elicit conjunctive predictions. To see if conjunctive predictions required the presentation of two separate objects, we tested an alternative way to present conjunction in this experiment. Specifically, we used two independent feature dimensions (color and texture) as the predictive cues, which were presented as a single object during the prediction phase (Treisman & Gelade, 1980; Singer & Gray, 1995).

3.3.1. Participants

A new group of 120 students (90 females, mean age=20.5 years, SD=2.8) from UBC participated for course credit.
3.3.2. Stimuli and Procedure

The stimuli and procedure were the same as those in Experiment 1, except for two important differences. First, during exposure there were two color dots (red and blue as reported in Experiment 1) and two textured dots (dotted and stripy dots, Figure 3.3a). The textured dots were presented in black (R/G/B: 0/0/0). As before, each dot predicted in which half of the display the target would appear. Second, during prediction, participants saw one dot first, followed by a search array. Each dot was created from one of the two textures in one of the two colors presented in the exposure phase (i.e., a blue stripy dot, a blue dotted dot, a red stripy dot, or a red dotted dot, Figure 3.3b).

3.3.3. Results and Discussion

Again, search accuracy in the prediction phase was high (96% in the explicit condition and 97% in the implicit condition), and RT in correct trials was analyzed.

As in Experiment 1, we performed a two-way mixed-design ANOVA on the RTs of correct trials (Figure 3.3c). It revealed a main effect of condition \(F(1,118)=23.04, p<.001, \eta^2_p=0.16\) and location type \(F(2,236)=31.06, p<.001, \eta^2_p=0.27\), and a reliable interaction \(F(2,236)=22.42, p<.001, \eta^2_p=0.12\). In the explicit condition, there was a main effect of location type \(F(2,118)=43.01, p<.001, \eta^2_p=0.42\). Based on post-hoc Tukey HSD analyses, all pair-wise comparisons were reliable \(p’s<.001\). In the implicit condition, there was still a main effect of location type \(F(2,118)=5.32, p<.001, \eta^2_p=0.24\), but the only reliable difference was between conjunctive and impossible locations \(p<.01\). The other pair-wise comparisons were not reliable \(p’s>.11\). The lack of difference between conjunctive and disjunctive locations could be explained by a lack of learning of the color-location associations in the implicit condition, since the test accuracy was 33%, which was not reliably above chance \(\text{chance} = 25\%, p=.07\).
These results again suggested a conjunctive prediction, at least when the color-location associations were learned explicitly.

**Figure 3.3. Experiment 3 paradigm and results.** a) During exposure, each of the two colors and two textures predicted in which half of the search array (indicated in gray) the target would appear. b) During the prediction phase, there were four dots made from the combinations of colors and textures. Again, there were three location types: the conjunctive (C), disjunctive (D), and impossible (I) locations. c) RT of visual search for each location type was graphed for the explicit and implicit conditions (Error bars reflect ±1 SEM; **p<.01, ***p<.001).

### 3.4. Chapter discussion

The experiments reported in the current chapter examined how people made predictions when seeing a pair of joint cues after learning that each cue predicted a specific outcome. It was found that participants prioritized the conjunctive quadrant over disjunctive ones for visual search upon seeing the two cues, each of which predicted a different half of the array (Experiment 1). This prioritization was not solely driven by the smaller spatial scope of the
conjunctive quadrant (Experiment 2), and was present when two cues were presented in two feature dimensions in a single object (Experiment 3). Prioritizing the conjunctive quadrant in visual search implied that participants expected to find the target in the quadrant shared by the two halves that were predicted by both cues. This suggested that when two cues were presented simultaneously, a conjunctive prediction was made of the outcome which was the overlap of the different outcomes associated with each cue. This conjunctive prediction seemed to depend on successful learning of the cue-outcome associations, either through explicit instructions (Experiments 1-3) or implicit statistical learning (Experiment 1).

This finding was important because the simultaneous presentation of the two cues did not dictate a conjunctive prediction. Participants were not told anything about where the target might appear when they saw the two cues during the prediction phase. In fact, in this phase, the target appeared in all quadrants with equal frequency. Therefore, the conjunctive prediction seemed to have spontaneously arisen when encountering the two cues.

The conjunctive prediction was consistent with the proposed weight summation framework, where the probability of target appearance in each quadrant was summed up from the previous probability associated with each cue. During exposure, each cue was associated with a probability distribution of target appearance across the search array to guide visual search (Figure 3.4a), similar to a saliency map (Itti & Koch, 2001). The simultaneous presentation of the two cues involved summing the two probability distributions associated with the cues (Figure 3.4b), rendering the conjunctive quadrant as the most likely (50%) to contain the target, the exclusive disjunctive quadrants as less likely (25%), and the impossible quadrant as impossible (0%). Indeed, using the RT data from Experiment 1, a saliency map is generated (Figure 3.4c) that resembled the summed distributions over the four quadrants (Figure 3.4b). Moreover, the RT
difference between conjunctive and disjunctive quadrants seemed similar to the difference between disjunctive and impossible quadrants in the explicit conditions of Experiments 1 and 3, closely matching the probability difference between these quadrants. Thus, these data provide preliminary support for the summation account.

**Figure 3.4. A summation account for the conjunctive prediction.** a) Probability distributions of target appearance (Pr(T)) during exposure in Experiment 1 for blue and red dots as two examples. b) Summed and normalized probability distribution from the two previous distributions from blue and red dots. Higher probabilities were represented by darker colors. c) RT in seconds (s) in each quadrant in the explicit condition in Experiment 1. Faster RTs were represented by darker colors.

However, differences in search time did not necessarily support that participants made conjunctive predictions. An alternative explanation for the faster search time in the conjunctive location was that when encountering the joint presentation of two cues (e.g., red and blue dots), participants attended to the two encountered cues one at a time. In this account, participants were perfectly faithful to the previous knowledge and made no predictions beyond what they had previously learned. Specifically, participants would process one cue first and search for the target based on that cue. When doing so, they would either first check the conjunctive quadrant for the target, or one of the disjunctive quadrants that was associated with this color. If the target was not found in these two quadrants, participants would then search for the target in the other disjunctive quadrant that was associated with the second cue. Based on this strategy, participants
would check the conjunctive location either first or second, but they would check one of the disjunctive locations third. Therefore, on average, search time in the conjunctive location would be faster. Based on the same rationale, if participants consistently failed to attend to both color cues, and always based their search strategy on only one color, search time in the conjunctive location would also be faster. This explanation that participants processed the two cues one at a time could explain the faster search time in the conjunctive location without any conjunctive predictions.

One important question to be addressed was how much did participants learn about the color-location associations in the implicit condition? This was especially important to interpreting the results of Experiment 2, because the observed lack of conjunctive predictions in the implicit condition could either be the result of poor learning, or reflect a genuine tendency for participants to make disjunctive predictions with implicitly acquired knowledge. One tentative analysis would be to categorize those who scored perfectly in the post-prediction knowledge test as “learners”, and assess whether those learners made conjunctive predictions (Figure 3.5). Indeed, search time in the conjunctive location was faster than that in the disjunctive location for learners in the implicit condition ($p<.05$), similar to the results in the explicit condition.

Nevertheless, it should be noted that this analysis was exploratory and contained important problems. First, as a result of the poor performance in the knowledge test, learners in the implicit condition were very few in number, thus lacking meaningful power. Second, the knowledge test took place after the prediction phase, thus it was not a direct measure of the knowledge during the exposure phase. Additionally, since there were only 4 multiple-choice questions, perfect performance in the knowledge test might be the result of random chance rather than reflecting adequate learning, especially when the learners were so few in number.
Figure 3.5. Prediction phase RT for “learners” in the implicit condition and participants in the explicit condition. The prediction phase RT for participants who scored perfectly in the knowledge test in the implicit condition was graphed on the left. Participants’ search RT in the prediction phase of the explicit condition was graphed on the right as a reference (Error bars reflect ±1 SEM; *p<.05).
3.5. Chapter 3 additional data

3.5A. Search accuracy during the prediction phase for all conditions across experiments.

**Figure 3.6. Accuracy during the prediction phase.** The accuracy in different types of locations was separately graphed for Experiments 1, 2, and 3. In each graph, the x-axis indicates the type of target location during the prediction phase. The blue bars represent the accuracy in the explicit condition, and the orange bars represent the accuracy in the implicit condition. The average accuracy in the search task across all experiments was high (97%), and there was no reliable difference in accuracy between the conjunction, disjunction, and impossible locations in Experiments 1, 2, and 3. This suggests that there was no speed-accuracy tradeoff. Error bars reflect ±1 SEM.
3.5B. Search RT over 8 epochs in the exposure phase for implicit and explicit conditions in all experiments.

![Experiment 1 Graph](image1)

![Experiment 2 Graph](image2)

![Experiment 3 Graph](image3)

**Figure 3.7. Time course of RT during the exposure phase.** The 160 trials during exposure were divided into 8 consecutive epochs (20 trials per epoch), and the RT over the 8 epochs was separately graphed for Experiments 1, 2, and 3. The orange lines represent RT in the implicit condition, and the blue lines represent RT in the explicit condition. For all experiments, a 2 (conditions: Explicit and implicit, between-subjects) × 8 (the 8 epochs, within-subjects) mixed ANOVA was performed on the search RT data during exposure. In Experiments 1 and 2, search RT in the implicit condition improved more than that in the explicit condition, but it was not the case in Experiment 3. Error bars reflect ±1 SEM.
3.5C. RT for all unique color combinations for the prediction phase of Experiment 1.

Figure 3.8. RT profile for all color combinations. The average RTs for the conjunctive, disjunctive, and impossible locations were graphed for each unique color combination in Experiment 1. The results in explicit and implicit conditions were graphed separately. The dark blue bars represent the RT in the conjunctive location for each color combination, the dark orange bars represent the RT in the disjunctive location, and the gray bars represent the RT in the impossible location. Each two-dot color combination is shown above the corresponding RT data. For both implicit and explicit conditions, the RT profiles for the six unique color combinations were consistent, so the effect in the prediction phase was likely not driven by any subset of color combinations.
Chapter 4: Do people choose the conjunctive outcome first?

As discussed in Chapter 3, the results did not conclusively indicate that participants made conjunctive predictions because processing the color cues one at a time during the prediction phase could also explain the faster response time in the conjunctive location. Additionally, the response time measure also presented another important problem. That is, even in the explicit condition where participants were told about the specific color-location associations, the procedures of the experiment could not directly assess whether participants were learning and using the knowledge of associations to search for the target during exposure.

To efficiently address these two concerns, the experiments in the current chapter used an attention tracking paradigm to analyze participants’ search strategy. Attention tracking is an efficient method because the analyzed data could show where participants first searched for the target, therefore directly indicating their search strategy.

Unfortunately, because of the pandemic and the resulting restrictions on in-person research, experiments had to be run online, and eye-tracking paradigms were not feasible to measure participants’ overt attention. To accommodate for an online platform, all subsequent experiments in the current research used an online attention tracking method called BubbleView. The idea of online attention tracking came from the paradigm of Kim et al. (2017, https://bubbleview.namwkim.org/), and based on that idea, I programmed an online paradigm for the specific needs of the current experiments. In this chapter, this online attention tracking paradigm was validated by replicating the findings in Experiment 1.

Specifically, in the current BubbleView paradigm, participants viewed a blurred display of shapes where the location of each shape was discernible, but the specific identity of each shape was not. Participants had to first move their cursor to the center of the screen to activate a
red probe circle. They could then move the probe circle around, and the shapes within the circle would be fully revealed. The size of the circle was designed so that the shapes can only be revealed one at a time. A quick demonstration of the paradigm can be found online at: ruqiyu.psych. ubc.ca/democonj.mp4. The complete interface for the experiment can be found at: ruqiyu.psych. ubc.ca/imlog.

4.1. Experiment 4: An online version of the implicit condition

The goal of Experiment 4 was to extend the findings in the implicit condition of Experiment 1. This was important for an online platform, where participants completed the study in a less controlled environment, and the data were expected to contain more variability. This would be especially critical for the implicit condition, because results from Chapter 1 showed weak learning in this condition.

4.1.1. Participants

A total of 60 students (32 females, mean age=19.8 years, SD=2.5) from UBC participated in this experiment for course credit. Unlike in Experiments 1-3 where participants came in to the laboratory to complete the study, participants in this and all subsequent studies completed the study online through a web link provided to them.

4.1.2. Stimuli

Participants saw the same four colored circles (R/G/B): blue (0/0/255), red (255/0/0), yellow (255/255/0), and grey (192/192/192) as in Experiment 1. Each circle was followed by the same search array where participants had to find a target “T” and indicate which way the target was pointing at. The experiment was run online, and participants used their own computers to view the stimuli. Therefore, the study did not control for the physical size of the stimuli on
participants’ computer screens, because of the variability in screens and internet browsers. Rather, the study defined the size of the stimuli in pixels. The size of each colored circle was 50 pixels in diameter, and each object in the search array was 48 pixels in length, and the gap between two adjacent quadrants was 60 pixels. As previously discussed, the experiment used a BubbleView paradigm to track participants’ visual attention during the trial. Therefore, each trial started with a blurred version of the display, and participants had to move the probe circle to reveal the shapes in the display one at a time.

4.1.3. Procedure

The procedure of the current experiment was exactly the same as that of Experiment 1 with two minor modifications.

First, to make sure that the participants understood the task, they had to go through a practice before exposure. The search display in the practice trials did not follow any colored circles, but was otherwise the same as the task in exposure. In the practice, participants had to respond correctly in four consecutive trials in order to move on the actual experiment.

Second, to prevent participants from responding without examining the display, the program actively checked whether participants had moved the probe circle. If the probe circle was never moved in a trial but participants had responded, they would receive a warning message, asking them to find the target before responding. That particular trial would then restart until participants responded after moving the probe circle.

4.1.4. Results and Discussion

Since data were collected online, additional measures were performed to clean up the data. If overall search accuracy in the prediction phase was below 60%, the data from that
participant would be taken out. Details on the treatment of trials with outlier RT are discussed in chapter discussion (section 4.4). The same practice was used for all subsequent experiments. With this threshold, we collected data from 65 participants, and data from 5 of the participants were taken out. For the remaining participants, the accuracy was 96%.

First, whether participants successfully learned the color-location associations during exposure had to be verified. As in Experiment 1, a multiple-choice knowledge test was administered after the prediction phase, where participants saw a colored dot and chose the location where the target mostly appeared following the dot. The accuracy in this task was 29%, not reliably above the chance level of 25% \( p=0.30 \).

A better way to quantify learning during the exposure phase was to analyze whether participants first entered the quadrants associated with the preceding color to search for the target. For example, if the preceding color was blue, and it predicted that the following target would appear in the top half of the display, participants should check either the top-left or top-right quadrant first for the target. Using the tracking data of participants’ cursor locations, the first entry into a quadrant for each trial could be found, and whether participants accurately entered the location that was predicted by the preceding color could be quantified. For each participant, we first computed her/his accuracy during all the exposure trials, and computed the accuracy across all the participants. The accuracy across participants was 57% (M=0.57, SD=0.12), reliably above chance \( p<.001 \), but at a low level.

To visualize participants’ progress during exposure, a trial-by-trial graph was presented (Figure 4.1). For each trial, the proportion of participants who correctly entered the half of the display predicted by the preceding color was plotted. Overall, participants’ first entry accuracy was consistently at a low level.
Figure 4.1. The time course of participants’ first entry accuracy in the exposure of Experiment 4. There were 160 trials during exposure, the same length as in Experiments 1-3. If participants first entered the quadrants predicted by the preceding color to search for the target, the trial counted as a correct trial. For each trial, the proportion of accurate participants was graphed.

Response time (RT) of correct trials in the prediction phase were then analyzed. Trials in the prediction phase were grouped into three types: conjunction, disjunction, and impossible. We first wanted to see if the RT data could replicate the results in Experiment 1 (Figure 4.2).

Figure 4.2. Experiment 4 prediction phase response time. The response time (RT) data for the conjunctive (C), disjunctive (D), and impossible (I) locations were graphed. (Error bars reflect ± 1 SE; **p<.01).
A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA revealed a significant main effect \([F(2,118)=5.76, p<.01, \eta^2_p=0.09\)]. This suggested that participants attended to the four quadrants differently during the prediction phase. Post-hoc Tukey HSD tests showed that RT in the impossible trials was reliably slower than that in the conjunction trials \([p<.01\].

**Figure 4.3. First entry scenarios and simulations.** a) In the example pair of red and blue, if participants were processing one color cue at a time, they would first attend to either blue or red. If they first processed blue, they would think the target should appear in the top half. Then 50\% of the time they would first enter the top-left quadrant to search for the target, which was the conjunctive quadrant (C), and 50\% of the time they would first enter the top-right quadrant, which was one of the disjunctive quadrants (D). Likewise, if participants first processed red, they would also first enter the conjunctive quadrant 50\% of the time, and the disjunctive quadrant 50\% of the time. b) Given the previous rationale, if participants processed the two colors individually, they would first enter the conjunctive location 50\% of the time, and one of the disjunctive locations 50\% of the time. This would mean that the frequency for first entry into the conjunctive quadrant (C) would be the same as the combined frequency of first entry into the two disjunctive locations (D). If participants made conjunctive predictions beyond the original color-location associations, they would first enter location C more frequently than for location D. On the other hand, participants might not use the previous knowledge of associations between single colors and locations in the prediction phase, and they would check all locations randomly. This would result in higher frequency of first entry for location D, since it was larger in spatial scope (2 quadrants) than location C (1 quadrant).
Importantly, we analyzed the tracking data of correct trials and computed the location that participants first entered. Since the goal was to examine whether participant first entered the conjunctive location, trials where the two colors were associated with two non-overlapping halves (top half and bottom half) were excluded in this analysis. This was because participants could only enter a disjunctive quadrant in these trials. In this analysis, we wanted to examine the alternative account where participants were attending to the two colors one at a time during the predictions phase.

Using the blue and red pair as an example, if participants were individually processing the two colors, they would attend to either blue or red during the trial, and search for the target based on that single color (Figure 4.3a). When they attended to blue, they would think that the target should appear in the top half of the display, therefore first searching for the target in the top-left quadrant 50% of the time and in the top-right quadrant 50% of the time. The top-left quadrant was the conjunctive quadrant for the blue-red pair, and the top-right quadrant was one of the disjunctive quadrants for the blue-red pair. Likewise, if participants attended to red, they would also first search for the target in the conjunctive quadrant 50% of the time and in one of the disjunctive quadrants 50% of the time. When summing up the frequency of first entry into the conjunctive and disjunctive locations, the frequency for first entry into the conjunctive location (C) should be the same as the summed frequency of first entry into the disjunctive location (D), if participants attended to the two colors individually (Figure 4.3b).

On the other hand, if participants were representing the weighted sum for the probability of the possible outcomes, the conjunctive quadrant would stand out as the location with the highest probability. Therefore, according to the weighted summation framework discussed in Chapter 2, participants would consistently prioritize the conjunctive location in their search
strategy, and the frequency of first entry into the conjunctive quadrant should be higher than the summed frequency in the two disjunctive quadrants (Figure 4.3b).

Simply put, when first entry frequency in the conjunctive location is higher than the summed frequency in the disjunctive locations, participants are making conjunctive predictions. When the frequency in conjunctive location is not different from the summed frequency in the disjunctive locations, participants are not making conjunctive predictions.

As discussed in Chapter 2, it is important to note that participants’ first entry frequency reflects whether they are prioritizing the location with the highest summed probability, rather than reflecting their representation of the probability of each possible outcome.

Another possible search strategy would be the result of participants’ realization that colors no longer predicted target locations in the prediction phase. In this scenario, first entry into the disjunctive location should be the highest since that location contained two quadrants (Figure 4.3b).

Therefore, the critical comparison to see whether participants made conjunctive predictions would be whether the frequency of first entry into the conjunctive quadrant was the higher than the frequency for other locations.
Figure 4.4. Experiment 4 prediction phase tracking results. The average frequency of first entry into the different types of locations across participants was graphed on the left. Note that the frequency in the disjunctive location (D) was the summed frequency of the two disjunctive quadrants. On the right was a trial-by-trial analysis of the first entry into different types of locations. The time course analysis is different. Specifically, in a given trial, the proportion of participants who first entered the conjunction location was plotted in blue, the proportion for the disjunction location in orange, and the proportion for the impossible location in grey. (Error bars reflect ± 1 SE; *p<.05, **p<.001).

A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA of first entry frequencies across participants revealed a significant main effect [F(2,118)=49.32, p<.001, ηp²=0.46]. Post-hoc Tukey HSD tests showed that first entry into the disjunctive location was reliably more frequent than that for the other two types of locations [p’s<.001], and the first entry frequency into the impossible location was reliably lower than that for the conjunctive location [p=.02] (Figure 4.4). The time course data of the prediction suggested that first entry into the disjunctive location was consistently the most frequent in the prediction phase. The most likely interpretation was that participants were searching randomly among the locations without relying on the exposure phase associations. And because the disjunctive location contained two quadrants, its first entry frequency would be higher. Additionally, participants’ first entry results were relatively consistent over time. This would be unlikely if participants based their search strategy on exposure-phase associations, where the gradual extinction of knowledge in the prediction phase would lead to inconsistent strategy over time. The extinction would be caused by the memory interference of the lack of color-location associations during the prediction phase.

Overall, there was no strong evidence to confirm that participants learned the color-location associations online. Weak learning meant that participants would be unable to make any predictions based on the exposure-phase associations. Indeed, participants’ search strategy in the prediction phase suggested that most participants did not make any predictions about the target
location because they were not prioritizing target search in any quadrant. Therefore, the implicit condition would not be an appropriate paradigm to probe participants’ predictions with data collected online.

4.2. Experiment 5: An online version of the explicit condition

Experiment 5 aimed to extend the findings in the explicit condition of Experiment 1.

4.2.1. Participants

A new group of 40 students (27 females, mean age=21.0 years, SD=2.8) from UBC participated for course credit. This reduced number of participants was because a slightly modified version of this experiment was conducted in Experiment 6, and the results of the current experiment served as a pilot.

4.2.2. Stimuli and Procedure

The stimuli and procedure were identical to those in Experiment 4, except that participants were explicitly told about the color-location associations before exposure. The instructions were the same as those for the explicit condition of Experiment 1. Additionally, as participants’ search performance improved quickly in the explicit condition (Figure 3.5B), the length of exposure was reduced to 24 trials, where each color-location association was presented for 6 times. This reduced exposure also served to reduce participants’ fatigue.

4.2.3. Results and Discussion

Data from 45 participants were collected, and data from 5 of the participants were taken out due to low accuracy. For the remaining participants, the accuracy was 98%.
First, participants’ accuracy in first entering the correct quadrants associated with the preceding color was analyzed. The accuracy across participants was 80% (M=0.80, SD=0.20), reliably above chance \([p<.001]\), at a significantly higher level than the accuracy in Experiment 4. Like in Experiment 4, to visualize participants’ progress, a trial-by-trial time course was graphed in Figure 4.5, where for each trial, the proportion of correct participants was plotted.

![Accuracy of first entry](image)

**Figure 4.5. The time course of participants’ first entry accuracy in the exposure of Experiment 5.** There were 24 trials during exposure, and accuracy in each trial was counted in the same way as in Experiment 4.

We then analyzed the RT of correct trials in the prediction phase. We again grouped the trials in the prediction phase into three types: conjunction, disjunction, and impossible. (Figure 4.6). A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA revealed a significant main effect \([F(2,78)=15.21, p<.001, \eta^2_p=0.28]\). Post-hoc Tukey HSD tests showed that RT in the impossible trials was reliably slower than that in the conjunction and disjunction trials \([p’s<.01]\).
Figure 4.6. **Experiment 5 prediction phase response time.** The response time (RT) data for the conjunctive, disjunctive, and impossible locations were graphed. (Error bars reflect ± 1 SE; **p<.01, ***p<.001).

Importantly, we analyzed the tracking data of correct trials and computed the location that participants first entered. A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA of first entry frequencies revealed a significant main effect \(F(2,78)=24.61, p<.001, \eta_p^2=0.39\). Post-hoc Tukey HSD tests showed that first entry into the disjunctive location and conjunctive location was reliably more frequent than that for the impossible location \(p’\text{s}<.001\), but the first entry frequency was not different for the conjunctive and disjunctive locations \(p=.19\).

Figure 4.7. **Experiment 5 prediction phase tracking results.** The average frequency of first entry into the different types of locations was graphed on the left. Note that the frequency in the disjunctive location (D) was the sum of frequencies for the two disjunctive quadrants. On the right was a trial-by-trial analysis of the first entry into the different types of locations. (Error bars reflect ± 1 SE; *p<.05, ***p<.001).
This said, there were 24 trials during the prediction phase, where the colors no longer predicted the target location. As a result, participants might have initially made conjunctive predictions but would then start searching for the target randomly as the phase progressed. Therefore, the time course of participants’ first entry into different types of locations was again plotted (Figure 4.2.3). Using a McNemar’s test, it was found that for trial 1 (out of 24), the proportion of participants who first entered the conjunctive location was higher than those who first entered the disjunctive location \( p < .05 \). As time progressed, this proportion lowered.

Overall, there was stronger evidence that participants used the knowledge of color-location associations during exposure. Participants’ search strategy in the prediction phase suggested that some participants might have initially made conjunctive predictions. However, the drawback of the current paradigm was that it could not verify whether participants perfectly retained the knowledge of exposure color-location associations during the prediction phase.

4.3. Experiment 6: The explicit condition with additional tests

In Experiment 5, some evidence emerged to support that participants made conjunctive predictions. However, the data were not conclusive. This could be caused by the deterioration of the knowledge of color-location associations before the prediction phase. To ensure participants’ knowledge of the associations going into the prediction phase, they took an additional knowledge test after the exposure phase.

4.3.1. Participants

A new group of 60 students (45 females, mean age=20.8 years, SD=1.9) from UBC participated for course credit.
4.3.2. Stimuli and Procedure

The stimuli and procedure were the same as those in Experiment 2, except for one key difference. To ensure participants’ knowledge of the color-location associations, they were tested on these associations in a multiple-choice format before exposure. The test was administered continuously until perfect accuracy was reached. Next, the program would start the exposure phase. Following the exposure, the same test procedures were administered again to ensure participants’ knowledge of the color-location associations going into the prediction phase. This test paradigm was used for all the subsequent experiments.

4.3.3. Results and Discussion

Data were collected from 67 participants, and data from 7 of the participants were taken out. For the remaining participants, the accuracy was 96%.

First, participants’ accuracy in first entering the correct quadrants associated with the preceding color to search for the target was analyzed. The accuracy across participants during exposure was 85% (M=0.85, SD=0.18) which was reliably above chance \([p<.001]\), at an even higher level. Again, to visualize participants’ progress, a trial-by-trial time course was graphed in Figure 4.8, where the proportion of correct participants for each trial was plotted.
Figure 4.8. The time course of participants’ first entry accuracy in the exposure of Experiment 6. There were 24 trials during exposure. Accuracy was counted in the same way as in previous experiments.

We then analyzed the RT of correct trials in the prediction phase. We again grouped the trials in the prediction phase into three types: conjunction, disjunction, and impossible. (Figure 4.9). A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA revealed a significant main effect \( F(2,118)=4.94, p<.01, \eta^2_p=0.09 \). Post-hoc Tukey HSD tests showed that RT in the impossible trials was reliably slower than that in the conjunction trials \( p=.03 \).

![Response time (RT) results](image)

Figure 4.9. Experiment 6 prediction phase response time. The response time (RT) for each type of locations was graphed for the conjunctive, disjunctive, and impossible locations. (Error bars reflect ± 1 SE; *\( p<.05 \)).

Importantly, we analyzed the tracking data of correct trials and computed the location that participants first entered. A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA of first entry frequencies revealed a significant main effect \( F(2,118)=43.46, p<.001, \eta^2_p=0.42 \). However, Post-hoc Tukey HSD tests showed that first entry into the conjunctive location was not reliably more frequent than that for the disjunctive locations \( p=.87 \), while first entry frequency into the impossible location was reliably lower \( p’s<.001 \) than the other two locations.
Figure 4.10. Experiment 6 prediction phase tracking results. The average frequency of first entry into the different types of locations was graphed on the left. On the right is a trial-by-trial analysis of the first entry into different types of locations (Error bars reflect ± 1 SE; *$p<.05$, ***$p<.001$).

As previously mentioned, there were 24 trials during the prediction phase, where the colors no longer predicted the target location. As a result, participants might initially make conjunctive predictions but start searching for the target randomly as the phase progressed. Therefore, we again plotted the time course of participants’ first entry into different types of locations (Figure 4.10). The proportion of participants who first entered the conjunctive location was numerically higher than those who first entered the disjunctive location, and this difference was reliable in trials 1, 2, and 4 [p’s<.05]. As time progressed, this proportion lowered. These time course results suggested that participants initially made conjunctive predictions, but as they might have realized that the colors no longer predicted target locations, they started searching for the target randomly. This process of dissociating the colors from the target locations is similar to extinction learning, and could be caused by retroactive memory interference introduced by the lack of color-location associations in the prediction phase (e.g., Anderson & Neely, 1996).

Indeed, when participants were asked again about the original color-location associations, the accuracy dropped to 0.51 (SD=0.41), reliably lower than perfect performance which they had to achieve to start the prediction phase, $p<.001$). It should be noted that the time course analysis
was exploratory, and more thorough interpretations of these results would be elaborated in the Chapter discussion section.

The preliminary results in search strategy suggested that participants prioritized the conjunctive location in search strategy and thus made conjunctive predictions. To verify the current framework, it would then be important to assess whether such conjunctive predictions were indeed based on a weighted summation process to represent the probability of the outcomes. The representation of different outcomes’ probability should be better indexed by the time people spent in each location, rather than first entry in target search. For example, though people might prioritize the conjunctive location in search, they should still represent its overall probability as 50%. Consequently, though participants might consistently first enter the conjunctive location, they should quickly shift their attention to other possible locations should the target be absent in the conjunctive location. Therefore, to gauge participants’ representation of the probability of each location, we computed their dwell time in each location for a given trial. Specifically, for what proportion of each trial’s length did participants’ cursor dwell in the conjunctive, disjunctive, and impossible locations? This measure assesses the overall time participants spent in each location, and the order of participants’ entry into each location would not directly affect the dwell time result.

If participants’ representation indeed followed the weighted summation process, their dwell time in the conjunctive location and the summed dwell time in two disjunctive locations should both be 50% of the total length of the trial (Figure 4.11a). We found a main effect of location type on dwell time \(F(2,118)=110.80, \ p<.001, \ \eta^2_p=0.65\], and post-hoc Tukey tests showed that dwell time was longer in the disjunctive location than in the conjunctive location, which in turn is faster than in the impossible location \(p’s<.001\). The dwell time in location C
was less than expected based on the weighted summation process, and the time in location I was more than expected (Figure 4.11b). Again, this could be caused by the memory interference resulting from the lack of color-location associations during the prediction phase. A time-course analysis indicated that during the first 10 trials prediction phase, the dwell time in the conjunctive and disjunction locations was similar, both between 0.4 and 0.5 of a trial’s total length. The dwell time in the impossible location was low, between 0.1 and 0.2 of a trial’s total length. These results suggested that most participants represented the probability of the conjunctive and disjunctive locations as the weighted sum of the exposure cue-outcome associations during the early trials of the prediction phase. This provided further evidence for the proposed weighted summation framework.

Figure 4.11. Experiment 6 prediction phase dwell time results. a) A hypothetical data graph if all participants were following the weighted summation framework perfectly. Specifically, the dwell time was computed as the proportion of each trial’s length for each type of location. The dwell time in locations C and D (conjunctive and disjunctive, respectively) each takes 0.5 of the trial’s length, and should be 0 in location I (impossible). b) The actual dwell time in locations C, D, and I across participants was graphed. c) A trial-by-trial time course of dwell time was graphed for locations C, D, and I. (Error bars reflect ± 1 SE; ***p<.001).
Overall, these results showed that participants more frequently searched for the target in the conjunctive location, ruling out the alternative explanation where participants might process the two cues one at a time after the joint presentation of the two cues. This suggested that participants made conjunctive predictions upon seeing both color cues. Further dwell time analyses suggested that the conjunctive predictions were likely based on a weighted summation process to represent the probability of the outcomes.

4.4. Chapter discussion

In this chapter, participants’ predictions were measured directly through their search strategy. This paradigm addressed the second proposition that participants would choose the conjunctive outcome first. Additionally, experiments in this chapter quantified participants’ learning during the exposure, and validated the online attention tracking paradigm. Overall, search time results in the prediction phase replicated the patterns found in Chapter 3. The tracking data and the first entry analyses showed that during exposure, participants frequently used the color-location associations to guide their search in the explicit conditions (Experiments 5 and 6), but not in the implicit condition (Experiment 4). This suggested that learning was weak in the implicit condition. In the prediction phase, first entry analyses showed stronger evidence of conjunctive predictions in Experiment 6, where participants were reminded of the color-location associations before the prediction phase.

In the exposure phase of Experiment 4 (replicating the implicit condition of Experiment 1), participants did not frequently use the predictive associations between the color cues and target location to guide their search strategy. This strongly suggested that these associations were poorly learned in the implicit condition. This was corroborated with participants’ poor performance in the knowledge test after the prediction phase (Mean accuracy=29%,
chance=25%). The lack of implicit learning meant that it was not possible to assess whether implicitly learned knowledge could lead to conjunctive predictions. Nevertheless, as discussed in Chapter 3, one tentative method to assess conjunctive predictions resulting from implicit learning would be to categorize participants who performed well as learners. In the current attention tracking paradigm, the most direct way to gauge participants’ learning was through their first entry accuracy during exposure. That is, whether participants first checked the location predicted by the preceding color. Since the mean exposure search accuracy was 80% in the explicit condition (Experiment 5), participants whose accuracy was higher than 80% in the implicit condition (Experiment 4) were categorized as learners in this analysis. In total, there were six learners (out of 60) in Experiment 4. Then, their first entry results during the prediction phase were analyzed (Figure 4.12). The results were numerically consistent with those in Experiments 5 and 6 (explicit condition). However, because there were few learners, no comparisons were reliable nor statistically meaningful. This exploratory analysis favored the account that implicitly learned knowledge could lead to conjunctive predictions. However, it should be noted that this analysis contained important problems and should be for reference only. First, the threshold for determining learners was arbitrary. The 80% cut-off was based on the exposure accuracy of the explicit condition in Experiment 5, and might not adequately reflect participants’ learning in the implicit condition. Additionally, the number of participants who passed the threshold was few and might not reflect how participants in the implicit condition might typically behave.
In Experiment 4 (replicating the implicit condition of Experiment 1), participants whose exposure search accuracy was higher than 80% were categorized as learners, and their tracking results were graphed (Error bars reflect ± 1 SE).

Data from online participants can be noisy, so there might be more trials where participants were distracted. In terms of dealing with outlier trials, one drawback of the online attention tracking method was that it could take participants a long time to find the target because the display was blurred. Therefore, it would be difficult to tease apart trials where participants were distracted and trials where participants did take a long time to find the target. A sample examination of the RT distribution of Experiment 4 (for all correct trials in the prediction phase) showed a positive skew (0.88), which was not surprising as participants could not respond faster than 0 seconds (Figure 4.13). The distribution was also leptokurtic (5.38). However, the frequency of extreme outliers was low, with RT higher than 30 seconds occurring in only 3 trials. This was likely the result of various methods applied to curb the frequency of outlier trials. For example, participants went through extensive practice before the experiment, and trials were restarted if participants responded without moving the cursor. Additionally, RT tracking did not start until participants moved the cursor in a trial. Taking out outliers did not affect the results of the statistical analyses reported in this chapter. Therefore, the analyses reported in this and subsequent chapters included RT from all correct trials.
Figure 4.13. RT distribution of Experiment 4. The distribution included all trials in the prediction phase and had a positive skew, and was leptokurtic.

It should be noted that the evidence for conjunctive predictions in Experiments 5 and 6 came from the prediction phase time course data. This was because the colors no longer predicted target locations in the prediction phase, and knowledge from exposure would go through extinction as time progressed. But the timeline of extinction was not directly measured, so the time course analyses were exploratory. A better way to examine conjunctive predictions would be to reduce the effect of extinction. This could be done by lowering the color-location associations during exposure. This experiment was run in Chapter 6, and the detailed results were reported there.

In Experiments 5 and 6 reported in this chapter, participants received explicit instructions about the color-location associations. Therefore, when encountering the joint presentation of color cues, participants’ search strategy might have been more affected by explicit reasoning. Nevertheless, this possibility would not alter the way the current results should be interpreted. As discussed in the previous chapter, the conjunctive predictions were incidental, since participants
were never told to make any predictions beyond exposure-phase knowledge, nor were there any reliable previous examples of target appearance in the conjunctive location. Exploring such incidental and spontaneous predictions was the focus of the current research, rather than finding out whether or not such predictions were based on the explicitly acquired knowledge of the cue-outcome associations.

On the other hand, the explicit instructions in Experiments 5 and 6 did raise the possibility that participants might have spontaneously prioritized possible conjunctive locations during the exposure phase. In this scenario, the conjunctive predictions during the prediction phase might reflect participants’ search habits during the exposure phase. For example, when participants received the instructions that red predicted the top half of the screen and blue predicted the left half of the screen, they might have already realized that there was an overlap in the outcomes associated with red and blue: the top-left quadrant. Therefore, after seeing red during exposure, blue might be automatically brought to mind because of the overlap in the colors’ associated outcomes. As a result, participants might prioritize the conjunctive location during exposure because both red and blue were in the mind during the visual search.

To empirically examine this possibility, participants’ search strategy during exposure was further analyzed. In the current paradigm, both quadrants associated with a color could form a spatial conjunction with the location associated with another color. For example, the top half of the screen (the top-left and top-right quadrants) was associated with red. The top-left quadrant would be the spatial conjunction between red and the color that was associated with the left half of the screen, and the top-right quadrant would be the spatial conjunction between red and the color that was associated with the right half of the screen. Because both quadrants associated with a color could form spatial conjunction with another color, it would not be meaningful to
directly compare the overall search behaviors in the two quadrants. Nevertheless, it would be sensible to examine search strategies for trials where there would be a spatial conjunction between the associated outcomes of the current color and the previous color. If participants were prioritizing conjunction in these trials during exposure, they should first search for the target in the “conjunctive location”. This analysis was performed for the exposure trials of Experiment 6 (Figure 4.14), and it was found that participants first searched for the target in the “conjunctive location” 49% of the time (M=0.49, SD=0.19, chance was at 50% since participants would only search for two quadrants given the preceding predictive color), not reliably above chance \(p=0.85\), suggesting that participants were not prioritizing the conjunction during exposure.

![Figure 4.14. A schematic representation of the analysis.](image)

Trials where there was a spatial conjunction between the current (\(n^{th}\) trial) and the previous trial ((\(n-1\))\(^{th}\) trial) were analyzed. For this example in the previous trial, red appeared before the search array and was associated with the top half of the screen (colored in gray). The target appeared in the top-left quadrant in that trial. In the current trial, blue appeared before the search array and was associated with the left half of the screen. The spatial conjunction between red and blue was the top-left quadrant, and we examined whether participants first searched for the target in the top-left quadrant or in the bottom-left quadrant. If the target did not appear in the conjunctive location (i.e., the top-left quadrant in this example) in the previous trial, these trials were not included for this analysis.
Chapter 5: Extending conjunctive predictions

The current chapter aimed to extend the findings in previous chapters. Specifically, two questions were examined. First, can conjunctive predictions be made over conceptual categories (Proposition 3)? Second, can predictions be based on a weighted subtraction (Proposition 4)?

5.1. Experiment 7: Conjunction of conceptual categories

In previous experiments, the conjunction of outcomes (e.g., target appearance in the top-left quadrant) was already presented to the participants during exposure. Therefore, conjunctive predictions might have been generated simply based on the frequency of the encountered exemplars that were associated with the joint cues. To examine whether conjunctive predictions could be made beyond encountered exemplars, the current experiment employed cue-category associations in exposure. Importantly during the prediction phase, the images for conceptual conjunction were novel and were never previously seen being associated with the cues.

5.1.1. Participants

A total of 60 students (45 female, mean age=21.3 years, SD=1.5) from UBC participated for course credit.

5.1.2. Stimuli and procedure

The paradigm of the current experiment substantially differed from that of previous experiments in the following ways.

First, in the search array following each colored dot, only four shapes appeared on the screen. Three of the shapes were rotated “L”s, and one of them was a rotated target “T”. (Figure 5.1). These shapes were blurred during the search task, and participants had to move the cursor to reveal them one at a time. Each shape appeared on a grayscale image of a certain object. There
were four categories of objects: large animate objects, small animate objects, large inanimate objects, and small inanimate objects. The images of the objects were not blurred, and were of the same physical size, modified from the image set from Long, Yu, and Konkle (2018).

Second, during exposure, the color of the preceding dot predicted the category of images on which the target could appear. The color was no longer directly associated with the spatial location of the target. For example, after blue, the target always appeared on animate objects, which would include both large and small animate objects (Figure 5.1); after yellow, the target always appeared on large objects, which would include both large animate and large inanimate objects. The knowledge of these color-category associations was again explicit. The locations of the four types of object images were randomized for each trial, and the specific color-category associations were randomized across participants.

Lastly, in the prediction phase that followed the exposure, participants again saw the joint presentation of two dots on the screen, followed by the search array (Figure 5.1). The color of the dots no longer predicted on which category of images the target would appear. For each image pair, there were three image types (images consistent with a conjunctive prediction, images consistent with a disjunctive prediction, and impossible images) following their joint presentation (Figure 5.1). New images for each category were used. Participants’ response time and cursor movements were again recorded for analysis. Image pairs that did not overlap in their associated outcomes were not presented. For example, the blue-red pair was not presented, because blue and red were associated with animate and inanimate objects, respectively, and these two categories had no overlap. This resulted in 4 color pairs, and the target appeared once on each of the four image types after each color pair, resulting in 16 trials in the prediction phase.
Figure 5.1: **Experiment 7 paradigm.** During exposure, participants viewed search arrays following each colored dot. Four shapes (3 “L”s and a target “T”) appeared on four different types of object images. These shapes were blurred and participants had to move the cursor to reveal them. The object images were not blurred. Each color predicted on which category of object images the target would appear. During the prediction phase, participants again saw the joint presentation of two colored dots before each search array. A new set of images was used for each category. The target appeared on all images with equal frequency. Following each pair of colors, there were three types of images: conjunction (C), disjunction (D), and impossible (I). Illustrated here are only examples of possible color-category associations.

### 5.1.3. Results and Discussion

Data from 12 participants were taken out due to low accuracy. The accuracy of the remaining participants was 99%.

We again first verified learning of the color-location associations during the exposure phase. Accuracy was computed as whether participants first searched for the locations predicted by the preceding color. The overall exposure accuracy across participants was 74% (SD=0.18)
which was reliably above chance \( p < .001 \), suggesting that participants indeed went to the correct image to search for the target.

We then analyzed the response time (RT) of correct trials in the prediction phase (Figure 5.2). A one-way repeated-measures (image types: conjunction, disjunction, and impossible) ANOVA revealed a significant main effect \( F(2,118)=9.20, p < .001, \eta^2_p=0.13 \). Post-hoc Tukey HSD tests showed that RT in the conjunction trials was reliably faster than that in the disjunction and impossible trials \( p ' s < .01 \).

![Response time (RT) results](image)

**Figure 5.2. Experiment 7 prediction phase response time.** The response time (RT) data for the conjunctive (C), disjunctive (D), and impossible (I) images were graphed. (Error bars reflect ± 1 SE; **\( p < .01 \)).

Then, we analyzed the tracking data of correct trials and computed the images participants first checked for the target. In the example pair of blue and yellow, if participants first checked the large animate image to search for the target, this would indicate that they made a conjunctive prediction about target appearance. A one-way repeated-measures ANOVA of first entry frequencies revealed a significant main effect of image types \( F(2,118)=25.08, p < .001, \)
\[ \eta^2_p = 0.30 \]. However, Post-hoc Tukey HSD tests showed that first entry for conjunctive images was not reliably more frequent than that for disjunctive images \([p=.76]\) (Figure 5.3).

The time course of participants’ first entry into different types of images was again plotted (Figure 5.3). In trials 2-6 (out of 16), the proportion of participants who first entered the conjunctive image was higher than those who first entered disjunctive images, and this difference was reliable for trials 3 and 5 \([p’s<.05]\). As time progressed, this difference dissipated. These time course results again suggested that participants initially made conjunctive predictions, but as they might have realized that the colors no longer predicted target images, they started searching for the target randomly. We did not follow the first entry results with dwell time analyses because the target did not appear in evenly divided quadrants on the screen. Instead, the targets appeared on top of visible images, and only the targets were blurred. Therefore, dwell time analyses in this paradigm would be frivolous.

Figure 5.3. Experiment 7 prediction phase tracking results. The average frequency of first entry into the different types of locations was graphed on the left. On the right was a trial-by-trial analysis of the first entry into different types of locations. (Error bars reflect ± 1 SE; \(*p<.05\), \(**p<.01\), \(***p<.001\)).
5.2. Experiment 8: Weighted subtraction

In all previous experiments, it was found that predictions were based on the probability summing of the previously learned associations. The current experiment examined whether predictions could be based on a subtraction of the probabilities.

5.2.1. Participants

A new group of 60 students (38 females, mean age=20.2 years, SD=2.5) from UBC participated for course credit.

5.2.2. Stimuli and Procedure

The stimuli and procedure in the experiment were mostly the same as those in Experiment 6 (Chapter 4), except for two important differences.

First, during the exposure, participants saw paired colored dots presented jointly on the screen. The same four colors were used, and they were grouped into two pairs. The target search task was the same as that for Experiment 1 following each pair. The two color pairs predicted that the target would appear in two non-overlapping halves of the screen (e.g., if the blue-red pair predicted the top half, then the yellow-grey pair predicted the bottom half). During exposure, there were trials with single dots as well. A single dot was randomly selected from each pair, and it predicted that the target would appear in a quadrant that was a subset of its color pair’s association. For example, after blue and red, the target always appeared on the top of the array; so after blue, the target would always appear in the top-left or the top-right quadrant of the display. Each color pair and single dot was presented 10 times, resulting in 40 trials. The knowledge of the color-location associations was again explicit. The order of the color pair and single dot trials was randomized.
Next, during the prediction phase, the other single colored dot from each of the two pairs was presented on the screen. These were the single dots that were never presented alone during exposure. Again, following each single dot, the target appeared in all four quadrants once, resulting in 8 trials in total. There were three types of locations (Figure 5.4). Take the red color as an example, the bottom half was never associated with the blue-red pair, so it would be the impossible location (locations 3). Both the top-left and top-right quadrants were associated with the blue-red pair during exposure, but blue alone was associated with the top-left quadrant. So if participants subtracted blue’s associated outcome from the pair’s associated outcome, they would predict that the target should appear in the top-right quadrant. Therefore, the top-left quadrant would be the subtracted location (location 1). The remaining top-left quadrant was the associated location (location 2), since it was associated with both the red-blue pair and blue alone during exposure.

**Figure 5.4. Experiment 8 paradigm.** During exposure, a color pair predicted that the target would appear in one half of the array (e.g., blue-red predicted the top half). There were two pairs in total, and the other pair predicted a non-overlapping half (e.g., the bottom half). A single colored dot from each color pair predicted that the target would appear in a quadrant, which was a subset of its pair’s associated location (e.g., blue predicted the top-left quadrant). During the prediction phase, the other single color from each pair (e.g., red) was presented alone, and the target appeared in all four quadrants with equal frequency following that single color. For red in this example, it was not associated with the bottom half during exposure, making the bottom half the impossible location (denoted as locations 3). The top-left quadrant was associated with red through the blue-red pair, making it the associated location (denoted as location 2). The top-right was also associated with the blue-red pair, but not blue alone. So if blue’s associated outcome was subtracted from blue-red pair’s associated outcome, participants would predict the target to appear in the top-right quadrant, making it the subtracted location (denoted as location 1).
5.2.3. Results and Discussion

Data from 6 participants were taken out due to low overall accuracy. The resulting accuracy was 98%. The overall exposure first entry accuracy across participants was 87% (SD=0.12) which was reliably above chance \( p<.001 \), suggesting that participants reliably applied the knowledge of associations during exposure.

![Figure 5.5. Experiment 8 prediction phase response time.](image)

The response time (RT) data for locations 1, 2, and 3 were graphed. (Error bars reflect ± 1 SE; ***\( p<.001 \)).

As before, we analyzed RT of correct trials in the prediction phase (Figure 5.5). Take the red dot as an example, if RT was faster in the top-right quadrant (location 1) than the other quadrants, it would indicate that participants made a prediction based on subtracting blue’s associated outcome from the blue-red pair’s associated outcome. If RT was not different in the top-right (location 1) and top-left (location 2) quadrants, this would suggest that participants made predictions based on all outcomes that were previously associated with the blue-red pair. A one-way repeated-measures ANOVA revealed a main effect of location type \( F(2,118)=9.17, p<.001, \eta^2_p=0.13 \). Post-hoc Tukey HSD tests showed that the only difference in RT was that RT in the impossible location 3 was reliably slower than that in location 1 and location 2 \( p’<.01 \).
Figure 5.6. Experiment 8 prediction phase tracking results. The average frequency of first entry into the different types of locations was graphed on the left. On the right was a trial-by-trial analysis of the first entry into different types of locations. (Error bars reflect ± 1 SE; **p < .01, ***p < .001).

Then, we analyzed the tracking data of correct trials and computed the locations participants first searched for the target (Figure 5.6). There were two impossible quadrants (locations 3), and for each participant, the analysis took the mean frequency of first entry into the two quadrants rather than the sum. Then, this frequency was averaged across participants. This differed from how frequency was computed for the disjunctive location in Chapter 4, because locations 3 in the current experiment were never associated with any color, thus entry into this location would not be caused by alternative strategies. A one-way repeated-measures ANOVA of first entry frequencies revealed a significant main effect of location types \[ F(2,118)=11.17, p<.001, \eta_p^2=0.17 \]. Again, post-hoc Tukey HSD tests showed that the only difference was that frequency for locations 3 was reliably lower than that in location 1 or the location 2 \[ p’s<.01 \]. The time course data were consistent with this finding.

Overall, these results suggested that participants’ predictions were based on associations learned during exposure, but their predictions were not based on subtracting the single color’s associated outcome from the corresponding color pair’s associated outcome.
5.3. **Experiment 9: Indirect associations**

Results in Experiment 8 demonstrated that participants’ predictions were based on previous positive associations, not based on a subtraction of the associated outcomes. The current experiment examined whether predictions could be based on indirect associations.

5.3.1. Participants

A new group of 60 students (38 females, mean age=20.5 years, SD=2.2) from UBC participated for course credit.

5.3.2. Stimuli and Procedure

The stimuli and procedure were the same as those in Experiment 8, except for one key difference. During exposure, a color pair (e.g., blue and red) predicted target location in one quadrant of the screen (e.g., the top-left quadrant, see Figure 5.7), and a single color from that pair (e.g., blue) predicted target location in a half of the screen (e.g., the top half). During prediction, the other color was presented alone (e.g., red), and participants searched for the target, which appeared in all locations with equal frequency. For the other color (red), the top-left quadrant was directly associated with it during exposure (location 2), and the top-right quadrant was indirectly associated with it through the blue color (location 3). The bottom-left quadrant was consistent with a reverse-conjunction (i.e., if participants inferred that red predicted the left half, in the same way that blue predicted the top half, location 1). The bottom-right quadrant was not associated with red at all (location 0).
**Figure 5.7. Experiment 9 paradigm.** During exposure, a color pair predicted that the target would appear in one quadrant of the array (e.g., blue-red predicted the top-left quadrant). There were two pairs in total. A single colored dot from each color pair predicted that the target would appear in one half of the display, which was a superset of its pair’s associated location (e.g., blue predicted the top half). During the prediction phase, the other single color from each pair (e.g., red) was presented alone, and the target appeared in all four quadrants with equal frequency following the single color. For red, it was not associated with the bottom-right quadrant during exposure, making it the impossible location (denoted as location 0). The bottom-left quadrant (denoted as location 1) was consistent with a reverse conjunction, where participants might expect that red predicted the left half in the same way as blue predicted the top half. The top-left quadrant was associated with red through the blue-red pair (denoted as location 2). The top-right was also associated indirectly with red through blue (denoted as location 3).

### 5.3.3. Results and Discussion

Data from 10 of the participants were taken out due to low accuracy. For the remaining participants, the accuracy was 98%.

The overall exposure first entry accuracy across participants was 87% (SD=0.14) which was reliably above chance \(p<.001\), suggesting that participants reliably applied the knowledge of associations during exposure.

As before, RT of correct trials in the prediction phase was analyzed (Figure 5.8). Take the red dot as an example, if RT was faster in the top-right quadrant (location 2) than the other quadrants, it would indicate that participants made a prediction based on previous locations that were directly associated with the color. If RT was not different in the top-right (location 2) and top-left (location 3) quadrants, this would suggest that participants made predictions based on both direct and indirect associations. A one-way repeated-measures ANOVA revealed a main effect of location type \(F(3,177)=6.51, p<.001, \eta_p^2=0.10\). Post-hoc Tukey HSD tests showed that RT was not different between locations 0 and 1, or between locations 2 and 3, but RT in locations 2 and 3 was reliably faster than that in locations 0 and 1 \(p's<.05\).
Figure 5.8. **Experiment 9 prediction phase response time.** The response time (RT) for each type of trials was graphed for the locations 0, 1, 2, and 3. (Error bars reflect ± 1 SE; *p<.05, **p<.01).

Importantly, the tracking data of correct trials were analyzed and the location that participants first entered was computed. A one-way repeated-measures ANOVA of first entry frequencies revealed a significant main effect of locations \(F(3,177)=8.28, p<.001, \eta^2_p=0.12\). Post-hoc Tukey HSD tests showed that first entry into the directly associated location 2 was reliably higher than the other locations \(p's<.01\), and no other comparisons were reliable (Figure 5.9). This suggested that participants’ predictions were mainly based on the directly associated location. The time course data were consistent with this finding.

Figure 5.9. **Experiment 9 prediction phase tracking results.** The average frequency of first entry into the different types of locations was graphed on the left. On the right is a trial-by-trial analysis of the first entry into different types of locations. (Error bars reflect ± 1 SE; *p<.05, **p<.01, ***p<.001).
5.4. Chapter discussion

In this chapter, the experiments examined whether the previous findings for conjunctive predictions can be further extended to conceptual categories and subtractive operations. Specifically, this chapter examined propositions 3 and 4: the weighted summation framework can be applied to the conjunction of abstract categories beyond spatial conjunctions, and predictions can also be based on a weighted subtraction process.

Results from Experiment 7 supported proposition 3, suggesting that conjunctive predictions can be made over abstract conceptual categories. Importantly, these results showed that conjunctive predictions were not necessarily based on encountered exemplars in the past, but can be generalized to new stimuli that were conceptually consistent. The tendency to make conjunctive predictions for conceptual categories suggested that the conjunction of joint predictive cues may be processed in a similar way to the conjunction of semantic categories that people experience frequently in natural languages (e.g., tall trees, white flowers). The tendency to make conjunctive predictions may explain why semantic combinations could often result in representations that are integrated (e.g., Smith & Osherson, 1984). For example, people tend to automatically think of brown apples as a new concept, rather than the thinking of all brown stuff and all the apples.

On the other hand, results from Experiments 8 provided evidence against proposition 4. Nevertheless, as evidence from Chapters 3 and 4 consistently supported the framework, these results did not necessarily refute the weighted summation framework which posits that people prioritize the most probable outcome after weighted summation. Rather, the results from Experiment 8 more likely demonstrated that predictions were based on all previous associations, rather than based on a subtraction of the associated outcomes. One possible reason was that
predictions could only be based on a cumulative representation of the associations, and could not be based on a more flexible arithmetic computation such as subtraction or multiplication. Thus, subtraction of the associated outcomes would be difficult when generating predictions. These nuances should be considered when assessing people’s predictions in the future. Results from Experiment 9 echoed the findings in Experiment 8 and further suggested that participants made predictions from direct cue-outcome associations, and indirect associations did not elicit robust conjunctive predictions. It is important to acknowledge that the lack of subtractive predictions could also result from the failure of the current paradigm to capture the effect of subtractive predictions. The current null results have not ruled out the possibility that predictions based on subtraction could be generated.
Chapter 6: The effect of exposure on predictions

In all previous chapters, the color-location associations during exposure were 100%. The current chapter examined whether exposure to such perfect association was necessary for people to make conjunctive predictions, and how different types of exposure could affect conjunctive predictions. To examine these questions, the exposure phase of the experiments in this chapter was modified in different ways.

6.1. Experiment 10: No exposure

In the exposure phase of all previous experiments, participants had to complete the exposure task where they searched for the target after seeing the preceding color cues. This procedure was used even though participants were explicitly told about the color-location associations. Therefore, participants’ later search strategy in the prediction phase could be based on previous episodes of motor learning. To examine whether motor learning experiences were necessary for subsequent conjunctive predictions, participants in this experiment directly went into the prediction phase without exposure.

6.1.1. Participants

A total of 60 students (42 female, mean age=21.9 years, SD=2.4) from UBC participated in this experiment for course credit.

6.1.2. Stimuli and procedure

The paradigm of the current experiment was exactly the same as that for Experiment 6, except that there were no exposure trials. Specifically, participants were told about the color-location associations in the instructions, and had to pass a test of the knowledge. Then, they would directly start the experiment with the prediction phase.
6.1.3. Results and Discussion

Data from 10 participants were taken out due to low accuracy. The accuracy of the remaining participants was 95%.

The response time (RT) of correct trials in the prediction phase was first analyzed (Figure 6.1). A one-way repeated-measures (location types: conjunction, disjunction, and impossible) ANOVA revealed a significant main effect \[ F(2,118)=11.35, \ p<.001, \ \eta^2_p=0.16 \]. Post-hoc Tukey HSD tests showed that RT for the conjunction trials was reliably faster than that in the disjunction and impossible trials \[ p’s<.05 \].

![Figure 6.1. Experiment 10 prediction phase response time.](image)

The response time (RT) data for the conjunctive (C), disjunctive (D), and impossible (I) locations were graphed. (Error bars reflect ± 1 SE; *\( p<.05 \), ***\( p<.001 \)).

Then, we analyzed the tracking data of correct trials. A one-way repeated-measures ANOVA of first entry frequencies revealed a significant main effect of location types \[ F(2,118)=35.59, \ p<.001, \ \eta^2_p=0.38 \]. Post-hoc Tukey HSD tests showed that frequency for first entry into the impossible location was reliably lower than for the other two locations \[ p’s<.001 \] (Figure 6.1.2).

The time course of participants’ first entry into different types of locations was plotted (Figure 6.2). It was found that in trials 2, 3, and 5, the proportion of participants who first entered
the conjunctive location was reliably higher than those who first entered the disjunctive location. As time progressed, this difference dissipated. These time course results again suggested that participants initially made conjunctive predictions, but as they might have realized that the colors no longer predicted target locations, they started searching for the target randomly.

Figure 6.2. Experiment 10 prediction phase tracking results. The average frequency of first entry into the different types of locations was graphed on the left. On the right was a trial-by-trial analysis of the first entry into different types of locations. (Error bars reflect ± 1 SE; *p < .05, **p < .01, ***p < .001).

6.2. Experiment 11: Reduced color-location contingency

As mentioned in previous experiments, the time course analyses in the prediction phase were exploratory, because the extinction of the knowledge for color-location associations affected participants’ predictions but could not be directly measured. One way to circumvent this problem was to reduce the strength of color-location associations during exposure from 100% in previous experiments to lower levels so that extinction in the prediction phase could be reduced. To implement this idea in the current experiment, the strength of color-location association was reduced during the exposure.
6.2.1. Participants

A new group of 120 students (102 females, mean age=21.3 years, SD=1.9) from UBC participated for course credit. There were three between-subjects conditions, with 60 participants in the 80% condition and 30 participants in each of the two 50% conditions.

6.2.2. Stimuli and Procedure

The stimuli and procedure in the experiment were mostly the same as those in Experiment 6 (Chapter 4), except that the color cue no longer perfectly predicted target location in the search display during exposure. Because of the lowered contingency, there were 40 trials during exposure.

There were three between-subjects conditions. In the 80% condition (N=60), the colors predicted target location in one half of the display 80% of the time. For example, after blue, the target appeared on the top half of the display 80% of the time. For the remaining 20% of the time, the target appeared on the bottom half of the display. Additionally, participants were explicitly told about the weakened associations in the instructions before the exposure.

In the 50% (priming one half) condition (N=30), the colors predicted target location in one half of the display 50% of the time. Participants were explicitly told about the weakened association in the instructions before exposure, but were not told about other possible target locations. For example, participants were told that “after blue, the target appeared on the top half of the display 50% of the time”, but they were not told that the target also appeared on the bottom half 50% of the time. Therefore, participants could still make the interpretation that the target most likely appeared on the top half of the display, because they might have assumed that in some trials, the target did not appear in the search display, among other possibilities.
In the 50% (both halves) condition (N=30), the paradigm was the same as that for the 50% (priming one half) condition, except that participants were told that the target could appear in both the top and bottom halves (or left and right halves) following each color. For example, they were told that “after blue, the target appeared on the top half of the display 50% of the time, and the bottom half of the display 50% of the time”.

6.2.3. Results and Discussion

First, data from the 80% condition were analyzed. Data from 3 participants were taken out due to low accuracy. The accuracy of the remaining participants was 98%.

In the 80% condition, participants’ performance during exposure was first examined to assess whether they used the knowledge of color-location associations despite the lowered contingency (Figure 6.3). Overall accuracy across participants was 82% (M=0.82, SD=0.16), at a high level, reliably above chance \( p<.001 \) but not above the 80% exposure contingency \( p=.26 \). Again, to visualize participants’ progress, a trial-by-trial time course was graphed in Figure 6.3, where the proportion of correct participants for each trial was plotted.

**Figure 6.3. The time course of participants’ first entry accuracy in the exposure of Experiment 11 80% condition.** There were 40 trials during exposure of Experiment 11. Accuracy was counted in the same way as for experiments in Chapter 4.
As before, RT of correct trials in the prediction phase was analyzed (Figure 6.4). A one-way repeated-measures ANOVA revealed a main effect of location type [$F(2,118)=74.97$, $p<.001$, $\eta_p^2=0.56$]. Post-hoc Tukey HSD tests showed that RT in the conjunction trials was faster than that in the disjunction trials, which in turn was faster than that in the impossible trials [$p$’s$<.001$].
Then, the tracking data of correct trials were analyzed and the locations participants first searched for the target were computed (Figure 6.5). A one-way repeated-measures ANOVA of first entry frequencies revealed a significant main effect of location types \([F(2,118)=78, p<.001, \eta^2_p=0.57]\). Post-hoc Tukey HSD tests showed that the frequency in the conjunctive location was reliably higher than that in the disjunctive location, which in turn was higher than that in the impossible location \([p’s<.001]\). The time course data were consistent with this finding. The evidence for conjunctive predictions was robust and the strongest across all experiments.

Following the first entry results, a dwell time analysis was performed. This analysis was meaningful for this experiment because the exposure-phase associations were reduced to 80%. In this case, the weighted sum of the conjunctive location would be 40%. It would be interesting to see whether participants represented the weighted sum for the probability of different locations according to this reduced contingency. The results were largely consistent with the weighted summation process, where the dwell time in the conjunctive location being around 0.4 of the trial length (Figure 6.6a and b). There was a main effect of location type on dwell time \([F(2,118)=152.30, p<.001, \eta^2_p=0.72]\), and post-hoc Tukey tests showed that dwell time was longer in the conjunctive and disjunctive location than in the impossible location \((p’s<.001)\).
These results suggested that participants made robust conjunctive predictions when the strength of color-location associations was reduced to 80% during exposure. This finding likely resulted from slower extinction of the exposure-phase knowledge.

In the 50% (priming one half), data from 1 participant were taken out due to low accuracy. The accuracy of the remaining participants was 94%.

We found that participants first entered the half that was mentioned in the instruction 68% of the time (M=0.68, SD=0.20), which was reliably above chance \[p<.001\]. This was surprising because the color cues did not reliably predict target locations during exposure. The results implied that participants were primed by the location mentioned in the instructions, prioritizing search in that half of the display over the half that was not mentioned. Again, to visualize participants’ progress, a trial-by-trial time course was graphed in Figure 6.7, where the proportion of correct participants for each trial was plotted.

Figure 6.7. The time course of participants’ first entry “accuracy” in the exposure of Experiment 11, 50% (priming one half) condition. There were 40 trials during exposure. Accuracy was computed as whether participants first entered the locations associated with the preceding color mentioned in the instructions. Please note that the preceding colors did not actually predict target locations reliably.
Figure 6.8. Experiment 11, 50% (priming one half) condition prediction phase response time. The response time (RT) data for the conjunctive, disjunctive, and impossible locations were graphed. (Error bars reflect ± 1 SE; ***p < .001).

As before, RT of correct trials in the prediction phase was analyzed (Figure 6.8). A one-way repeated-measures ANOVA revealed a main effect of location type \[ F(2,58)=12.86, \ p < .001, \ \eta^2_p=0.31 \]. Post-hoc Tukey HSD tests showed that RT in the conjunction trials was faster than that in the disjunction and the impossible trials \[ p's < .001 \].

Figure 6.9. Experiment 11 50% (priming one half) condition prediction phase tracking results. The average frequency of first entry into the different types of locations was graphed on the left. On the right was a trial-by-trial analysis of the first entry into different types of locations. (Error bars reflect ± 1 SE; *p < .05, **p < .01, ***p < .001).

Then, the tracking data of correct trials were analyzed and the locations participants first searched for the target were computed (Figure 6.9). A one-way repeated-measures ANOVA of
first entry frequencies revealed a significant main effect of location types \([F(2,118)=17.53, p<.001, \eta_p^2=0.38]\). Post-hoc Tukey HSD tests showed that the frequency in the conjunctive location was reliably higher than that in the disjunctive location, which in turn was faster than that in the impossible location \([p’s<.05]\). The time course data were consistent with this finding. The evidence for conjunctive predictions was also robust.

Again, following the first entry results, a dwell time analysis was performed. This analysis was meaningful for this experiment because the exposure-phase associations were reduced to 50%. In this case, the weighted sum of the conjunctive location would be 25%. Did participants faithfully represent this weighted sum despite prioritizations of conjunction revealed by first entry results? The dwell time results were largely consistent with the weighted summation process, where the dwell time in the conjunctive location being around 0.25 of the trial length, even numerically lower than the impossible location (Figure 6.10a and b). The dwell time in the disjunctive location was around 0.5, twice as much as that for the conjunctive location, reflecting the larger spatial scope of the two disjunctive quadrants. These results were very consistent with a weighted summation process based on the color-location associations exposed to the participants during exposure. Statistically, there was a main effect of location type \([F(2,58)=67.58, p<.001, \eta_p^2=0.70]\), and post-hoc Tukey tests showed that dwell time was longer in the disjunctive location than in the conjunctive and impossible locations \((p’s<.001)\).
Figure 6.10. **Experiment 11 50% (priming one half) prediction phase dwell time results.** a) The dwell time in locations C (conjunction), D (disjunction), and I (impossible) across participants were graphed. b) A trial-by-trial time course of dwell time was graphed for locations C, D, and I. (Error bars reflect ± 1 SE; ***p<.001).

These results showed that participants made clear conjunctive predictions during the prediction phase, even when the color cue did not actually reliably predict the target location. The effect reported here could only come from participants’ interpretation of the instructions.

Lastly, in the 50% (both halves) condition, data from 4 participants were taken out. The accuracy of the remaining participants was 97%. Although the color cues in this condition no longer predicted target location during exposure, we found that participants first entered the half that was first mentioned in the instruction 57% of the time (M=0.57, SD=0.17), which was reliably above chance \( p<.05 \). Again, to visualize participants’ progress, a trial-by-trial time course was graphed in Figure 6.11, where the proportion of correct participants for each trial was plotted. This meant that for example if participants were first told that the blue dot predicted target appearance on the top half 50% of the time and then the bottom half 50% of the time, the order of information would prime the association between the blue dot and the top half of the display. Thus, participants were primed by the half that was first mentioned in the instruction, prioritizing search in that half of the display over the half that was second mentioned in the
instruction, despite the fact that they were told that target was now equally likely to appear in either half. It was also notable that “accuracy” decreased reliably over the course of the exposure \[p<.001\], suggesting that exposure to the lack of color-location association might have helped participants to reduce the bias to search for the target in the first mentioned half (Figure 6.11).

**Figure 6.11.** The time course of participants’ first entry “accuracy” in the exposure of Experiment 11, 50\% (both halves) condition. There were 40 trials during exposure of Experiment 11. Accuracy was counted as first entering the location that was first mentioned in the instructions following each color.

**Figure 6.12.** Experiment 11 50\% (both halves) condition prediction phase response time. The response time (RT) data for the conjunctive, disjunctive, and impossible locations were graphed. (Error bars reflect ± 1 SE).
As before, RT of correct trials in the prediction phase was analyzed (Figure 6.12). A one-way repeated-measures ANOVA revealed no main effect of location type [$F(2,58)=0.17, p=.85, \eta^2_p=0.01$]. Post-hoc Tukey HSD tests revealed no differences in RT between any of the locations.

![First entry results](image)

**Figure 6.13.** Experiment 11 50% (priming both halves) prediction phase tracking results. The average frequency of first entry into the different types of locations was graphed on the left. On the right was a trial-by-trial analysis of the first entry into different types of locations. (Error bars reflect ± 1 SE; *$p<.05$, **$p<.01$, ***$p<.001$).

Then, the tracking data of correct trials were analyzed and the locations participants first searched for the target were computed (Figure 6.13). A one-way repeated-measures ANOVA of first entry frequencies revealed a significant main effect of location types [$F(2,58)=8.14, p<.001, \eta^2_p=0.22$]. Post-hoc Tukey HSD tests showed that the frequency in the impossible location was reliably lower than that in the conjunctive and disjunctive locations [$p$’s<.01]. This was surprising because participants were told that the target could appear in all locations (e.g., following blue, the target could appear on the top, and also the bottom) with an equal chance. The “impossible” location here was only an artifact of the order in which participants received the instructions. The time course data showed that in trial 5, the proportion of participants first entering the conjunctive location was reliably higher than that for the disjunctive location.
These results were mixed. While the RT data showed no evidence of conjunctive, or even disjunctive predictions, the time course of first entry data suggested that some participants might have made conjunctive predictions at the beginning of the prediction phase.

6.3. Chapter discussion

This chapter examined proposition 5: If conjunctive predictions were based on predictor-outcome associations, then exposure to the associations should modulate conjunctive predictions.

In Experiment 10, participants did not go through any exposure trials and went straight to the prediction phase after being explicitly told about the color-location associations. The results suggested that participants made conjunctive predictions at the beginning of the prediction phase. In this paradigm, participants did not directly experience color-location associations where they searched for the target after seeing the color cues. Therefore, the fact that participants still made conjunctive predictions meant that written instructions were sufficient for conjunctive predictions, and neither episodic nor motor learning experiences were necessary.

The fact that participants only needed explicit instructions to make conjunctive predictions raised the possibility that participants might be explicitly reasoning about the target location before responding in the prediction phase. If the process for conjunctive predictions was completely explicit, participants would need to first verbally retrieve the associated outcome for each color cue from the written instructions, then explicitly find the conjunction of the two outcomes, and make the decision that the conjunctive outcome was the most rational choice. This complete process would take a significant amount of time to complete. To examine this possibility, tracking data in Experiment 10 were further analyzed. Specifically, the time it took for participants to move the cursor to enter the first quadrant to reveal a blurred shape was analyzed. The results indicated that this initiation time was relatively short overall (see Figure
6.12, M = 1.2 seconds, SD = 0.09 seconds across participants). Compared with previous literature on explicit reasoning, this amount of response time was likely insufficient if participants had to verbally retrieve the color-location associations, explicitly finding the conjunctive location, and making a deliberate conjunctive prediction in search strategy (Cherniak, 1984; De Jong, Weertman, Horselenberg, & van den Hout, 1997). This suggested that participants’ conjunctive predictions were at least partially based on an implicit process. For example, the retrieval of previous color-location associations might be automatic rather than verbal and deliberate. Furthermore, an examination of the initiation time in previous experiments (Experiments 4 and 6) revealed that participants responded even more quickly, with an average time of less than 1 second starting from the first trial of the prediction phase (Figure 6.13). Specifically, there were two important observations. First, participants in Experiment 6 (explicit instructions with exposure) responded more quickly (p<.001) than participants in Experiment 10 (explicit instructions with no exposure), suggesting that though instructions were sufficient for conjunctive predictions (Experiment 10), the predictions were slower thus likely more deliberate than those found originally in Experiment 6. Second, there was no difference in initiation time between Experiment 4 (online implicit condition) and Experiment 6 (online explicit condition). This further suggested that participants in the explicit condition minimally relied on an explicit reasoning process to make predictions.
Figure 6.12. The time course of participants’ initiation time in Experiment 10. Data presented in the figure came from the prediction phase of Experiment 10. The initiation time was the time difference between the onset of the search display and participants cursor entry into the first quadrant to reveal a blurred shape. For each trial, the initiation time was average across participants. Error bars reflect ± 1 SE.

Figure 6.13. The time course of participants’ initiation time in Experiments 4 and 6. Data presented in the figure came from the prediction phase of Experiment 4 (the implicit condition) and Experiment 6 (the explicit condition). Error bars reflect ± 1 SE.

One surprising finding was that results from Experiment 11 (80% condition) showed that in the prediction phase, participants robustly and consistently made conjunctive predictions. This was not expected because according to the weighted summation model, the conjunctive location has a lower probability in this Experiment than in previous Experiments. Specifically during exposure, each cue predicted target location 80% of the time. For example, after red, the target would appear in the top half of the display 80% of the time. This meant that the target appeared in the top-left quadrant 40% of the time, the top-right quadrant 40% of the time, and the target also appeared in the bottom-left and bottom-right quadrants 10% of the time (Figure 6.14a). Consequently, after a weighted summation process as discussed in Chapter 2, the probability of the conjunctive location would become 40%, and the probability of the disjunctive locations would be 25% (Figure 6.14b).
Figure 6.14. Schematic representation of weighted summation for Experiment 11, 80% condition. a). In the 80% condition, the color-location associations during exposure were 80%. In the example of red, this meant that the target would appear in the top-left and top-right quadrants 40% of the time, and the bottom-left and bottom-right quadrants 10% of the time. b). After the weighted summation process, the conjunctive location would have a probability of 40%. The two disjunctive locations would have a probability of 25%, and the impossible location would have a probability of 10%.

Despite the decreased difference between the probability of the conjunctive and disjunctive locations, participants showed more consistent and robust evidence of conjunctive predictions in Experiment 11. Why? This likely resulted from reduced memory interference during prediction phase thus less extinction for the knowledge of color-location associations. In previous chapters, when the knowledge of the color-location associations was explicit, and the association was 100%, it was more likely for participants to stop using the associations to guide their search when encountering exceptions to the associations in the prediction phase. This type of extinction could be occurring without conscious awareness, or could be the result of an explicit choice. In Experiment 11, extinction was reduced because participants knew that there would be exceptions to the color-location associations. The results of Experiment 11, combined
with the evidence from Chapters 3 and 4, suggested that participants indeed made conjunctive predictions and would consistently search for the target in the conjunctive location if their knowledge did not go through extinction.

The results in the two 50% conditions additionally showed that conjunctive predictions can be made by priming participants with a set of cue-outcome associations, even when the cues did not actually reliably predict the outcome. This priming effect may affect participants’ predictions through an implicit bias in the representation for the chance of the cue-outcome associations. For example, in the 50% (priming one half) condition, participants searched for the target in the instructed half 68% of the time during exposure, even though they were told that the probability was 50% in the instructions. Likewise in the 50% (priming both halves) condition, participants searched for the target in the first instructed half 57% of the time during exposure. It should be noted that participants were still explicitly aware of the 50% contingency between color and target locations through the instructions, so there might be more nuanced interactions between participants’ implicit bias and their explicit knowledge.

It might be intuitive to think that such priming effects were only present for tasks involving memory (e.g., Tulving & Schacter, 1990) or implicit learning (e.g., Jiang et al., 2013), but recent evidence does suggest that priming effects also existed for explicit reasoning tasks (Bar-Hillel, Peer, & Acquisti, 2014). Specifically, when people were asked to generate a sequence of “heads or tails”, they would start with a head 80% of the time, even though they were explicitly told to randomly generate the sequence. The results of the 50% condition provided additional evidence for such priming effects in an explicit task. On the other hand, the exposure time course data in the 50% (both halves) condition showed that the order effect in explicit instructions could be reduced by exposure to the lack of cue-outcome associations.
Chapter 7. Conclusion and general discussion

7.1. Summary of findings

The current research examined how people made predictions after encountering the joint presentation of predictive cues. I proposed a weighted summation framework to model the possible predictions (Chapter 2). In the framework, the probability of the outcomes associated with the predictors is weighted and summed, and the outcome subset with the highest probability (i.e., the overlap/conjunction of the outcomes) is consistently prioritized and thus predicted as the plausible outcome. This framework was tested in a visual search paradigm, where participants’ free responses to the joint cues could be observed and quantified.

Experiments 1-3 of Chapter 3 examined whether it was faster for participants to find the target in the location consistent with a conjunctive prediction (Proposition 1). In the three experiments, participants were first exposed to the perfect associations between a preceding color/texture cue and the target location in the following search array. Before exposure, participants were either told to only pay attention to the colored dot (implicit condition), or they were explicitly told about the specific color-location associations. A prediction phase followed exposure, where participants saw jointly presented predictive cues, and completed the same search task. The joint cues were not associated with target locations in the prediction phase. It was found that search time in the location consistent with a conjunctive prediction was faster in both the explicit and implicit conditions (Experiment 1). When equating the spatial scope of conjunctive and non-conjunctive locations, search time was reliably faster in the conjunctive location for the explicit condition (Experiment 2). When the joint cues were made into a new object through feature binding, search time was reliably faster in the conjunctive location for the explicit condition, but only numerically faster for the implicit condition (Experiment 3).
The overall results in Chapter 3 provided preliminary evidence that participants made conjunctive predictions when encountering joint cues. Nevertheless, there were two important concerns to address. First, faster search time could be explained by attending to one color cue at a time without making any conjunctive predictions (See Discussion of Chapter 3 for more details). Second, data in the implicit condition did not consistently show faster search time in the conjunctive location, and thus it was unclear whether this resulted from a lack of learning during exposure, or a lack of conjunctive predictions.

To address these two concerns, Experiments 4-6 (Chapter 4) extended Experiment 1 with an additional attention tracking measure. Through tracking, participants’ search strategy could be revealed. Thus it would be clear whether participants individually processed the colors to search for the target during exposure or whether they prioritized target search in the conjunctive location during the prediction phase (Proposition 2). We found that when the knowledge of color-location associations was implicit, participants often searched for the target in all locations equally in both the exposure phase and the prediction phase as a result of weak learning (Experiment 4). When the knowledge of associations was explicit, participants searched for the target accordingly during exposure (Experiment 5). When participants were reminded of the associations before the prediction phase, they more frequently searched for the target in the conjunctive location in the early trials of the prediction phase (Experiment 6).

Then, Experiment 7 (Chapter 5) extended the findings in Chapter 4 beyond spatial conjunction and found that people made conjunctive predictions for conceptual categories (Proposition 3). Specifically, participants were first exposed to predictive relationships between color cues and target appearance on images of different conceptual categories. Then, during the prediction phase, a new set of images was used. The results suggested that participants searched
for the target on images that were consistent with the conceptual conjunction of the categories predicted by the joint cues. This finding showed that conjunctive predictions can be made at the level of abstract categories for exemplars that were never previously encountered.

Then, Experiments 8 and 9 (Chapter 5) examined whether predictions based on weighted subtraction were possible (Proposition 4). Using the spatial search paradigm, the results suggested that participants likely did not make predictions based on subtraction. Rather than evidence against the weighted summation framework, these results likely suggested that people made predictions based on cumulative representations of the associated outcomes, not based on a subtraction of the associated outcomes. Additionally, direct associations resulted in stronger predictions than indirect associations. These results suggested that the associations were represented cumulatively, and subtracting an associated outcome from another was unlikely.

Lastly, Experiments 10 and 11 (Chapter 6) modified exposure to examine the effect of exposure on later conjunctive predictions (Proposition 5). With only explicit instructions and no exposure, evidence of conjunctive predictions was still found (Experiment 10). With reduced contingency of color-location associations, participants surprisingly showed more robust and persistent conjunctive predictions that could be partly affected by a priming effect (Experiment 11). The more robust and persistent conjunctive predictions likely resulted from reduced extinction for the knowledge of associations during the prediction phase.

7.2. Predictions based on explicit versus implicit knowledge

Although some evidence of conjunctive predictions was found in the implicit conditions of Experiments 1 and 3, the majority of evidence supporting conjunctive predictions came from experiments where participants were explicitly told about the specific color-location associations before the exposure phase.
It is important to clarify that the choice of an explicit paradigm in Experiments 4-11 was the result of weak learning in the implicit condition of online experiments and did not mean that participants cannot make conjunctive predictions should they have learned the associations implicitly. Online participants could be more easily distracted and their immediate environment was poorly controlled during the learning task. This made it more difficult for the participants to learn, especially in the implicit condition. However, due to the pandemic, experiments had to be run online. Therefore an explicit paradigm had to be used to make sure that participants acquired the knowledge of cue-outcome associations that was necessary for subsequent predictions.

The choice of an explicit paradigm for online experiments resulted in a lack of meaningful findings for implicit learning because findings in the explicit condition could not be used to make inferences about implicit learning. This was due to the key differences between implicit learning and explicit learning: explicit knowledge can be updated more quickly (e.g., Mitchell et al., 2012), and can be used in verbal reasoning tasks (e.g., Tversky & Kahneman, 1973). Although implicitly learned patterns might enter conscious awareness and become explicit after prolonged exposure (e.g., Goujon, Didierjean, & Poulet, 2014), the current discussion would assume that the knowledge resulting from implicit learning is also implicit, as in most cases of implicit learning (e.g., Reber, 1989; Turk-Browne et al., 2005). Therefore, the current research could not provide any direct evidence to answer how do participants in the implicit condition make predictions if they have implicitly learned the color-location associations during exposure. To definitively examine predictions resulting from implicit learning, future research with in-lab participants and an extended exposure should be conducted.

How did participants make conjunctive predictions with explicit knowledge? Results from Experiment 10 suggested that these conjunctive predictions might be completely explicit
because some form of explicit processing was sufficient in generating conjunctive predictions. Specifically, participants’ knowledge of the color-location associations in this task came only from written instructions. Nevertheless, as mentioned in the discussion section of Chapter 6, the initial cursor movement time suggested that participants’ response in Experiment 10 was relatively quick, likely insufficient for explicit memory retrieval and verbal reasoning. Additionally, cursor movement time in Experiment 6 (explicit learning) and in Experiment 4 (implicit learning) did not differ, further suggesting that conjunctive predictions with explicit knowledge may not be a completely explicit process. These results together pointed to the possibility that explicit instructions resulted in a spatial, rather than a verbal representation of the knowledge, which might then be quickly and automatically brought to mind upon seeing the joint cues to generate conjunctive predictions. Based on this speculation, participants in an implicit learning paradigm likely would still make conjunctive predictions if they could learn to spatially represent the knowledge of cue-outcome associations. But the predictions might be weaker than those in the explicit condition, similar to the findings in Experiment 3.

7.2.1. Challenges when using implicit learning paradigms

Based on the current results and the relevant literature, it should be pointed out that implicit learning is a challenging paradigm to adequately instill knowledge in participants. As found in Experiment 4, when learning implicitly, participants barely used the reliable color-location associations to search for the target during exposure, and their subsequent performance in an explicit knowledge test was not above chance. While this lack of learning and knowledge could be explained by the online platform in Experiment 4, past results in implicit learning did indicate general challenges in employing implicit learning paradigms, which would often lead to lower quality of learning.
For example, in implicit probability cueing, participants often did not use the knowledge as frequently, even though bias in spatial attention was reliable and persistent. For example, when the target appeared in a quadrant 50% of the time, participants’ first saccade entered that quadrant only 36% of the time (Jiang et al., 2014). This was either the result of weak learning or a lack of effort to use the implicitly acquired knowledge. In either situation, this would be evidence for inadequate implicit learning in participants.

Additionally, as discussed in Chapter 1, since participants in most cases cannot verbally report the implicitly learned knowledge, the assessment of implicit learning was difficult and indirect which could result in contrasting results (e.g. Musz, Weber, & Thompson-Schill, 2014; Turk-Browne et al., 2005). Moreover, participants often failed to learn more complicated structures in implicit learning paradigms (Yim et al., 2020). Such failure could partly explain the results in Experiment 2, where participants in the implicit condition might have difficulty learning the more complex associations between a color and three quadrants for target locations.

### 7.2.2. Predictions were spontaneous

It is important to note that the main goal of the current research was to examine what type of predictions participants would make upon seeing joint cues, regardless of whether the predictions were based on explicit or implicit knowledge. In all experiments, participants were not told to make any predictions, nor did they encounter any previous examples of conjunctive outcomes following joint cues. Therefore, the more important finding was that participants incidentally made conjunctive predictions when encountering joint cues, and these predictions were not the direct result of any previous instructions or experiences of conjunction.
7.3. Bias in attention and conjunctive predictions

As discussed in Chapter 1, attention can be persistently drawn to the visual features and spatial locations of predictive relationships both for explicit learning (e.g., Le Pelley et al., 2013) and implicit learning (e.g., Barakat et al., 2013; Jiang et al., 2013). Since the current research used a spatial search paradigm, bias in spatial attention resulting from learning could partially explain the current results. One quick note was that in the current research, this bias in spatial attention was likely not the result of motor habit to attend to specific locations. This was demonstrated in Experiment 7, where the color cues predicted image categories that did not appear in specific locations, and also in Experiment 10, where participants were only given written instructions about the color-location associations.

Among the findings of the current research, faster response time in the conjunctive location found in Chapter 3 could be fully explained by this bias in spatial attention. Specifically, as mentioned in the discussion of Chapter 3, if participants processed one predictive cue at a time during the prediction phase and attended to the location predicted by the individual cues, search time in the conjunctive location would be faster. However, attention tracking data from the subsequent experiments (e.g., Experiment 6 and Experiment 11) demonstrated that participants consistently first entered the conjunctive location to search for the target, which could not be solely explained by the bias in spatial attention resulting from individually processing the cues. Nevertheless, the bias in spatial attention would still be useful in forming conjunctive predictions, especially in helping participants avoid the disjunctive location.

This bias in spatial attention might play a bigger role in forming conjunctive predictions in the implicit condition. As demonstrated in many previous studies, the bias in spatial attention resulting from implicit learning is robust and persistent (e.g., Jiang et al., 2013; Jungé et al.,
In the current paradigm, this would mean that the bias in spatial attention formed during exposure might be less susceptible to memory interference and go through slower extinction in the prediction phase of the implicit condition. Unfortunately as previously mentioned, learning during exposure was poor in Experiment 4, and this lack of learning prevented further meaningful analyses.

7.4. Predictor-outcome contingency, memory interference, and extinction

One surprising finding of the current research was that participants showed the most robust conjunctive predictions when the exposure contingency between color cues and target locations was reduced to 80% in Experiment 11. There were two important factors. First, extinction of the color-location associations was lower in the prediction phase of Experiment 11. This was driven by the lowered contingency of color-location associations during exposure, which resulted in reduced memory interference during the prediction phase. In all previous experiments, the association contingency was 100% during exposure. Therefore, any violations of the associations during the prediction phase would interfere with participants’ knowledge of the associations, thus participants would update their knowledge more quickly in these experiments. On the other hand, the lowered color-location contingency in Experiment 11 meant that participants were expecting exceptions to the associations, and it would take them longer to update the knowledge of these associations (Bouton, 2004). Additionally, the effect of memory interference and extinction can be avoided by future research paradigms that do not show participants the target. Instead, participants would only click on a quadrant where they think the target will appear. Although this paradigm does not allow participants to freely make responses, it is viable for future research where memory interference needs to be completely avoided.
It was apparent that extinction during the prediction phase of Experiments 5-11 involved explicit processes, as target location violated participants’ explicit knowledge. The involvement of explicit awareness made the extinction process different from that in a classical conditioning paradigm. Therefore, it would be interesting to find out what would be the cause of the extinction during the prediction phase in Experiments 5-11. Was target appearance in the impossible location the primary cause of memory interference and extinction, or would any violation to the weighted sum of target distribution be sufficient and cause the extinction (e.g., the target did not appear in the conjunctive location twice as frequently as in a disjunctive quadrant)? Further examination into the nature of extinction could reveal how the knowledge of color-location associations was represented during the prediction phase.

The second important factor that caused robust conjunctive predictions in Experiment 11 was that the lowered contingency did not affect participants’ learning of the associations. This was because participants were explicitly told about the color-location associations and the corresponding contingency in the instructions. As demonstrated in Experiment 10, explicit instructions on the associations were sufficient to generate conjunctive predictions.

7.5. Why did participants make conjunctive predictions?

In the weighted summation framework, upon seeing the joint cues, the probability of the associated outcomes is weighted and summed, and importantly, the subset of the outcomes with the highest summed probability (the conjunctive outcome) is consistently predicted.

The best example to illustrate this point was Experiment 11 where there was minimal extinction of the association knowledge. Specifically, in the spatial search task of the 80% condition (Figure 6.14), the weighted summed probability of the conjunctive location was 40%, and 25% for each of the two disjunctive locations. If participants were faithfully following the
weighted sum of outcome probabilities without making further predictions, they would be searching for the target in the conjunctive location 40% of the time. On the contrary, the results showed that participants consistently searched for the target in the conjunctive location significantly more frequently. Specifically, participants in the 80% condition first entered the conjunctive location to search for the target 62% of the time (mean first entry frequency into conjunctive location was 10, out of 16 included trials, see Figure 6.5), at a clearly higher level than the weighted sum for that location (40%). This meant that participants were making predictions rather than simply matching outcome frequencies represented by the summed probabilities. Nevertheless, these predictions were based on representing the weighted sum of the outcome probabilities. Specifically, the dwell time data in Experiments 6 and 11 demonstrated that the dwell time in different locations closely matched the probabilities resulting from weighted summation. This suggested that participants did represent the probabilities of outcomes in terms of the weighted sum, and they consistently based their predictions on the weighted sum by prioritizing the outcome subset with the highest probability, resulting in an exaggeration of the frequency of conjunctive predictions.

What could explain such predictions? The first explanation came from the findings in conjunction fallacy studies. As discussed in Chapter 2, in the decision-making literature, people tend to over-report the probability of the conjunction of two representative statements (e.g., Tversky & Kahneman, 1983). Specifically, when participants were given written descriptions of a person and asked to predict the most probable characteristics of the person, they chose the conjunction of two plausible characteristics, rather than any single one. This over-report of conjunctive probability is a genuine bias in human judgment, rather than a superficial misunderstanding of the written instructions (Bonini et al., 2004).
Such bias is common in day-to-day lives. For example, when people think of apples, they tend to think of the typical red apples rather than all possible apples (Osherson & Smith, 1981). Therefore, participants might prioritize the conjunction of the associated outcomes in a similar way. That is, even if the summed probability of the conjunctive outcome was only 40% (Experiment 11, 80% condition), participants would see the conjunction as the representative outcome. Therefore, the mind would prioritize conjunction at a higher percentage of the trials, motivating participants to consistently make conjunctive predictions.

The second explanation focused on prediction accuracy. Specifically, it might be a rational choice to consistently choose the outcome with the highest probability. In the same example of Experiment 11 (80% condition) the weighted sum of the conjunctive location was 40%, higher than any other locations. If participants believed that the probability of target appearance in the conjunctive location would be 40%, then the most rational choice would be to constantly search for the target in the conjunctive location first. This was because by following this strategy, participants would have a guaranteed accuracy of 40%. Any other strategy would result in lower accuracy, because even if participants knew about the overall chance of target appearance in different locations, they did not know in which specific trials the target would appear in these locations.

A good way to tease apart these two explanations would be to assign a higher probability to a non-conjunctive location. Again, the blue-red pair would be used as an example. During exposure, blue predicted that the following target would appear on the top half of the display, and red predicted the left half. However, following blue, the target appeared in the top-left quadrant only 20% of the time, but in the top-right quadrant 80% of the time. Likewise, following red, the target appeared in the top-left quadrant 20% of the time, but the bottom-left
quadrant 80% of the time. As a result, the weighted sum for the probability of the conjunctive outcome (i.e., the top-left quadrant) would only be 20%, and the weighted sum of the probability of each disjunctive outcome would be 40%. In this scenario, would participants make conjunctive predictions, or would they make disjunctive predictions? If participants still made conjunctive predictions, this would suggest that they prioritize the overlap/conjunction of the outcomes at a higher percentage. On the other hand, if participants made disjunctive predictions, this would suggest that they were strictly basing their predictions on the outcome with the highest summed probability. This would be an important follow-up study that was not examined due to the limited scope of the current research.

7.6. Implications and limitations of the current research

The current research showed that people incidentally made conjunctive predictions upon seeing joint predictive cues. Because the presence of joint cues is common, especially in the visual environment, knowledge of people’s subsequent predictions could be informative for signage designs. For example, when putting up the right-turn sign and the speed limit sign next to each other, traffic authorities should be aware that drivers unfamiliar with this road might expect a slow right-turn ahead. Such signage could be for public infrastructures such as road traffic and recycling, or could be for commercial purposes such as poster advertisement and product labeling.

The current research could also serve as a bridge between the visual attention and explicit reasoning literature. Specifically, the over-report of conjunction has mostly been examined with explicit judgment tasks, where participants were asked to choose the most probable outcome (e.g., Tentori et al., 2004; Tversky & Kahneman, 1983). Similarly, research in human semantics examined the over-report of conceptual conjunction by asking participants to subjectively rate
the typicality for the conjunction of two conceptual categories (Smith & Osherson, 1984; Zadeh, 1965). The current research, on the other hand, employed a spatial search paradigm that was common in the research of visual attention (e.g., Treisman & Sato, 1990; Wolfe, Cave, & Franzel, 1989), and demonstrated that the over-report of conjunction not only could be measured through explicit judgment, but could also be measured through visual attention in a spatial cueing paradigm.

The main limitation of the current research was the lack of evidence for how people would make predictions after implicitly learning the associations. Implicit learning was mostly unsuccessful in the current research because of the limitations caused by the choice of an online platform. As discussed in Chapter 1, there was a rich literature on implicit learning of similar associations (e.g., probability cueing, contextual cueing, statistical learning), demonstrating that learning was incidental (e.g., Chun, 2000, Turk-Browne et al., 2005) and long-lasting (e.g., Jiang et al., 2013, Kim et al., 2009). As a result, finding whether participants could make conjunctive predictions based on implicitly learned knowledge could help elucidate why implicit learning took place and why would implicit knowledge persist long into the future. Consequently, the lack of implicit learning in the current research meant that these results could not directly connect with the implicit learning literature to better complement past findings.

Another important limitation of the current research was that the cognitive mechanisms involved in forming the weighted summation framework were not directly examined. Specifically, was the weighted sum of the associated outcomes computed automatically and implicitly in working memory to affect later search strategy, or was the weighted sum computed verbally resulting in a more deliberate search strategy? Directly examining these questions could
help evaluate the automaticity of conjunctive predictions, and could reveal possible individual differences in making the predictions.

The last limitation of the current research was that it only examined predictions resulting from simple predictive relationships. Specifically in the current research, the outcomes always immediately followed the predictors. The mind can automatically pick up and consolidate such associations after few exposures (Bayer & Blimcher, 2005; Shohamy & Adcock, 2010). On the other hand, the real-world environment contains a number of more complex predictive structures, such as the complicated event structures in daily tasks such as cooking a steak. In this example, not only are there multiple steps in preparing and frying the steak, people also have to make sure that the pan would reach the right temperature when putting in the steak and the time duration of frying was on spot. Learning and segmenting these structures would involve more effort and take longer to complete (Zacks et al., 2001; Zacks & Swallow, 2007). Consequently, the current research could not adequately reveal the type of predictions that people tend to make when the previous knowledge contains more complicated associations such as event structures.

7.7. Future research directions

In the current research, there were two unexpected findings. First, participants did not base predictions on a weighted subtraction process. Second, the most robust conjunctive predictions were found in Experiment 11, where the contingency of color-location association was reduced to 80%. In Experiments 1-7, the association was 100%. As discussed previously, these findings likely resulted from the nuances caused by the design of the prediction phase in the current research. Specifically, to observe spontaneous predictions, participants were not verbally asked to make predictions and they freely searched for the target which appeared randomly on the screen following the joint cues. As a result, the lack of explicit effort made it
difficult for participants to process the subtraction of probabilities in Experiment 8, and the lack of color-location associations during the prediction phase interfered with participants’ exposure phase knowledge in Experiment 1-7, where the colors perfectly predicted target locations. To eliminate these nuances, future research can employ a verbal reasoning paradigm in the prediction phase, where participants are verbally asked to predict where the target should appear after seeing the joint presentation of predictive cues. With this paradigm, participants can put more effort into reasoning about the outcome, possibly allowing them to represent the probability of associated outcome with a subtraction process. Additionally in this verbal paradigm, participants will not perform the search task, so this design eliminates the memory interference caused by the lack of color-location associations during the prediction phase.

Another direction that needs further investigation is why participants could efficiently combine the outcomes associated with the joint cues to make conjunctive predictions. Results from previous research suggested that the representations of reliably co-occurring objects or events became more similar in working memory (Yu & Zhao, 2018a), and neural activation patterns (Paz et al., 2010; Schapiro, Kustner, & Turk-Browne, 2012). Therefore, it is possible that upon seeing the joint predictive cues, the representations of their associated outcomes would be represented more similarly in working memory. As the associated outcomes become more similar, the common property of the two would then become over-represented in working memory, guiding people’s subsequent predictions.

A direct way to examine this account would be to use neural imaging techniques. Specifically, the neural representations of the associated outcomes A and B are first recorded when participants first encounter these outcomes. Then, immediately after seeing the joint presentation of two predictive cues, participants are presented with outcome A alone. The
resulting neural representations are again recorded. Then, whether the representations of A have become more similar to the representations of B could be quantified by analyzing A’s representations before and after seeing the joint cues.

Alternatively, behavioral measures could be used to quantify whether the representations become more similar to each other. This could be done by a simple recall task (e.g., Yu & Zhao, 2018). For example, color cue A predicts an object A’ with size X, and color B predicts an object B’ with a different size Y. After seeing the joint presentation of A and B, participants would be then asked to recall the size of A’. If the recalled size of A’ was biased toward the size of B’, this would suggest that the representations of A’ and B’ have become more similar to each other.

If the representations of the associated outcomes do become more similar to each other after seeing the joint predictive cues, it would also be interesting to examine whether such assimilated representations are transient or long-lasting. Specifically, if transient, then the associated outcomes for cues A and B are represented more similarly after the joint presentation of A and B, but this assimilation can dissipate quickly. Consequently, upon seeing a novel combination of A and C, their associated outcomes can again be represented more similarly, without interference from the previous exposure to the AB combination. Such findings would be novel and can reveal how the mind may flexibly represent previously learned knowledge.

The second direction of future research focuses on modifying the relationship between the associated outcomes. Specifically, in the current study, there was usually a possible conjunction/overlap between the associated outcomes. For example, the top-left quadrant was both on the left half and on the top half, and large animals were both large and animals. Nevertheless, many conceptual categories in the real world do not have any possible overlap (e.g., Levi, 1978), thus conjunctive predictions would not be possible for those combinations.
For example, there is no overlap between the category *basketball* and the category *hoop*. In other words, no subset of basketball is a hoop, nor is there any subset of hoop being a basketball. If the associated outcomes of the joint predictive cues represent such non-overlapping conceptual categories, what type of predictions do people make? One possibility is that participants may predict a new concept that is superordinate to the associated outcomes, thus encompassing both concepts (Medin & Smith, 1984; Quinn, Eimas, & Rosenkrantz, 1993). In the example of *basketball* and *hoop*, a superordinate concept could be round objects. If this were the case, then participants not only would expect basketballs and hoops after jointly seeing their predictive cues, but would also expect other round objects such as the sun. Alternatively, participants may predict a new concept that can meaningfully link the two associated outcomes together (Wilkenfeld & Ward, 2000; Wisniewski, 1996). In the example of *basketball* and *hoop*, people may think of a subset of *hoop* that is closely associated with *basketball* – basketball hoops. Both the formation of superordinate concepts and the emergence of a compound linking the two categories are important components of human vocabulary (Downing, 1977). Therefore, finding out how people make predictions to combine such conceptual categories could elucidate how meaningful concepts and word compounds in semantics automatically arise in human languages.

Overall, this study used a visual search paradigm to show that when seeing joint predictive cues, people made conjunctive predictions about the outcome. The conjunctive predictions could be explained by the proposed weighted summation framework, suggesting that joint cues were jointly processed and conjunction was over-represented.
Bibliography


