COGNITIVE PROCESSES INVOLVED IN HYPOTHESIS JUDGMENT AND UNDERLYING FUNCTIONAL BRAIN NETWORKS

by

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Abstract

The manner in which we judge multiple hypotheses and consider multiple items of evidence is fundamental to diverse aspects of behaviour. One goal of the studies reported here was to identify cognitive biases in this process. A probabilistic reasoning paradigm involving objectively quantifiable evidence allowed the manipulation of factors biasing hypothesis judgment while mathematically normative responses were kept constant. This revealed two cognitive biases. The first was a tendency to overestimate the strength of gradually accumulated evidence. The second was a tendency to judge a self-selected hypothesis as being more probable than an externally selected one, despite equivalent supporting evidence. This selection bias was exacerbated in delusional schizophrenia patients.

Our second goal was to describe brain networks involved in hypothesis judgment. To this purpose, we collected functional magnetic resonance imaging (fMRI) data during performance of a probabilistic reasoning task. Functionally connected brain networks were identified using constrained principal component analysis (CPCA). The fMRI results showed task-related activity in a network including the dorsal anterior cingulate cortex (dACC) and bilateral parietal cortex. The activity of this dACC-based network was strongest when the evidence was consistent with the hypothesis being judged (evidence-hypothesis matches). This result is discussed in terms of functional connectivity between the dACC and other brain regions as a possible mechanism for coherence between components of a mental representation. Both our behavioural results
and our neuroimaging results show evidence of processing unique to situations involving cognitive coherence between the hypothesis being judged and the relevant evidence.
Preface

With the exception of the introduction and discussion (Chapters 1 and 7), all chapters of this thesis stem from published manuscripts in peer-reviewed journals. A reference list, by chapter, has been provided below. In all of the work in Chapter 2 through to Chapter 6, my role involved generating the empirical questions addressed in each experiment, finding much of the cited literature, designing and programming the cognitive paradigms, supervising and aiding research assistants in collecting the data, analyzing all of the data, and writing (as first author) the manuscripts reporting the results (or the review, in the case of Chapter 6). In the analysis of functional Magnetic Resonance Imaging (fMRI) data using a multivariate statistical method known as constrained principal component analysis (CPCA), I played a collaborative role in the development of the fMRI-CPCA Matlab-based software used. I collaboratively developed novel applications of CPCA in Chapter 5. This involved adjusting the fMRI-CPCA technique to independently assess the time courses of activity in different regions of a functionally connected brain network.

While all of the work represents collaboration between Dr. Todd Woodward and me, Chapters 4, 5, and 6 involved other collaborators. In Chapter 4, Susan Kuo organized and analyzed several measures of cognitive function (IQ and education), clinical symptom severity, and demographics. She also played a role in the application of exclusion criteria to the dataset. Dr. Mahesh Menon made an intellectual contribution to the discussion of Kapur’s aberrant salience hypothesis of schizophrenia. In Chapter 5, Paul Metzak and Katie Lavigne made intellectual contributions to the discussion of the
role of the dorsal anterior cingulate cortex (dACC) in changing a mental set. In Chapter 6, Lawrence Ward brought to my attention a substantial portion of the literature cited.

All research was approved by the UBC Behavioural Research Ethics Board (Certificate Number: H08-00187), the UBC Clinical Research Ethics Board (Certificate Number: H07-02409), and the VCHA Clinical Trials Administration Office (Vancouver Coastal Health Authority Research Study #V08-0014).

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Glossary

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
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<tr>
<td>BOLD</td>
<td>Blood-oxygen-level-dependent</td>
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<tr>
<td>CPCA</td>
<td>Constrained principal component analysis</td>
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<tr>
<td>dACC</td>
<td>Dorsal anterior cingulate cortex</td>
</tr>
<tr>
<td>df</td>
<td>degrees of freedom</td>
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<tr>
<td>DLPFC</td>
<td>Dorsal/lateral prefrontal cortex</td>
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<tr>
<td>EEG</td>
<td>electroencephalography</td>
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<tr>
<td>FIR</td>
<td>Finite impulse response</td>
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<tr>
<td>fMRI</td>
<td>Functional magnetic resonance imaging</td>
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<tr>
<td>K-BIT</td>
<td>Kaufman brief intelligence test</td>
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<tr>
<td>MEG</td>
<td>Magnetoencephalography</td>
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<td>QUICK</td>
<td>Ammons quick test</td>
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<td>SD</td>
<td>Standard deviation</td>
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1 An Introduction to Hypothesis Judgment

Judging the validity of a given hypothesis is fundamental to such diverse situations as interpreting social behaviour, making financial choices, and making perceptual decisions. In order to choose the most likely hypothesis, we often assess the strengths of multiple sources of evidence and then compare them. This process is affected not only by objectively quantifiable evidence strengths, but also by cognitive factors such as salience, coherence, and tendencies to give more weight to certain types of evidence. Understanding how hypotheses are judged requires isolating the different factors involved and identifying those that bias judgments. It also requires identifying how those factors interact. These requirements can be met partly through behavioural studies, and partly through neuroimaging studies of the brain networks underlying hypothesis comparison.

1.1 Probabilistic reasoning and the beads task

We used a probabilistic reasoning paradigm to investigate cognitive factors involved in hypothesis judgment. This allowed us to objectively quantify the strength of the evidence considered. There are two approaches a researcher can take when applying such paradigms in behavioural studies. The first is to compare individuals’ behaviour to mathematical norms, investigating whether judgments change more or less quickly than those norms in response to a given change in evidence strength. This was done extensively in early work on probabilistic reasoning (Beach, 1968; Ducharme, 1970; Fischhoff & Beythmarom, 1983; Peterson, Ducharme, & Edwards, 1968; Peterson, Schneider, & Miller, 1965). The second is to keep evidence strength constant, thus keeping mathematically normative responses constant, while manipulating other factors. These can be factors suspected to influence hypothesis judgment
despite being irrelevant to a mathematically ideal reasoner. The cognitive biases reported in Chapters 2 to 4 of this thesis were identified using this second approach.

One paradigm used extensively in studies of probabilistic reasoning is known as the ‘beads from a jar task’ (Beach, 1968; Ducharme & Peterson, 1969; Freeman, Pugh, & Garety, 2008; Hemsley & Garety, 1986; Lopes, 1985; Moritz, Woodward, & Lambert, 2007; Shanteau, 1970, 1975; Speechley, Whitman, & Woodward, 2010). Typically, the participant is presented with a series of beads, one at a time, and is told that the entire series is drawn with replacement from one of two jars, referred to hereafter as jar A and jar B. The participant must rate the probability that the entire series came from jar A rather than jar B. If jar A contained 80% red beads and 20% blue beads and jar B contained 30% red beads and 70% blue beads, and the series of draws contained mostly red beads, jar A would be the most likely origin of the series. For a series of two draws, D1 and D2, the odds that the entire series came from jar A rather than jar B are derived from Bayes’ Theorem

\[
\frac{p(A \mid D_1 \& D_2)}{p(B \mid D_1 \& D_2)} = \frac{p(D_2 \mid A) \times p(D_1 \mid A) \times p(A)}{p(D_2 \mid B) \times p(D_1 \mid B) \times p(B)}
\]

As there are two jars (with equal numbers of beads), the probability of a bead being sampled from jar A, p(A), and the probability of a bead being sampled from jar B, p(B), are both 0.5. If the first draw, D1, was a red bead, and the second draw, D2, was a blue bead, then p(D1|A) = 0.8, p(D2|A) = 0.2, p(D1|B) = 0.3, and p(D2|B) = 0.7. This equation can also be rearranged to express the probability that the series came from jar A rather than jar B:
As more beads in a series are drawn, healthy individuals have been shown to be conservative in increasing ratings of the probability that the series came from the most likely lake, relative to the Bayesian norm (Beach, 1968; Ducharme, 1970; Peterson et al., 1968; Peterson et al., 1965). Another variant of the task involves asking participants to decide from which jar the series of beads is being drawn once they feel enough information has been accumulated. In this version of the task, delusional schizophrenia patients decide on a jar earlier than healthy controls and non-delusional patients - in other words, they jump to conclusions (Averbeck, Evans, Chouhan, Bristow, & Shergill, 2011; Moritz et al., 2007; Moritz & Woodward, 2005; Woodward, Munz, LeClerc, & Lecomte, 2009). If probability judgments are required after each draw, then one can also test whether delusional individuals’ probability ratings increase faster than those of healthy participants.

A cause for concern with the beads-from-a-jar paradigm is that participants do not always understand that the entire series came from the same jar. Specifically, they might mistakenly see it as possible for the first bead to come from jar A and for the second bead to come from jar B (Balzan, Delfabbro, Galletly, & Woodward, 2012; Speechley et al., 2010). Such misunderstandings call into question previous findings regarding conservatism or jumping to conclusions. However, the beads paradigm remains useful because, even before any Bayesian updating is necessary, the cognitive processes involved when only a single bead is drawn are fundamental to hypothesis judgment and not yet adequately understood.

One recent improvement to the task involves a scenario in which fish are drawn from one of
two lakes. The instructions tend to be more easily understood by participants in the more naturalistic lakes scenario, although it is otherwise equivalent to the traditional beads-from-a-jar scenario in terms of cognitive processing required and mathematical norms (Speechley et al., 2010).

1.2 Cognitive components of probabilistic reasoning elucidated by the beads task / fish task

Several cognitive processes contribute to performance on the beads task (or fish task) described above. In a basic, single-draw version of this paradigm, one must assess the strength of evidence supporting each hypothesis before those evidence strengths can be compared. Thus, hypothesis judgments could be affected either during evidence assessment or during comparison. We explored this distinction between biased assessment and biased comparison when investigating each cognitive factor affecting hypothesis judgments in the beads / fish task.

One cognitive factor sometimes involved in the beads / fish task is the choice of a preferred hypothesis. Participants may consider and accumulate evidence until it is sufficient to choose one hypothesis, as they are assumed to do in the variant of the task used to study jumping to conclusions (Moritz et al., 2007; Moritz & Woodward, 2005; Woodward et al., 2009). They may also erroneously reverse that order of operations, allowing prior choices to affect how they consider and accumulate further evidence. Mathematically normative performance requires that the choice of preferred hypothesis be determined by previously presented evidence. That choice should not affect the interpretation of subsequently presented evidence. However, previous reports of confirmation bias (Klayman & Ha, 1987;
Wason, 1960) and bias against disconfirmatory evidence (Buchy, Woodward, & Liotti, 2007; Moritz & Woodward, 2006; Woodward, Buchy, Moritz, & Liotti, 2007) suggest that the choice of a preferred hypothesis can bias the evaluation of later evidence. However, this has yet to be tested in a paradigm manipulating whether a preferred hypothesis is chosen (self-selected) while controlling for the strength of the evidence presented.

The sequence of events described above highlights yet another important factor to consider; the gradual accumulation of evidence. Many reported biases in reasoning, such as confirmation bias (Adsit & London, 1997; Gale & Ball, 2006; Klayman & Ha, 1987; Sanbonmatsu, Posavac, Kardes, & Mantel, 1998; Wason, 1960), conservatism in probability revision (Beach, 1968; Ducharme, 1970; Ducharme & Peterson, 1969), and bias against disconfirmatory evidence (Buchy et al., 2007; Moritz & Woodward, 2006; Woodward et al., 2007; Woodward, Moritz, & Chen, 2006; Woodward, Moritz, Cuttler, & Whitman, 2006) involve the gradual presentation of evidence in sequential portions. However, it remains unknown whether the gradual presentation itself affects hypothesis judgments. If a given amount of evidence were presented in several sequential portions, would it be evaluated differently than if the same evidence were all presented instantaneously? If so, would the gradual presentation affect the assessment of evidence strength, the comparison between hypotheses, or both?

One final factor considered in the current studies is whether the evidence supports the hypothesis being judged, referred to hereafter as the focal hypothesis. If evidence strongly supports the focal hypothesis, we can say that the evidence and hypothesis form a coherent mental representation, or gestalt. Coherence is thought to make mental representations more stable and salient (Köhler, 1929; Metzger, 2006). In the current studies, we explore how this
cognitive coherence affects biases identified in behavioural data. We also investigate how 
cognitive coherence affects the operation of functional brain networks, as is described in 
more detail in the next section.

1.3 Functional connectivity in brain networks involved in hypothesis comparison

In order to investigate the functional brain networks involved in hypothesis 
comparison, we used a single-draw version of the beads task. This allowed us to investigate 
the functional brain activity underlying hypothesis comparison, as well as that underlying an 
evidence assessment task. The evidence assessment task served as a control condition for the 
hypothesis comparison task. It was equated to the hypothesis comparison task in terms of 
visual stimuli presented and the motor activity involved in responding. Thus, the tasks 
differed only in whether they required a comparison of evidence strengths between two 
hypotheses. Within the hypothesis comparison task, we manipulated whether the evidence 
was coherent with the hypothesis being judged, referred to hereafter as the focal hypothesis. 
Our goals in the neuroimaging studies were (1) to identify brain networks involved in the 
comparison of evidence strengths for competing hypotheses, (2) to identify how activity in 
those networks varied as a function of evidence strength, and (3) to identify how activity in 
those networks varied as a function of whether the available evidence was coherent with the 
focal hypothesis - in other words, whether it supported accepting or refuting it.

As hypothesis comparison is a complex cognitive task, we expected it to involve 
multiple cognitive processes and multiple brain regions working in concert. Optimizing our 
analysis for characterizing the activity of distributed brain networks underlying hypothesis 
comparison required accurate description of how those networks were distributed across
brain regions. We met these requirements by analyzing fMRI data using Constrained Principal Component Analysis, or CPCA (Hunter & Takane, 1998, 2002). CPCA can be used to identify functional brain networks exhibiting task-related changes in activity (Woodward, Cairo, et al., 2006). A detailed mathematical description of CPCA is provided in Chapter 5. Here, we provide a brief overview. The first stage of CPCA uses regression to split the variance in the full dataset into variance attributable to the task being performed, and residual variance unrelated to the task. This regression is important in separating the small amount of variance related to the experimental manipulations of interest from the large amount of variance reflecting neural activity unrelated to the task being performed and any artifacts in the signal not perfectly corrected for.

Once the analysis had been constrained to the (usually relatively small) proportion of variance related to the experimental manipulations of interest, we used principal component analysis to identify functional brain networks evident within that portion of the signal. Each component has a unique time course of activity (the component scores) and a unique spatial network of loadings across brain regions. The loadings for a given component can be overlaid on a brain image, and thresholded to indicate the regions that are most strongly involved in that network. For each component, we also obtain descriptions of the time course of activity (in each condition and subject separately) following the start of a trial.

In fMRI data, each time course should resemble a hemodynamic response (HDR) function. CPCA provides a separate estimate of the post-stimulus time course for each brain network, participant, and experimental condition. These are referred to as the predictor weights, and are calculated from computations involving the component scores and the model. The model is composed of the task-timing-based predictors that were used in the
regression stage described above. Each predictor weight time course involved one HDR estimate every 2 seconds following the start of a trial.

1.4 Research goals and expected findings

The general goal of our investigations of hypothesis judgment was to identify cognitive factors affecting judgments, and to characterize their interactions. In behavioural studies, this involved identifying factors which affected judgments even though mathematically normative models would predict no effect. In neuroimaging studies, factors affecting judgments in a mathematically normative manner were also of interest, provided that they corresponded to differences in the activity of underlying brain networks. Identifying several factors affecting hypothesis judgments (or the brain networks underlying those judgments) and characterizing their interactions laid the groundwork for a general theoretical framework describing the roles of cognitive coherence and salience in hypothesis comparison.

In the behavioural studies we focused on two factors expected to bias hypothesis judgments. First, as is reported in Chapter 2, we manipulated whether evidence was gradually accumulated. We expected that a given amount of evidence would affect judgments more strongly if it were presented in sequential portions than if it were presented all at once. If each portion of evidence was consistent with the others in terms of which hypothesis was indicated to be most probable, a gradual evidence effect could arise from anchoring to the first judgment made. If this were the case, we would expect to see a primacy effect, whereby final judgments were more strongly affected by the first portion of evidence presented than by the final portion. Another way of describing such an anchoring effect would be to say that
cognitive coherence between an initial judgment and subsequently presented evidence augmented the effects of that evidence. If there were a bias in favour of gradually accumulated evidence driven by cognitive coherence, we might also expect that bias to be strongest when the evidence was most coherent with, or provided the strongest support for, the focal hypothesis.

Alternately, we might find a gradual evidence effect independent of both (1) the order of evidence presentation and (2) the level of coherence between the evidence and the focal hypothesis. This would be more analogous to packing effects (Bonini & Gonzalez, 2005; Rottenstreich & Tversky, 1997; Tversky & Koehler, 1994), whereby a given possibility (i.e., that someone will die of natural causes rather than accidental death) seems more probable if unpacked into constituent possibilities (i.e., the probability that someone will either die of a heart attack or cancer or a viral infection). A packing effect for evidence would cause that evidence to seem more convincing, regardless of which hypothesis it supported, if it were presented in separate portions than if the same evidence were presented as one portion.

The second factor expected to bias hypothesis judgments in behavioural studies was whether a preferred hypothesis was explicitly chosen. The novel aspect of this investigation was the use of a paradigm, namely the beads / fish probabilistic reasoning task, in which the objective strength of the evidence considered could be matched between self-selected hypotheses and those selected by an external source. We expected participants to judge self-selected hypotheses as more probable than externally selected ones despite equivalent supporting evidence. This would be consistent with the findings of previous investigations not controlling for evidence strength (Sieck & Arkes, 2005; Sieck, Merkle, & Van Zandt, 2007; Sieck & Yates, 1997).
This investigation of self-selected hypotheses was also extended to a population prone to biased probabilistic reasoning – namely, schizophrenia patients, many of whom experience delusions. Delusions are defined as fixed false beliefs that (i) are maintained despite counter-evidence and rational counter-argument; (ii) would be dismissed by members of the same social-cultural environment; and (iii) are held with great conviction (American Psychiatric Association, 2000). For a belief to be considered delusional, it is not sufficient that the belief be unsupported by available evidence. It is also required that it deviate from cultural norms, since many culturally normative beliefs are not adequately supported by evidence (Mullen, 1979). Thus, for a belief to be a delusion, it must be a self-generated or self-selected hypothesis. For this reason, we predicted an exacerbated bias in favour of self-selected hypotheses in delusional patients.

Another prediction was that a bias in favour of self-selected hypotheses would interact with an effect of gradual evidence. If there were a gradual evidence effect resulting from cognitive coherence between the initial judgment and the subsequently presented evidence (an anchoring effect), we might expect it to be affected by the subjective salience of the hypothesis that was most probable at the time of the initial judgment. Given that self-selected focal hypotheses were more salient than externally selected ones, we would expect the evaluation of evidence presented late in a trial to be more strongly anchored to a self-selected focal hypothesis. If the gradual evidence effect were the result of anchoring, we would then expect the gradual evidence effect to be stronger if the focal hypothesis were self-selected. However, it could be that the gradual evidence effect resulted not from coherence effects, but rather from unpacked evidence being more salient. In that case, we would expect
the effect of gradual evidence accumulation to be independent of any bias in favour of self-selected hypotheses.

We also investigated the effects of cognitive coherence on brain networks involved in hypothesis judgment. We used a more basic, single-draw version of the beads / fish task. Participants were required to judge the relative probability that a fish had been drawn from one lake (the focal hypothesis), rather than another lake (the alternative hypothesis). The focal hypothesis being judged was never self-selected, and the relevant evidence was always all presented instantaneously (rather than gradually). When the focal hypothesis and the relevant evidence are cognitively coherent, gestalt psychology (Köhler, 1929; Metzger, 2006) would predict the formation of a stable, salient mental representation of that hypothesis together with the supporting evidence. We expected this salience and cognitive coherence to involve an augmented signal from the functionally connected brain networks involved in the hypothesis judgment task. We also expected that strength of the network signal would reflect the strength of the evidence being considered, since the strongest evidence would be most salient.

Provided that our neuroimaging data showed (1) an effect of whether the evidence supported or refuted the focal hypothesis, and (2) an effect of evidence strength, we would also wish to know whether those effects interacted or were independent. If they were independent, we might expect them to involve distinct brain networks with distinct time courses. This could be detected in our neuroimaging data because of the high spatial and temporal resolution afforded by our multimodal analysis. If the effects were not independent, there should be at least one network in which the activity level was sensitive to the interaction of evidence strength with coherence.
To summarize the above predictions, we expected to observe the following effects in our behavioural data:

(1) A bias towards treating gradually accumulated evidence as stronger than the same evidence presented instantaneously.

(2) An anchoring effect underlying the bias in favour of gradually accumulated evidence.

(3) A stronger effect of gradual evidence accumulation when the evidence most strongly supported the focal hypothesis.

(4) A bias towards judging self-selected hypotheses to be more probable than externally selected ones supported by equivalent evidence.

(5) A stronger selection bias when the evidence most strongly supported the focal hypothesis.

(6) A stronger effect of gradual evidence accumulation when the focal hypothesis was self-selected.

(7) An exacerbated selection bias in delusional schizophrenia patients.

In our neuroimaging data, we expected to observe the following:

(1) A stronger signal from task-relevant functionally connected brain networks during hypothesis comparison than during an evidence assessment control task.

(2) A stronger signal from those networks when the available evidence was coherent with the focal hypothesis being judged (in other words, on trials with evidence-hypothesis matches).

(3) At least one brain network sensitive to an interaction between evidence strength and whether the evidence supported the focal hypothesis.
If the above predictions were correct, the results would be consistent with a theoretical framework specifying a role for cognitive coherence in evidence evaluation and hypothesis judgment. In this framework, not only is there a mathematically normative effect of evidence on judgments, there is also a bias in which those judgments affect the perceived strength of subsequent evidence. Specifically, when evidence is initially presented and judged, a bias in favour of that judgment is formed. Then, new evidence is presented, or else the initially presented evidence is re-considered. The evaluation of the new (or else re-considered) evidence is biased to agree with the initial judgment. Thus, evidence coherent with the initial judgment is perceived to be strongest.

Considering this order of cognitive events highlights two distinct possibilities fitting within the general framework of cognitive coherence. One possibility is that the degree to which the initially presented evidence supports the focal hypothesis (the degree of objectively quantifiable coherence), would predict the strength of the bias later observed. Alternately, the presence or absence of a bias may depend on a binary distinction, namely whether the initially presented evidence supports or refutes the focal hypothesis. In other words, this second possibility pertains to the presence or absence of coherence, rather than the level of coherence. This proposed binary processing holds some validity for the many real-life judgment and decision-making situations in which evidence strength cannot be quantified, and there is no objectively quantifiable level of coherence. In either case, once the initially presented evidence had been evaluated, the judge would subsequently be in favour of evidence coherent with that evaluation because coherent mental representations form a stable, salient gestalt.
Evidence Affects Hypothesis Judgments More if Accumulated Gradually than if Presented Instantaneously

As was stated in Chapter 1, when we judge the probability of a hypothesis, the evidence for that hypothesis is often gradually accumulated, rather than becoming available instantaneously. If a given amount of evidence is presented in sequential portions (gradually accumulated), this distributed presentation might increase the extent to which that evidence is processed. That increase in processing could increase the salience or fluency of the corresponding mental representation, in turn increasing its perceived strength. Consequently, gradual accumulation would cause evidence consistent with a given hypothesis to be seen to support it more strongly, and evidence inconsistent with a given hypothesis to be seen to refute it more strongly. In the current studies, we assessed the perceived strength of gradually accumulated versus instantaneously accumulated evidence by measuring how strongly it affected comparative judgments made between a focal hypothesis and its alternative.

An alternative possibility is that of anchoring effects, which are dependent not only on the gradual presentation of evidence, as in the first possibility described above, but also on the order in which evidence is presented. Anchoring would cause the subjective evaluation of evidence presented late in a trial to be biased towards being consistent with the judgment of evidence presented at the beginning of a trial. We tested for the possibility of anchoring effects in the current study by testing whether a final
judgment meant to incorporate three sequential portions of evidence was more strongly affected by the first portion than by the second portion. Incidentally, this design also allowed us to test for recency effects by testing whether final judgments were more strongly affected by the final (third) portion of evidence than by the second portion.

While an extensive body of research has employed paradigms in which objectively quantifiable evidence is gradually accumulated, (e.g. Beach, 1968; Usher & McClelland, 2001; Woodward et al., 2009), those studies confounded gradual versus instantaneous evidence accumulation with the overall strength of evidence. For example, in previous variations of the beads task, the strength of evidence changed with each bead drawn. In contrast, the purpose of the current research was to manipulate those factors independently. In order to do so in the current study, we precisely matched our gradual and instantaneous evidence conditions in terms of the total strength of evidence supporting each hypothesis. Specifically, the evidence visible on the final event of a given gradual evidence accumulation trial was equivalent, in terms of support for the focal hypothesis and support for its alternative, to the evidence visible on the corresponding instantaneous-evidence control trial. Thus, if there were no bias caused by the gradual accumulation of evidence, we would expect the final judgments made on gradual evidence accumulation trials to equal those made on the corresponding control trials.

We also wished to be able to compare subjective probability judgments to an objective mathematical norm. To that purpose, we used a paradigm with objectively quantifiable evidence strength. This was a modified version of the well-known beads-from-a-jar task (Beach, 1968; Fischhoff & Beythmarom, 1983; Moritz et al., 2007;
Moritz & Woodward, 2005; Speechley et al., 2010; Woodward et al., 2009). In the traditional version, participants judge the most likely origin of a short sequence of red and blue beads drawn with replacement from one of two jars, each containing a different proportion of the two colours. The mathematical norm for that task involves Bayesian updating (Beach, 1968; Fischhoff & Beythmarom, 1983; Lopes, 1985), where the probability of hypothesis A rather than B, given two observed data, \( p(A \sim B \mid D_1, D_2) \), is

\[
\frac{p(D_2 \mid A) p(A \mid D_1)}{p(D_2 \mid A) p(A \mid D_1) + p(D_2 \mid B) p(B \mid D_1)}.
\]

(3)

It should be noted that the Bayesian norm specifies the same relative probabilities regardless of whether \( D_1 \) and \( D_2 \) are observed sequentially, or at the same time. We modified the task to involve several types of evidence, corresponding to several bead colours. In addition, instead of using jars as containers and beads as the objects in those jars, we used lakes containing fish. Three fish, each of a different colour and known to have been drawn from one of two lakes, were visible throughout each trial. Each of the two lakes (corresponding to the focal hypothesis and its alternative) contained fish of four different colours. Three of the four colours, referred to hereafter as the relevant colours, corresponded to the three fish that had originated from one of the lakes. The fourth colour in the two lakes was a filler colour, used to ensure that the total number of fish in each lake was the same. On gradual evidence trials, the fish within the lakes became visible one colour at a time. On control trials, all of the fish within each lake, regardless of colour, became visible instantaneously. The Bayesian model predicts that responses
would be the same whether evidence was gradually accumulated or all presented instantaneously. However, as will be discussed below and is tested in two experiments in the current study, behavioral responses differ between the instantaneous and gradual evidence conditions.

In the current studies, we expected that gradual (rather than instantaneous) presentation would increase the extent to which each item of evidence was processed, which would in turn increase the salience of the corresponding mental representations. As a result of that increased salience, we expected a given amount evidence to seem subjectively stronger when gradually accumulated than when presented instantaneously. It follows that gradual evidence more consistent with the focal hypothesis than with its alternative would be seen to support it more strongly, and would lead to a greater increase in ratings of the relative probability of the focal hypothesis. It also follows that gradual evidence less consistent with the focal hypothesis than with its alternative would be seen to refute it more strongly, and would lead to a greater decrease in ratings of the relative probability of the focal hypothesis.

2.1 Experiment 1

2.1.1 Methods

2.1.1.1 Participants

Sixty-eight volunteers (fifty females, eighteen males) with a mean age of 27.7 years (SD=7.9) participated in this experiment. Participants were recruited via posters on the University of British Columbia campus and in community centers in the greater
Vancouver area, and also via postings on electronic bulletin boards. All participants were reimbursed $10 per hour for their time plus parking and transportation expenses.

2.1.1.2 Materials and Procedure

On each trial of the task, participants were presented with a scene depicting three lakes, two of which were upstream from the third (see Figure 2.1 and Figure 2.2). Throughout each trial, three fish were presented in the bottom lake. The participants were told that any fish appearing in the downstream lake originated in either the left-hand upstream lake or the right-hand upstream lake. Each of the upstream lakes contained 120 fish on every trial. Although this consistency was obvious due to the visual displays, the exact number of fish was not explicitly mentioned to participants. They were discouraged from explicitly counting all of the fish in each lake, as that would slow task performance too much. The positions of fish within each upstream lake were randomized over trials, so that any two trials with identical ratios of fish of each colour would not be identical in appearance.
Figure 2.1. An example of the general format of the display used throughout the experiment.
Figure 2.2. The sequence of events during a gradual evidence accumulation trial, with the relevant colours being white, gold, and black.
The four fish colours used were red, gold, black, and white. The three fish visible in the downstream lake were each of a different colour. We will refer to these as the relevant colours, and to the fourth colour as the filler colour. If an upstream lake contained a high percentage of fish of the relevant colours and a low percentage of fish of the filler colour, then there was a high probability that it was the origin of the fish in the downstream lake. The assignment of the four fish colours to the relevant and filler colours was randomized across trials.

Table 2.1. Experiment 1: Numbers of Fish of the Three Relevant Colours for each of Four Levels of Support for a Given Hypothesis.

<table>
<thead>
<tr>
<th>Relevant Colour #1</th>
<th>Relevant Colour #2</th>
<th>Relevant Colour #3</th>
<th>Total # Fish of Relevant Colours</th>
<th>Total as a Percentage of the 120 Fish in the Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>8</td>
<td>8</td>
<td>24</td>
<td>20 %</td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>24</td>
<td>40</td>
<td>33 %</td>
</tr>
<tr>
<td>8</td>
<td>24</td>
<td>24</td>
<td>56</td>
<td>47 %</td>
</tr>
<tr>
<td>24</td>
<td>24</td>
<td>24</td>
<td>72</td>
<td>60 %</td>
</tr>
</tbody>
</table>

Note. In the overall experiment, there were four possible levels of support for the focal hypothesis and four possible levels of support for its alternative. The above table outlines those four levels for just one hypothesis. The numbering of the three relevant colours above is arbitrary and does not refer to presentation order. On any given trial, the three relevant colours used for the three fish in the downstream lake were randomly selected from four possibilities: red, white, gold, and black.

Half of the trials had three events (gradually accumulated evidence), with a new relevant colour becoming visible in the upstream lakes on each event. The other half of the trials had one event (instantaneously presented evidence). There were four levels of evidence strength for each lake, corresponding to different total numbers of fish of the
relevant colours. The rest of the fish in each lake were of the filler colour. Of the 120 fish in each upstream lake, the total number of fish of the relevant colours would be either 24 (20%), 40 (33%), 56 (47%), or 72 (60%). As shown in Table 2.1, these numbers were based on the fact that the number of fish of each individual relevant colour could be either 8 or 24. Thus, there were 32 cells in the experimental design: 4 levels for the focal lake × 4 levels for the alternative lake × 2 types of evidence presentation (gradual versus instantaneous evidence). In each of these cells there were 4 trials, so each participant completed 128 trials in total. The assignment of the left-hand and right-hand upstream lakes to the focal and alternative hypotheses was randomized across trials.

On each event, the participant rated the probability that the three fish in the downstream lake all came from one upstream lake (the focal hypothesis) rather than the other upstream lake (the alternative hypothesis). Ratings were made on a vertical scale, with the labels "definitely true" at the top end and "impossible" at the bottom end. To the right of the rating scale was a phrase telling participants which lake was the focal lake on the current trial (e.g., "fish in the bottom lake came from left-hand lake rather than right-hand lake"). Participants used a mouse to move the slider smoothly up and down the scale and clicked the left mouse button when it was in the desired location. At the beginning of each trial, the slider was set at the mid-point of the response scale. On the second and third events of gradual evidence accumulation trials, it was set at the location corresponding to the rating made on the previous event.
Table 2.2. Experiment 1: Ratings of the Probability that the Focal Hypothesis, Rather than its Alternative, is Correct.

<table>
<thead>
<tr>
<th>Strength of Evidence Supporting the Focal Hypothesis</th>
<th>Strength of Evidence Supporting the Alternative Hypothesis</th>
<th>Rating Predicted by Bayesian Norm</th>
<th>Instantaneous Evidence</th>
<th>Gradual Evidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>20</td>
<td>50.0</td>
<td>51.2</td>
<td>50.1</td>
</tr>
<tr>
<td>20</td>
<td>33</td>
<td>25.0</td>
<td>41.8</td>
<td>41.3</td>
</tr>
<tr>
<td>20</td>
<td>47</td>
<td>10.0</td>
<td>37.0</td>
<td>32.5</td>
</tr>
<tr>
<td>20</td>
<td>60</td>
<td>3.6</td>
<td>31.4</td>
<td>31.3</td>
</tr>
<tr>
<td>33</td>
<td>20</td>
<td>75.0</td>
<td>58.6</td>
<td>61.9</td>
</tr>
<tr>
<td>33</td>
<td>33</td>
<td>50.0</td>
<td>51.0</td>
<td>50.9</td>
</tr>
<tr>
<td>33</td>
<td>47</td>
<td>25.0</td>
<td>43.3</td>
<td>42.4</td>
</tr>
<tr>
<td>33</td>
<td>60</td>
<td>10.0</td>
<td>36.8</td>
<td>36.8</td>
</tr>
<tr>
<td>47</td>
<td>20</td>
<td>90.0</td>
<td>65.5</td>
<td>68.3</td>
</tr>
<tr>
<td>47</td>
<td>33</td>
<td>75.0</td>
<td>61.0</td>
<td>59.5</td>
</tr>
<tr>
<td>47</td>
<td>47</td>
<td>50.0</td>
<td>51.8</td>
<td>50.3</td>
</tr>
<tr>
<td>47</td>
<td>60</td>
<td>25.0</td>
<td>44.4</td>
<td>43.1</td>
</tr>
<tr>
<td>60</td>
<td>20</td>
<td>96.4</td>
<td>66.9</td>
<td>73.0</td>
</tr>
<tr>
<td>60</td>
<td>33</td>
<td>90.0</td>
<td>65.0</td>
<td>68.5</td>
</tr>
<tr>
<td>60</td>
<td>47</td>
<td>75.0</td>
<td>59.0</td>
<td>61.6</td>
</tr>
<tr>
<td>60</td>
<td>60</td>
<td>50.0</td>
<td>50.6</td>
<td>51.0</td>
</tr>
</tbody>
</table>

Note. Strength of evidence for each hypothesis is expressed as a percentage of the fish in the corresponding lake that are of the relevant colours. Ratings are expressed as a percentage of the height of the response scale.

2.1.2 Results and Discussion

The dependent variable reported in all of the analyses here is the final rating of relative probability made after all of the evidence becomes available. This is reported for each cell in the experimental design in Table 2.2 in columns labeled Instantaneous Evidence and Gradual Evidence.
2.1.2.1 Evidence of Competent Task Performance

There were significant main effects of the strength of evidence in the focal lake, $F(3,201)=97.23, p < .001$, and of the strength of evidence in the alternative lake, $F(3,201)=82.64, p < .001$. These both reflect competent performance of the task, with ratings of the relative probability of the focal hypothesis increasing as evidence strength in the focal lake increased, and decreasing as evidence strength in the alternative lake decreased. Additional evidence of competent task performance is shown by a significant interaction of evidence strength in the focal lake with evidence strength in the alternative lake, $F(9,603)=5.15, p < .001$. The mathematically correct answer on each trial is a ratio of evidence supporting the focal hypothesis to evidence summed across both hypotheses. Therefore, the effect of evidence supporting the focal hypothesis would be greatest when evidence supporting its alternative was low. Thus, responding in a mathematically normative manner would lead to an interaction of support for the focal hypothesis with support for its alternative.

2.1.2.2 Primacy and Recency Effects

We tested for effects of the order in which evidence was presented. In testing for a primacy effect, we tested whether the first item of evidence had a stronger effect on the final rating than the second item of evidence. This would lead to an interaction of Event (first versus second) with Evidence Strength (the extent to which the evidence presented on a given event favoured the focal hypothesis over its alternative). On each event there were three levels of Evidence Strength, corresponding to evidence favoring the focal hypothesis, evidence supporting both hypotheses equally, and evidence favoring the
alternate hypothesis. We found no significant interaction of Event (first versus second) with Evidence Strength, $F(2,134)=0.91, p=.41$. This shows that the final ratings on each trial gave equal weight to the evidence presented on the first event and the evidence presented on the second event.

If there were a recency effect, the third item of evidence to be presented would have a stronger effect on the final rating than the second item of evidence to be presented. This would lead to an interaction of Event (second versus third) with Evidence Strength (favoring the focal hypothesis, equally supporting both hypotheses, or favoring the alternate hypothesis). There was no significant interaction of Event with Evidence Strength, $F(12,134)=0.57, p=.57$, showing that final probability judgments gave equal weight to the evidence presented on the third event and the evidence presented on the second event.

### 2.1.2.3 Effects of Gradual Evidence Accumulation

In order to test whether the effect of evidence strength on ratings of relative probability depended on gradual versus instantaneous evidence presentation, we ran a $4 \times 4 \times 2$ ANOVA, with factors of Support-for-Focal (strength of evidence supporting the focal hypothesis; 4 levels), Support-for-Alternative (strength of the evidence supporting the alternative hypothesis; 4 levels), and Evidence Presentation (whether the relevant evidence was gradually accumulated or all presented instantaneously). There was a significant Support-for-Focal $\times$ Evidence Presentation interaction, $F(3,201)=6.54, p < .001$. This reflected stronger effects of strength of evidence supporting the focal hypothesis in the gradually accumulated evidence condition, $F(3,201)=93.60, p < .001, \eta^2$. 
than in the instantaneous evidence control condition, $F(3,201)=75.08, p < .001, \eta^2 = .53$, as shown in Figure 2.3.

Figure 2.3. Experiment 1: Effect of evidence supporting the focal hypothesis on ratings of relative probability. Error bars represent the standard error of the mean.
Figure 2.4. Experiment 1: Effect of evidence supporting the alternative hypothesis on ratings of relative probability. Error bars represent the standard error of the mean.

There was also a significant Support-for-Alternative × Evidence Presentation interaction, $F(3,201)=4.96, p < .01$. This reflected the fact that ratings of the relative probability of the focal hypothesis decreased more strongly as a function of strength of evidence supporting the alternative hypothesis in the gradually accumulated evidence condition, $F(3,201)=79.11, p < .001, \eta^2 = .54$, than in the instantaneous evidence control condition, $F(3,201)=67.03, p < .001, \eta^2 = .50$ as shown in Figure 2.4. Each of the two interactions reported above indicate that the gradual accumulation of evidence would cause that evidence to be weighted more heavily than in the control condition. A limitation of this
study is that the effects of gradual evidence accumulation were confounded with the effects of making multiple revised ratings. Experiment 2 was designed to dissociate these effects.

2.2 Experiment 2

The goals of Experiment 2 were (1) to replicate the findings of Experiment 1 and (2) to dissociate the effects of gradual evidence accumulation from the effects of making multiple revised ratings.

2.2.1 Methods

The methods of Experiment 2 were the same as those in Experiment 1 with the following exceptions.

2.2.1.1 Participants

Sixty-five volunteers (forty females, twenty-five males) with a mean age of 25.5 years (SD=7.0) participated in this experiment.

2.2.1.2 Materials and Procedure

In order to minimize the overall duration of the experiment we reduced the number of levels of evidence strength for each hypothesis from 4 to 3. Once all of the evidence was visible, each lake contained either 20%, 40%, or 60% fish of the relevant colours. The numbers of fish corresponding to each level of evidence strength are outlined in Table 2.3. There were 36 cells in the experimental design: 3 levels for the focal lake × 3 levels for the alternative lake × 4 types of evidence presentation (three
types of gradual evidence and one type of instantaneous evidence). In each of these cells there were 4 trials, so each participant completed 144 trials in total.

Table 2.3. Experiment 2: Numbers of Fish of the Three Relevant Colours for each of Three Levels of Support for a Given Hypothesis.

<table>
<thead>
<tr>
<th>Relevant colour #1</th>
<th>Relevant colour #2</th>
<th>Relevant colour #3</th>
<th>Total # Fish of Relevant colours</th>
<th>Total as a Percentage of the 120 Fish in the Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>16</td>
<td>4</td>
<td>24</td>
<td>20 %</td>
</tr>
<tr>
<td>4</td>
<td>16</td>
<td>28</td>
<td>48</td>
<td>40 %</td>
</tr>
<tr>
<td>28</td>
<td>16</td>
<td>28</td>
<td>72</td>
<td>60 %</td>
</tr>
</tbody>
</table>

Note. In the overall experiment, there were three possible levels of support for the focal hypothesis and three possible levels of support for its alternative. The above table outlines those three levels for just one hypothesis. The numbering of the three relevant colours above is arbitrary and does not refer to presentation order. On any given trial, the three relevant colours used for the three fish in the downstream lake were randomly selected from four possibilities: red, white, gold, and black.

We changed the sequence of events within a gradual evidence trial as follows: the display alternated between periods when the fish in the upstream lakes were visible and periods in which the cursor on the rating scale could be moved (see Figure 2.5). After viewing the fish in the upstream lakes, participants clicked the left mouse button to make the rating scale cursor movable, which also made the upstream fish disappear. On some gradual evidence trials, this caused the rating scale cursor to become movable on all three events. On others, it caused it to be movable only on the second and third events, or only
Figure 2.5 Experiment 2: The sequence of events in the gradual evidence accumulation condition in which a rating is required.
on the third event. Participants never knew ahead of time what type of gradual evidence trial they were on, and thus couldn't predict on any given event whether or not they would be required to make a rating after clicking the left mouse button. This ensured that participants always attended to the contents of the upstream lakes before clicking the mouse to advance through the trial. Otherwise, on gradual evidence trials requiring ratings only on the last event participants might have simply clicked the mouse quickly to advance to the end of the trial without even looking at the contents of the upstream lakes. Such a strategy would have effectively transformed a gradual evidence trial into an instantaneous evidence trial. Instead, we designed the experiment so that participants were required to attend to the contents of the upstream lakes on each event, and to prepare an accurate response in case they were required to make a rating.

As the instructions for Experiment 2 were somewhat more complex than those for Experiment 1, we started each testing session with a practice session. This involved four blocks of four trials each, with verbal instructions given before each block. Each block contained only one of the four response conditions. The first was the instantaneous evidence condition, which was followed by the gradual evidence condition with a rating made on each event, then the gradual evidence condition with a rating made on the last two events, then the gradual evidence condition with a rating made on the last event only. Once participants completed this practice session, they were informed that the four conditions would be randomly intermixed in the main experiment.
2.2.2 Results and Discussion

The dependent variable reported in all of the analyses here is the final rating made after all of the evidence becomes available. This is reported for each cell in the experimental design in Table 2.4.

2.2.2.1 Replication of Experiment 1

In order to test for replication of the results reported in Experiment 1, we submitted the data from the gradual evidence condition with ratings on each event and the data from the instantaneous evidence condition to a $3 \times 3 \times 2$ ANOVA. This had factors of Support-for-Focal (strength of evidence supporting the focal hypothesis; 3 levels), Support-for-Alternative (strength of the evidence supporting the alternative hypothesis; 3 levels), and Evidence Presentation (whether the relevant evidence was gradually accumulated or all presented instantaneously). As in Experiment 1, there was a significant Support-for-Focal $\times$ Evidence Presentation interaction, $F(2,128)=51.07, p < .001$. This reflected the fact that ratings of the relative probability of the focal hypothesis increased more strongly as a function of strength of evidence supporting the focal hypothesis in the gradually accumulated evidence condition, $F(2,128)=616.06, p < .001$, $\eta^2 = .91$, than in the instantaneous evidence control condition, $F(2,128)=394.93, p < .001$, $\eta^2 = .86$ (see Figure 2.6 and Figure 2.7). There was also, as in Experiment 1, a significant Support-for-Alternative $\times$ Evidence Presentation interaction, $F(2,128)=35.74, p < .001$. This reflected the stronger decrease in ratings of the relative probability of the focal hypothesis as a function of support for the alternative in the gradually accumulated evidence condition, $F(2,128)=567.10, p < .001$, $\eta^2 = .90$, than in the instantaneous
Table 2.4 Experiment 2: Ratings of the Probability that the Focal Hypothesis, Rather than its Alternative, is Correct.

<table>
<thead>
<tr>
<th>Strength of Evidence Supporting the Focal Hypothesis</th>
<th>Strength of Evidence Supporting the Alternative Hypothesis</th>
<th>Rating Predicted by Bayesian Norm</th>
<th>Instantaneous Evidence</th>
<th>Gradual Evidence, Rate on All Three Events</th>
<th>Gradual Evidence, Rate on Second and Third Events</th>
<th>Gradual Evidence, Rate on Third Event Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>20</td>
<td>50.0</td>
<td>49.6 0.4</td>
<td>49.8 0.4</td>
<td>49.5 0.5</td>
<td>49.8 0.5</td>
</tr>
<tr>
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<td>12.5</td>
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<td>29.4 1.1</td>
<td>29.0 1.1</td>
<td>29.0 1.1</td>
</tr>
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<td>18.9 1.2</td>
<td>20.2 1.2</td>
<td>21.4 1.2</td>
</tr>
<tr>
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<tr>
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<td>49.8 0.4</td>
<td>49.7 0.5</td>
<td>49.9 0.4</td>
</tr>
<tr>
<td>40</td>
<td>60</td>
<td>12.5</td>
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<td>28.8 1.2</td>
<td>31.7 1.0</td>
<td>30.8 1.1</td>
</tr>
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<td>81.6 1.4</td>
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<td>79.5 1.2</td>
</tr>
<tr>
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<td>87.5</td>
<td>67.7 1.2</td>
<td>71.9 1.2</td>
<td>69.4 1.2</td>
<td>71.5 1.2</td>
</tr>
<tr>
<td>60</td>
<td>60</td>
<td>50.0</td>
<td>49.8 0.4</td>
<td>50.3 0.5</td>
<td>49.7 0.6</td>
<td>50.1 0.5</td>
</tr>
</tbody>
</table>

Note. Strength of evidence for each hypothesis is expressed as a percentage the fish in the corresponding lake that are of the relevant colours. Ratings are expressed as a percentage of the height of the response scale.
evidence control condition, $F(2,128)=400.88$, $p < .001$, $\eta^2 = .86$ (see Figure 2.6 and Figure 2.7).

Figure 2.6. Experiment 2: Effect of evidence supporting the focal hypothesis on ratings of relative probability. Error bars represent the standard error of the mean.
2.2.2.2 Effects of Gradual Evidence Accumulation Controlling for Number of Ratings

In Experiment 2, we included a condition in which evidence was gradually accumulated but only a single rating was made, rather than a rating after each of the three portions of evidence, as in the above analysis. This allowed us to test for an effect of gradual evidence accumulation when the number of ratings made was held constant. This involved a $3 \times 3 \times 2$ ANOVA, with factors of Support-for-Focal (3 levels), Support-for-Alternative (3 levels), and Evidence Presentation (gradual versus instantaneous).
As in all analyses presented above for Experiments 1 and 2, we found a significant Support-for-Focal × Evidence Presentation interaction, $F(2,128) = 29.41, p < .001$. This reflected the fact that ratings of the relative probability of the focal hypothesis increased more strongly as a function of support for the focal hypothesis in the gradually accumulated evidence condition, $F(2,128) = 490.47, p < .001, \eta^2 = .89$, than in the instantaneous evidence control condition, $F(2,128) = 394.93, p < .001, \eta^2 = .86$ (see Figure 2.6). Second, as in all analyses presented above for Experiments 1 and 2, we found a significant Support-for-Alternative × Evidence Presentation interaction, $F(2,128) = 17.31, p < .001$. This reflected the fact that ratings of the relative probability of the focal hypothesis decreased more strongly as a function of strength of the evidence supporting the alternative hypothesis in the gradually accumulated evidence condition, $F(2,128) = 548.96, p < .001, \eta^2 = 90$, than in the instantaneous evidence control condition, $F(2,128) = 400.88, p < .001, \eta^2 = .86$ (see Figure 2.7). This analysis confirms that evidence affects ratings of relative probability more when gradually accumulated than when presented instantaneously, even if the total number of ratings made is controlled for. Thus, we can conclude that the effect is due to gradual evidence accumulation rather than to the act of making successive ratings.

2.3 General discussion

The main goal of the current research was to determine how gradual evidence accumulation affects comparative judgments. Those judgments were assessed via ratings of the relative probability that a focal hypothesis, rather than its alternative, was true. In
two studies, we found a given amount of evidence to affect ratings of relative probability more if gradually accumulated (presented in three sequential portions) than if presented instantaneously. Our investigation diverged from previous studies with objectively quantifiable evidence in that we kept the strength of evidence constant while manipulating whether it was accumulated gradually or all presented instantaneously. Thus, the key contribution of this work is that it dissociates the effects of gradual evidence accumulation from the effects of changing evidence strength.

Another goal of this study was to investigate whether successive ratings made in response to gradually accumulated evidence were subject to either a primacy effect (involving anchoring to the first rating made), or a recency effect. We found neither. Thus, the order in which portions of evidence are gradually accumulated does not affect comparative judgments made in this paradigm. However, as primacy and recency effects are normally seen in short-term memory retention tasks (Deese & Kaufman, 1957; Murdock, 1962; Sederberg, Howard, & Kahana, 2008), we would expect to see primacy and recency effects if we required participants to retain evidence in short-term memory.

While some previous experiments (Hogarth & Einhorn, 1992) manipulated whether evidence was gradually accumulated versus presented instantaneously, they produced inconsistent results, reporting an effect of gradual versus instantaneous evidence in some experiments but not others. Given that evidence strength in those experiments could not be objectively quantified and that the gradual versus instantaneous manipulation was between-subjects, their gradual versus instantaneous manipulation was necessarily confounded with individual differences in subjective evidence strength. In addition, that work did not manipulate gradual evidence presentation independently from...
making multiple successive ratings. Thus, our work is the first to report a replicable effect whereby gradual accumulation of objectively quantifiable evidence increases subjective strength. It is also the first to show that this effect is not due to making successively revised ratings.

A secondary finding evident in our data is that participant’s responses were conservative relative to the Bayesian norm, as has been reported previously in the beads task (Anderson, 1981; Juslin, Nilsson, & Winman, 2009; Lopes, 1985; Shanteau, 1975). Such conservatism has been attributed to misaggregation of evidence over time, with the combined value of several sequential samples being a weighted average of their individual scale values (Anderson, 1981; Lopes, 1985; Shanteau, 1975). If conservatism resulted from such misaggregation, one would predict more conservatism in response to gradually accumulated evidence than in response to the same evidence presented instantaneously. Interestingly, our results showed the opposite, indicating a need to revisit this theoretical account attributing conservatism to misaggregation of evidence over time.

In our data, the effect of gradual evidence accumulation was present regardless of whether the evidence favored the focal hypothesis or favored its alternative. If gradually accumulated, evidence supporting the focal hypothesis was seen to support it more strongly, while evidence supporting the alternative was seen to refute the focal hypothesis more strongly. These results are consistent with our prediction that processing evidence to a greater extent would lead to more salient mental representations, and consequently greater subjective strength. This tendency to give increased weight to evidence divided into three gradually accumulated portions can be thought of as a new type of packing effect. This is analogous to the effect observed with packed versus unpacked hypotheses,
(e.g. Bonini & Gonzalez, 2005; Rottenstreich & Tversky, 1997; Tversky & Koehler, 1994). A packed hypothesis (e.g., that someone will die of natural causes) is rated as less probable than its unpacked alternative (e.g., that they will die of either cancer, a heart attack, a stroke, or some other natural cause). One explanation for the tendency to rate unpacked hypotheses as more probable than packed ones is that explicitly mentioning one of the unpacked components of a hypothesis increases its salience, thereby increasing its perceived support (Rottenstreich & Tversky, 1997). Similarly, we found in the current studies that unpacked evidence (evidence presented in three portions) seemed to be subjectively more salient than packed evidence (the same evidence presented in a single portion), possibly as a result of being processed more extensively.

A secondary finding evident in Table 2.2 and Table 2.4 is that participant’s responses deviated substantially from those predicted by the Bayesian norm. An alternative model, which we will call the sum-across-features model, would involve participants calculating the total number of fish of the relevant colours in each lake (summing across three colours). They would then compare the number of fish of relevant colours in the focal lake to the total number of fish of relevant colours summed across both upstream lakes, as in Luce’s choice axiom (Luce, 1977). Figure 2.8 and Figure 2.9 demonstrate that participants’ responses are much more closely aligned to this sum-across-features model than to the Bayesian one. However, the Bayesian model and participants' responses both follow a bow-shaped pattern, while the sum-across-features model does not. Neither model accounts for the difference in ratings between the gradual and instantaneous evidence conditions. The development of a cognitive model that does account for this effect remains a direction for future research.
Figure 2.8. Experiment 1: Comparison of actual ratings made to those predicted by the Bayesian norm and the sum-across-features model.
Another interesting direction for future research would be a parallel investigation requiring participants to remember evidence in long-term memory. Such an investigation would allow application of these results to a wider range of everyday situations. For example, a political party's campaign could involve revealing all of the points in their platform at the same time, or else gradually revealing them over a period of days or weeks. Based on the results reported here, one would predict that revealing each point of a political platform in sequence would elicit more political support than presenting all of those points instantaneously.

While the gradual evidence effect found in this Chapter was predicted, we found
none of the interactions predicted in Chapter 1. We found no anchoring effect underlying the bias in favour of gradually accumulated evidence. Furthermore, the strength of the bias did not depend on whether evidence supported the focal hypothesis or the alternative. Thus, there is no evidence of the bias in favour of gradually accumulated evidence being driven by cognitive coherence. Rather, it appears to be simply a packing effect.
3 Self-Selection Bias in Hypothesis Comparison

When attempting to understand a situation, we often generate or select our own preferred hypothesis, and consider it alongside those provided by an external source such as a news report, an advertisement, or someone else's opinion. Forming our own opinion often involves assessing our level of agreement with all candidate hypotheses. The main goal of the series of experiments presented in this chapter was to investigate whether judgments can be biased in favor of self-selected hypotheses, relative to judgments of hypotheses specified by external sources, given equivalent supporting evidence. The secondary goals were to test whether or not this effect was moderated by other factors relating to hypothesis selection difficulty and the rate of evidence accumulation.

Previous investigations involving comparison of self-selected to other-selected material have required participants to choose from a range of options and rate their confidence that they chose correctly. This is compared to confidence that other-selected material was chosen correctly (Koehler, 1994; Ronis & Yates, 1987; Sieck, 2003; Sieck et al., 2007; Sieck & Yates, 2001; Sniezek, Paese, & Switzer, 1990). In the general knowledge and learning paradigms used in those studies, self-selection and confidence ratings are very likely to have been affected by familiarity with the subject matter, fluency in memory retrieval, or completeness of memory retrieval (Sieck, 2003; Sieck et al., 2007; Sieck & Yates, 2001). For example, participants learning to classify hypothetical patients with particular symptom patterns into disease categories often based
their judgments on the first category exemplar they could retrieve from memory (Sieck & Yates, 2001). As the experimenter has no control over these processes, it is difficult (or impossible) to equate them between the self-selected and other-selected conditions. Furthermore, in such an experimental setup, the assignment of a given question to the self-selected versus other-selected conditions was necessarily manipulated between-subjects. Consequently, the evidence considered for that question very likely would have differed between the individual making the ratings in the self-selected condition and the individual making the ratings in the other-selected condition. Various aspects of familiarity, personal experience, fluency, and completeness of memory retrieval for a question may differ between the individual who chooses one answer before rating it and the other individual who rates their level of agreement with that choice, making it difficult to isolate the factors causing ratings to differ between the self-selected and other-selected conditions.

In the current research, we wished to precisely match supporting evidence across the self-selected and other-selected conditions and avoid any differences in familiarity, past personal experience, or retrieval. To this purpose, we used a variation of the beads-from-a-jar probabilistic reasoning task (Beach, 1968; Freeman et al., 2008; Moritz et al., 2007; Peterson et al., 1965; Speechley et al., 2010). As was stated in Chapter 1, this task involves judging the likelihood that a series of beads is drawn from jar A and not jar B, based on the colours of the beads in jars A and B, and on the colours in the series of beads being drawn. Given that jars A and B differ only in their relative proportions of bead colours, the process of self-selecting can be based on a very restricted set of parameters, presumably almost entirely probability estimates. This paradigm allows us to
equate evidence within-subjects between the self-selected and other-selected conditions. The probability ratings following self- or other-selection of hypotheses can then be compared.

The version of the task used in the current study involved judging the probability that a single fish was drawn from one of three lakes. Specifically, participants judged the probability that the fish was drawn from a given self- or other-selected lake rather than being drawn from either of two alternatives. The self- or other-selected lake is referred to as the focal hypothesis. On all trials, the participant was required to indicate the likelihood of the focal hypothesis (rather than the other two alternatives) being true. We predicted a self-selection bias whereby ratings of the relative probability of the focal hypothesis would be higher if it were self-selected than if it were externally selected. Our secondary goal was to explore possible moderators of any self-selection bias, such as increased cognitive effort inherent to the selection process, or repeated activation of the mental representation of the self-selected focal hypothesis.

3.1 Experiment 1

The purpose of Experiment 1 was to assess whether self-selected hypotheses were judged to be more probable than externally selected ones, despite their being matched in terms of the mathematically normative probability rating. Our task was designed so that any such bias could not be attributable to either differences in the number of alternatives considered or differences in memory retrieval.
3.1.1 Method

3.1.1.1 Participants

Twenty-six volunteers (fourteen females and twelve males) with a mean age of 29.3 years ($SD = 9.2$) participated in this experiment. Participants were recruited via posters on the University of British Columbia campus and in community centers in the greater Vancouver area, and also via postings on electronic bulletin boards. All participants were reimbursed $10 per hour for their time plus parking and transportation expenses.

3.1.1.2 Materials & Procedure

Each trial of our probabilistic reasoning task involved a scene depicting four blue lakes (see Figure 3.1), three of which were upstream from the fourth. At the start of each trial, a single black or white fish was seen to jump from the downstream lake. The colour of this jumping fish, referred to hereafter as the relevant colour, was randomized across trials. Subsequently, the contents of each of the three upstream lakes became visible. Each contained a mixture of black and white fish (40 fish in total per lake), which remained in view until a rating had been made. Participants were told that the fish in the downstream lake originated from one of the upstream lakes. Thus, each upstream lake corresponded to a hypothesis about the origin of the jumping fish. The upstream lake with the most fish of the relevant colour was the most likely origin of the fish in the downstream lake. Subsequently, if the trial was one in which the focal hypothesis
Figure 3.1. Sequence of events within a trial of either Experiment 1, 2, or 3 in which the focal hypothesis is self-selected.
was to be self-selected, participants indicated the lake they deemed to be the most likely origin of the jumping fish by moving the mouse cursor (a red square) over their preferred lake and clicking with the left mouse button. This lake, referred to hereafter as the focal lake, then turned green. On trials with externally selected focal hypotheses, the focal lake was selected randomly from the three choices by the computer, and turned green immediately after the fish in the bottom lake jumped, at the same time as the fish in the upstream lakes became visible.

Once the focal lake was selected, participants then rated the relative probability that the focal hypothesis, rather than its alternative, was true. Ratings were made on a vertical scale, with the labels "definitely true" at the top end and "impossible" at the bottom end. Participants used a mouse to move the slider smoothly up and down the scale and clicked the left mouse button when it was in the desired location. The vertical position of the cursor, in pixels, was then recorded. In the results section, ratings are reported as a percentage of the total height of the response scale. At the beginning of each trial, the slider was set at the mid-point of the response scale. Trials with self-selected and externally selected focal hypotheses occurred in separate blocks. In total there were eighteen blocks of nine trials each, alternating between blocks in which the focal hypothesis was self-selected and blocks in which it was externally selected. The first block always consisted of trials in which the focal hypothesis was externally selected (by the computer).

In order to vary the strength of support for the focal hypothesis, as well as the strength of support for its alternatives, we manipulated the percentage of fish of the
Table 3.1. Experiment 1: Ratings of the Relative Probability that the Focal Hypothesis, Rather than its Alternatives, is True, as a Function of the Strength of the Evidence Supporting the Focal Hypothesis and of that Supporting each Alternative

<table>
<thead>
<tr>
<th>Strength of Evidence Supporting each Hypothesis</th>
<th>Rating (Percentage of Response Scale Height)</th>
<th>Self-Selection Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>(% Fish in that Lake of Relevant Colour)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Focal Hypothesis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alternative #1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alternative #2</td>
<td></td>
<td></td>
</tr>
<tr>
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<td></td>
<td></td>
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<tr>
<td>75 (F)</td>
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<td>75</td>
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<tr>
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<tr>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>100 * F/(F+A1+A2)</td>
<td>33.33</td>
<td>53.95</td>
</tr>
<tr>
<td>37.50</td>
<td>58.82</td>
<td>52.98</td>
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<tr>
<td>33.33</td>
<td>42.52</td>
<td>42.48</td>
</tr>
</tbody>
</table>

*Note. Each hypothesis corresponds to an upstream lake which is the possible origin of a fish seen in a downstream lake. The strength of evidence supporting each corresponds to the percentage of fish in that lake matching the colour of the downstream fish.*
relevant colour in each lake. Specifically, each of the three lakes contained either 25%, 50%, or 75% fish of the relevant colour. Any trials on which the participant made an error in selecting the most probable hypothesis as the focal hypothesis were rejected from the analysis. Note that this prevented us from employing a 3x3x3 design (3 levels of support for each lake), because support for the focal hypothesis had to match or exceed support for each alternative. Thus, within a given type of focal hypothesis (self-selected or externally selected), we used a design with 10 cells, as displayed in Table 3.1.

3.1.2 Results & Discussion

In order to ensure that participants clearly understood the instructions, we excluded their data if their accuracy in selecting the most probable hypothesis as the focal hypothesis was less than 80%. As a result, six participants were excluded from the analysis. For the remaining twenty participants, we excluded any trials in which the focal hypothesis was less probable than one of its alternatives, whether that focal hypothesis was selected by the participant or computer-selected. We excluded an average of 3.3% (SD=3.9%) of trials with self-selected focal hypotheses. As the computer was randomly selecting focal hypotheses, and as 19 of the 30 choices outlined in the first three columns of Table 3.1 are correct choices, the computer's accuracy in this experiment was 63.3%. Consequently, we excluded 36.7% of the trials with computer-selected focal hypotheses. Mean ratings for each condition are displayed in Table 3.1.

A t-test comparing the average rating of self-selected focal hypotheses to the average rating of externally selected ones revealed a significant self-selection bias, \( t(19) = 4.32, p < .001, \eta^2 = .50 \), involving higher mean probability ratings for self-selected
focal hypotheses ($M = 59.4$) than for externally selected ones ($M=56.2$). In order to adjust for moderate skew in the data, we also applied a rank transformation (Conover & Iman, 1981). Specifically, the entire set of scores (both dependent variables together) was rank-transformed, then the t-test was applied to the rank-transformed scores. When these data were transformed to rank scores, the effect remained significant. The ratings of self-selected focal hypotheses were higher for sixteen of the twenty participants. Unlike in previous paradigms involving judgments of one's own hypothesis (Koehler, 1994; Ronis & Yates, 1987; Sieck, 2003; Sieck et al., 2007; Sieck & Yates, 2001; Sniezek et al., 1990), the bias reported here cannot be attributed to differences in familiarity, personal experience, or memory retrieval, and is consistent with the notion that the cognitive operations involved in selecting one's own preferred focal hypothesis increase its perceived probability.

As can be seen in Table 3.1, the average rating, across conditions, is higher than the normative average. This may involve neglect of the fact that the base rate was 1/3, which would be consistent with previous reports of base rate neglect (Tversky & Kahneman, 1974). It may also be a bias induced by the demand characteristics of the experiment, because at the start of each trial the cursor was at the midpoint of the rating scale, rather than 1/3 of the way from the bottom. Regardless, both the base rate and the starting position of the mouse cursor on the rating scale are equated between the self-selected and externally selected conditions. Consequently, this overall tendency to make ratings higher than the norm is irrelevant to the main theme of this paper, namely the selection bias.
3.2 Experiment 2

One possible explanation for the results of Experiment 1 was that participants correctly noted that the computer was sometimes selecting something other than the most probable hypothesis to be the focal hypothesis, and thus considered the computer’s choices to be random or inaccurate. The purpose of Experiment 2 was to replicate results of Experiment 1 while explicitly matching the computer's choices to the participant's. This would ensure that the self-selection bias was not just the result of the participant generally assigning low ratings to the computer-selected focal hypotheses due to a perception that the computer is unreliable in selecting the focal hypothesis correctly.

3.2.1 Method

3.2.1.1 Participants

Forty-one volunteers (twenty-one females and twenty males) with a mean age of 27.7 years (SD = 8.5) participated in this experiment. Participants were recruited via posters on the University of British Columbia campus and in community centers in the greater Vancouver area, and also via postings on electronic bulletin boards. All participants were reimbursed $10 per hour for their time plus parking and transportation expenses.

3.2.1.2 Materials & Procedure

The methods of Experiment 2 were identical to those of Experiment 1 with the following exceptions. The first block always consisted of trials in which the focal hypothesis was self-selected. Each trial with an externally selected focal hypothesis was
Table 3.2. Experiment 2: Ratings of the Relative Probability that the Focal Hypothesis, Rather than its Alternatives, is True, as a Function of the Strength of the Evidence Supporting the Focal Hypothesis and of that Supporting each Alternative

<table>
<thead>
<tr>
<th>Strength of Evidence Supporting each Hypothesis</th>
<th>Rating (Percentage of Response Scale Height)</th>
<th>Self-Selection Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal Hypothesis (F)</td>
<td>Alternative #1 (A1)</td>
<td>Alternative #2 (A2)</td>
</tr>
<tr>
<td>75</td>
<td>75</td>
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essentially a repeat of a corresponding trial involving a self-selected focal hypothesis in the preceding block. Specifically, the choice of focal lake (focal hypothesis) made by the computer always matched a choice made by the participant on the corresponding trial in the preceding block. Thus, the computer’s accuracy in selecting the most probable hypothesis was identical to the participant’s accuracy. Within a matched pair of trials, the proportions of fish of each colour within each lake were kept constant. However, the positions of individual fish within those lakes varied randomly.

3.2.2 Results & Discussion

In order to ensure that participants clearly understood the instructions, we excluded their data if their accuracy in selecting the most probable hypothesis as the focal hypothesis was less than 80%. As a result, two participants were excluded from the analysis. For the remaining thirty-nine participants, we excluded any trials with selection errors (trials in which the self-selected focal hypothesis was less probable than one of its alternatives), whether that selection was made by the participant or by the computer. We excluded an average of 2.8% (SD=3.5%) of trials with self-selected focal hypotheses. The percentages were the same for trials with externally selected focal hypotheses, as accuracy was matched between the self and external conditions. Mean ratings for each condition are displayed in Table 3.2. A t-test comparing the average rating of self-selected focal hypotheses to the average rating of externally selected ones revealed a significant self-selection bias, \( t(38) = 3.75, p < .001, \eta^2 = .27 \), involving higher mean probability ratings for self-selected focal hypotheses (\( M = 53.3 \)) than for externally selected ones (\( M = 51.6 \)). As in Experiment 1, the effect remained significant when the
data were transformed to rank scores. The ratings of self-selected focal hypotheses were higher for thirty of the thirty-nine participants. Thus, the results of Experiment 2 replicated those of Experiment 1 and showed that the self-selection bias could not be attributed to overall differences in accuracy, between the participant and the computer, in selecting the most probable focal hypothesis. The smaller effect size in Experiment 2 ($\eta^2 = .50$) than Experiment 1 ($\eta^2 = .27$) is consistent with our concerns that perceptions of the computer's accuracy contributed in part to the selection bias in Experiment 1, although the magnitude of the bias did not differ significantly between experiments, $F(1,58) = 1.57, ns$. Still, the trend towards a smaller effect size, highlights the importance of the self-to-external accuracy matching implemented here and in our subsequent experiments.

3.3 **Experiment 3**

The process of selecting a focal hypothesis and then rating its probability (relative to its alternatives) might involve more total cognitive effort than merely judging the probability of an externally selected focal hypothesis. Thus, selecting a focal hypothesis might cause the salience of its mental representation to be greater than that of an externally selected focal hypothesis via more effortful processing. If so, then we would expect the strength of the self-selection bias to depend on the amount of cognitive effort involved in selecting the focal hypothesis. The goals of Experiment 3 were to replicate the self-selection bias found in Experiments 1 and 2, and to determine whether that bias depended on increased cognitive effort involved in focal hypothesis selection.

The process of selecting a preferred focal hypothesis with consistent accuracy necessarily involves comparisons between evidence supporting competing hypotheses.
Comparisons made between similar numbers are more difficult than comparisons made between dissimilar ones (Pinel, Dehaene, Riviere, & LeBihan, 2001). Thus, selecting the most probable hypothesis as the focal hypothesis will be most difficult if the strength of its supporting evidence is similar to the strength of the evidence supporting its alternatives. In the current experiment, we manipulated the degree of similarity between support for the focal hypothesis and support for its alternatives. The strength of support for the strongest alternative was either identical to that for the focal hypothesis, close (slightly lower), distant, or very distant. The support for the other alternative was varied in the same manner. If self-selection bias were the result of increased cognitive effort, we would expect it to be largest when support for the alternatives was most similar to support for the focal hypothesis.

3.3.1 Method

3.3.1.1 Participants

Seventy-nine volunteers (fifty-three females and twenty-six males) with a mean age of 27.7 years (SD = 7.9) participated in this experiment. Participants were recruited via posters on the University of British Columbia campus and in community centers in the greater Vancouver area, and also via postings on electronic bulletin boards. All participants were reimbursed $10 per hour for their time plus parking and transportation expenses.
3.3.1.2 Materials & Procedure

The methods were identical to those of Experiment 2 with the following exceptions. In total there were twelve blocks of ten trials each, alternating between blocks in which the focal hypothesis was self-selected and blocks in which it was externally selected. The focal lake contained either: 85%, 55%, or 25% fish of the relevant colour. Support for each alternative hypothesis was either identical to the support for the focal hypothesis, close (10% lower), distant (40% lower), or very distant (70% lower). Thus, each alternative lake contained either 85%, 75%, 55%, 45%, 25%, or 15% fish of the relevant colour. These manipulations are outlined in Table 3.3, which shows a complete list of the conditions used in this experiment. They allowed us to test whether the magnitude of any self-selection bias varied as a function of the difficulty of selecting the most probable hypothesis; in other words, the degree to which the focal and alternative hypotheses had similar levels of support.
Table 3.3. Experiment 3: Ratings of the Relative Probability that the Focal Hypothesis, Rather than its Alternatives, is True, as a Function of the Strength of the Evidence Supporting the Focal Hypothesis and of that Supporting each Alternative

<table>
<thead>
<tr>
<th>Strength of Evidence</th>
<th>Math. Norm</th>
<th>Rating Self</th>
<th>Rating External</th>
<th>Self-Selection Bias (Self - Ext)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal 85 Alt. 1 85 Alt. 2 85</td>
<td>33.33</td>
<td>44.86</td>
<td>42.89</td>
<td>1.97</td>
</tr>
<tr>
<td>85 85 75</td>
<td>34.69</td>
<td>48.44</td>
<td>45.88</td>
<td>2.56</td>
</tr>
<tr>
<td>85 75 75</td>
<td>36.17</td>
<td>50.12</td>
<td>48.10</td>
<td>2.02</td>
</tr>
<tr>
<td>85 85 45</td>
<td>39.53</td>
<td>54.69</td>
<td>52.88</td>
<td>1.81</td>
</tr>
<tr>
<td>85 85 15</td>
<td>45.95</td>
<td>56.91</td>
<td>56.37</td>
<td>0.54</td>
</tr>
<tr>
<td>85 75 45</td>
<td>41.46</td>
<td>55.51</td>
<td>53.49</td>
<td>2.02</td>
</tr>
<tr>
<td>85 75 15</td>
<td>48.57</td>
<td>59.99</td>
<td>58.64</td>
<td>1.35</td>
</tr>
<tr>
<td>85 45 45</td>
<td>48.57</td>
<td>62.39</td>
<td>60.47</td>
<td>1.92</td>
</tr>
<tr>
<td>85 45 15</td>
<td>58.62</td>
<td>65.85</td>
<td>65.64</td>
<td>0.21</td>
</tr>
<tr>
<td>85 15 15</td>
<td>73.91</td>
<td>75.21</td>
<td>74.28</td>
<td>0.93</td>
</tr>
<tr>
<td>55 55 55</td>
<td>33.33</td>
<td>45.12</td>
<td>44.17</td>
<td>0.95</td>
</tr>
<tr>
<td>55 55 45</td>
<td>35.48</td>
<td>45.60</td>
<td>44.78</td>
<td>0.82</td>
</tr>
<tr>
<td>55 45 45</td>
<td>37.93</td>
<td>46.36</td>
<td>45.94</td>
<td>0.42</td>
</tr>
<tr>
<td>55 55 15</td>
<td>44.00</td>
<td>53.30</td>
<td>53.52</td>
<td>-0.22</td>
</tr>
<tr>
<td>55 45 15</td>
<td>47.83</td>
<td>54.76</td>
<td>52.59</td>
<td>2.17</td>
</tr>
<tr>
<td>55 15 15</td>
<td>64.71</td>
<td>63.79</td>
<td>63.23</td>
<td>0.56</td>
</tr>
<tr>
<td>25 25 25</td>
<td>33.33</td>
<td>42.06</td>
<td>43.03</td>
<td>-0.97</td>
</tr>
<tr>
<td>25 25 15</td>
<td>38.46</td>
<td>45.34</td>
<td>45.68</td>
<td>-0.34</td>
</tr>
<tr>
<td>25 15 15</td>
<td>45.45</td>
<td>48.13</td>
<td>49.14</td>
<td>-1.01</td>
</tr>
</tbody>
</table>
Table 3.4. Experiment 3: Time Taken to Self-Select a Focal Hypothesis and to Make
Ratings of the Relative Probability that the Focal Hypothesis, Rather than its
Alternatives, is True, as a Function of the Strength of the Evidence Supporting the Focal
Hypothesis and of that Supporting each Alternative

<table>
<thead>
<tr>
<th>Strength of Evidence</th>
<th>Time Spent Self-Selecting Focal Hypothesis (ms)</th>
<th>Rating RT (ms)</th>
<th>Self - Ext Rating RT Difference (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal 85</td>
<td>85 85 85</td>
<td>6038.10</td>
<td>3225.43 7313.88 -4088.45</td>
</tr>
<tr>
<td>85 85 75</td>
<td>5543.75</td>
<td>3930.27 7494.03 -3563.76</td>
<td></td>
</tr>
<tr>
<td>85 75 75</td>
<td>4408.51</td>
<td>3585.57 7539.13 -3953.57</td>
<td></td>
</tr>
<tr>
<td>85 85 45</td>
<td>5329.80</td>
<td>3685.35 7706.17 -4020.82</td>
<td></td>
</tr>
<tr>
<td>85 85 15</td>
<td>5228.03</td>
<td>3781.71 7452.07 -3670.36</td>
<td></td>
</tr>
<tr>
<td>85 75 45</td>
<td>3917.59</td>
<td>4002.34 8085.35 -4083.01</td>
<td></td>
</tr>
<tr>
<td>85 75 15</td>
<td>3628.33</td>
<td>3835.74 7245.88 -3410.13</td>
<td></td>
</tr>
<tr>
<td>85 45 45</td>
<td>3373.96</td>
<td>4366.54 7705.75 -3339.21</td>
<td></td>
</tr>
<tr>
<td>85 45 15</td>
<td>3172.42</td>
<td>3763.80 6904.92 -3141.13</td>
<td></td>
</tr>
<tr>
<td>85 15 15</td>
<td>3205.72</td>
<td>3620.58 6829.95 -3209.37</td>
<td></td>
</tr>
<tr>
<td>55 55 55</td>
<td>6116.67</td>
<td>3082.15 8288.22 -5206.07</td>
<td></td>
</tr>
<tr>
<td>55 55 45</td>
<td>6220.15</td>
<td>3033.42 8657.94 -5624.52</td>
<td></td>
</tr>
<tr>
<td>55 45 45</td>
<td>5401.87</td>
<td>2933.10 7710.29 -4777.19</td>
<td></td>
</tr>
<tr>
<td>55 55 15</td>
<td>4931.23</td>
<td>3626.64 7979.03 -4352.40</td>
<td></td>
</tr>
<tr>
<td>55 45 15</td>
<td>4585.96</td>
<td>3723.67 8064.45 -4340.77</td>
<td></td>
</tr>
<tr>
<td>55 15 15</td>
<td>3529.96</td>
<td>4293.59 7473.59 -3179.99</td>
<td></td>
</tr>
<tr>
<td>25 25 25</td>
<td>6785.00</td>
<td>3273.57 8779.65 -5506.09</td>
<td></td>
</tr>
<tr>
<td>25 25 15</td>
<td>5421.04</td>
<td>3766.64 8669.46 -4902.82</td>
<td></td>
</tr>
<tr>
<td>25 15 15</td>
<td>4732.58</td>
<td>4234.24 7730.85 -3496.62</td>
<td></td>
</tr>
</tbody>
</table>
3.3.2 Results & Discussion

Unlike in Experiments 1 and 2, all of the participants in Experiment 3 had accuracy levels above 80% in selecting the most probable hypothesis as the focal hypothesis. Thus, all of the participants appeared to understand the instructions clearly, and none were excluded. We excluded any trials in which the focal hypothesis was less probable than one of its alternatives, whether it was selected by the participant or by the computer. We excluded an average of 2.1% ($SD=3.5\%$) of trials with self-selected focal hypotheses. The percentages were the same for trials with externally selected focal hypotheses, as accuracy was matched between the self and external conditions. Mean ratings for each condition are displayed in Table 3.3.

3.3.2.1 Replication of Self-selection Bias

We first tested for a self-selection bias as a main effect across all conditions. A t-test comparing the average rating of self-selected focal hypotheses to the average rating of externally selected ones revealed a significant self-selection bias, $t(78) = 2.82, p < .01$, $\eta^2 = .09$. As in Experiments 1 and 2, this involved higher ratings for self-selected focal hypotheses ($M = 53.6\%$) than for externally selected ones ($M = 52.7\%$). The ratings of self-selected focal hypotheses were higher for forty-seven of the seventy-nine participants. As in Experiments 1 and 2, the effect remained significant when the data were transformed to rank scores.
3.3.2.2 Similarity of Focal Hypothesis to Alternatives

Next, we tested the prediction that self-selection bias would be strongest when it was most difficult to select the focal hypothesis because its alternatives had similar levels of support. We computed the magnitude of the self-selection bias separately for each participant and each combination of support for the focal hypothesis and support for the alternatives. This was used as the dependent variable in a one-way ANOVA. In order to investigate a wide range of Closeness-of-Alternatives, we constrained this analysis to the two highest levels of Support-for-the-Focal-Hypothesis (85% and 55% fish of the relevant colour in the green lake). There were six levels of Closeness-of-Alternatives. In terms of how the percentage of fish of the relevant colour in each alternate lake differed from that in the focal lake, the six levels of Closeness-of-Alternatives were (1) both identical to the focal lake, (2) one identical and one 10% lower, (3) both 10% lower, (4) one identical and one 40% lower, (5) one 10% lower and one 40% lower, and (6) both 40% lower. As a manipulation check, we assessed whether the time taken to select the focal hypothesis was longest for the conditions that were presumably most difficult, when the alternatives had almost as much support as the focal hypothesis. We found that selection speed did increase as Closeness-of-Alternatives increased, $F(5,390) = 18.85, p < .001, \eta^2 = .20$, as can be seen in Table 3.4. However, in the probability ratings there was no significant effect of Closeness-of-Alternatives on the magnitude of the self-selection bias, $F(5,390) = 0.47, p = .80$. This did not support the notion that self-selection bias depended on cognitive effort.
3.4 Experiment 4

When the focal hypothesis is self-selected, evidence consistent with it is processed twice: first during focal hypothesis selection, and again when making a judgment of relative probability. In contrast, that evidence is processed only once if the focal hypothesis was externally selected. Repeated processing of supporting evidence might cause the mental representation of the focal hypothesis to be more salient as a consequence of repeated activation. In this experiment we investigated this possibility using a manipulation that we developed in previous work with the same paradigm.

In Chapter 2, we identified a bias towards giving more weight to evidence if it was accumulated gradually than if the same evidence was all presented instantaneously. Our account of this effect was that processing evidence to a greater extent would lead to more salient mental representations, and consequently greater subjective strength. The relevance of this to the current study was that this might share a common mechanism with the self-selection bias, relating to repeated activation of the mental representation of the focal hypothesis as a result of repeated processing of supporting evidence. If so, we would expect the selection bias and the overweighting of gradually accumulated evidence to be correlated across participants. In Experiment 4, we tested whether these two effects were correlated. We also considered the possibility that the selection bias might depend on whether evidence was gradually accumulated versus all presented instantaneously. In order to be able to test the above possibilities, we orthogonally manipulated (1) whether the focal hypothesis was self-selected or externally selected and (2) whether evidence was gradually accumulated versus instantaneously presented.
Our design included gradual evidence accumulation trials, in which only part of the evidence relevant to each hypothesis was presented on the first of two events. After an initial rating of relative probability was made, the remainder of the evidence relevant to each hypothesis was presented and a final revised rating was made. The gradual evidence accumulation trials were compared to instantaneous evidence control trials involving a single event on which all of the evidence relevant to each hypothesis was presented. On gradual evidence accumulation trials, the evidence obtained on the second event either increased the relative probability of the focal hypothesis, decreased it, or left it unchanged (the neutral condition).

3.4.1 Method

3.4.1.1 Participants

Forty-two volunteers (twenty-six females and sixteen males) with a mean age of 25.0 years ($SD = 7.6$) participated in this experiment. Participants were recruited via posters on the University of British Columbia campus and in community centers in the greater Vancouver area, and also via postings on electronic bulletin boards. All participants were reimbursed $10 per hour for their time plus parking and transportation expenses.

3.4.1.2 Materials & Procedure

As in Experiments 1 to 3, the experiment alternated between blocks in which the focal hypothesis was self-selected and blocks in which it was externally selected (by the computer). The first block always consisted of trials in which the focal hypothesis was
self-selected. In total, there were eight blocks of twelve trials each (four blocks in which the focal hypothesis was always self-selected, and four blocks in which it was externally selected).

The scene depicted on each trial of Experiment 4 was similar to that used in Experiments 1 to 3, except that the contents of each upstream lake were sometimes obscured near the outer edges, as shown in Figure 3.2. Specifically, twenty-five of the forty fish within each upstream lake were obscured on the first event of each trial with gradually accumulated evidence. On the second event of each of these trials, the entire contents of each lake became visible. On trials with instantaneously presented evidence, there was only one event, and the entire contents of each upstream lake were visible.

The sequence of events within a trial with gradually accumulated evidence and a self-selected focal hypothesis was as follows. First, a single black or white fish would be seen to jump from the downstream lake. Subsequently, the partially obscured contents of each of the three blue upstream lakes became visible. The participant indicated the lake most likely to be the origin of the downstream fish by moving the red mouse cursor over
Figure 3.2 Sequence of events within a trial of Experiment 4 in which the focal hypothesis is self-selected.
that lake and clicking on it. That lake then turned green. Subsequently, the participant rated the relative probability that the jumping fish came from the green upstream lake, rather than one of the blue upstream lakes, on the vertical rating scale. After that, the full contents of each upstream lake became visible, and the participant revised her or his rating by shifting the cursor on the response scale from the position corresponding to the previous rating to the position corresponding to the new rating. Within a trial with instantaneously presented evidence, the entire contents of each upstream lake became visible instantaneously after the downstream fish had jumped. Once the focal lake had been selected, a single rating of relative probability was made. For each of the above two types of trials with self-selected focal hypotheses (gradually presented evidence and instantaneous evidence), there were matching trials with externally selected focal hypotheses.

Within the four main trial types described above, there were four conditions defined by the proportions of fish in the upstream lakes. These are most easily described in terms of the sequence of events on trials with gradually accumulated evidence. On the first trial of each event, one of the three partially obscured upstream lakes would appear to contain 80% fish of the relevant colour (12 of the 15 visible fish), another would appear to contain 40% fish of the relevant colour (6 of the 15 visible fish), and the third lake would appear to contain 20% fish of the relevant colour (3 of the 15 visible fish). The lake with 80% fish of the relevant colour was thus the obvious choice for the most probable location of the jumping fish (the focal hypothesis).
The evidence presented on the second event then either confirmed the previous choice of focal hypothesis, disconfirmed it, or was neutral. In the Confirmatory Evidence condition, the percentage of fish of the relevant colour in the focal lake increased from 80% to 90%. The percentage in one alternate lake decreased from 40% to 15%. In the other it decreased from 20% to 10%. In the Disconfirmatory Evidence condition, the percentage of fish of the relevant colour in the focal lake decreased from 80% to 70%. The percentage of fish in one alternate lake increased from 40% to 77.5%. In the other it increased from 20% to 47.5%. Recall from the previous three experiments that the relative probability of the focal hypothesis is defined as the strength of evidence supporting the focal hypothesis divided by the sum of the evidence supporting all three hypotheses. The correct rating, as a percentage of the response scale height, is simply that probability multiplied by 100. In the Confirmatory Evidence condition, this increased from 57% to 90/(90+15+10) = 78%. In the Disconfirmatory Evidence condition, it decreased from 57% to 70/(70+77.5+47.5) = 36%. Thus, the relative probability of the focal hypothesis either increased or decreased by 21 percentage points.

There were also two types of neutral evidence condition. The relative probability of the focal hypothesis stayed constant at 57% in both of these conditions. In the Neutral-Up condition, the percentage of fish of the relevant colour in the focal lake increased from 80% to 90%, while the percentage in one alternate lake increased from 40% to 45% and the percentage in the other alternate lake increased from 20% to 22.5%. The relative probability of the focal hypothesis on the second event was thus 90/(90+45+22.5) = 57%. In the Neutral-Down condition, the percentage of fish of the relevant colour in the focal lake decreased from 80% to 70%, while the percentage in one alternate lake decreased
from 40% to 35% and the percentage in the other alternate lake decreased from 20% to 17.5%. The relative probability of the focal hypothesis on the second event was thus $70/(70+35+17.5) = 57\%$.

For each of the four conditions in which evidence was gradually accumulated (two events per trial), there was a corresponding condition in which it was all presented instantaneously (one event per trial). The evidence presented on an instantaneous-evidence trial was identical to the evidence on the second event of the corresponding gradually-accumulated-evidence trial. For example, for each confirmatory-evidence trial in the gradual evidence condition, there was a corresponding confirmatory-evidence-control trial in the instantaneous evidence condition. The evidence visible on the control trial was the same as the evidence visible on the final event of the gradual evidence trial. If, hypothetically, there were no biases caused by the gradual accumulation of evidence and behavior was instead mathematically normative, we would expect the rating made on the second event of a gradually-accumulated-evidence trial, when the complete contents of the lakes are visible, to be identical to the rating made on the corresponding instantaneous evidence control trial. In other words, a difference between these ratings would be evidence of a bias.

Data from the instantaneous-evidence control trials for the Disconfirmatory condition were excluded from the analysis. This was done because it was the only condition in which the correct choice of focal hypothesis was inconsistent between the instantaneous-evidence trials and the gradual-evidence trials. Thus, it was not possible to produce an instantaneous-evidence control condition that was equivalent to the
Table 3.5. Experiment 4: Ratings of the Relative Probability that the Focal Hypothesis, Rather than its Alternatives, is True, as a Function of the Strength of the Evidence Supporting the Focal Hypothesis and of that Supporting each Alternative

<table>
<thead>
<tr>
<th>Strength of Evidence Supporting Each Hypothesis (% Fish in that Lake of Relevant Colour)</th>
<th>Predicted Mathematically Normative Rating</th>
<th>Self-Selection Bias (Self - Ext)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Focal</td>
<td>Alt. 1</td>
</tr>
<tr>
<td>Confirmatory Evidence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Rating, Gradual</td>
<td>90</td>
<td>15</td>
</tr>
<tr>
<td>Only Rating, Instantaneous</td>
<td>90</td>
<td>15</td>
</tr>
<tr>
<td>Disconfirmatory Evidence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Rating, Gradual</td>
<td>70</td>
<td>77.5</td>
</tr>
<tr>
<td>Only Rating, Instantaneous</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Neutral Up</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Rating, Gradual</td>
<td>90</td>
<td>45</td>
</tr>
<tr>
<td>Only Rating, Instantaneous</td>
<td>90</td>
<td>45</td>
</tr>
<tr>
<td>Neutral Down</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Rating, Gradual</td>
<td>70</td>
<td>35</td>
</tr>
<tr>
<td>Only Rating, Instantaneous</td>
<td>70</td>
<td>35</td>
</tr>
</tbody>
</table>

Note. In the disconfirmatory evidence condition, the balance of the evidence at the end of the trial refuted the focal hypothesis, so that support for the focal hypothesis (70%) was lower than support for its strongest alternative (77.5%). For this condition, it was not possible to include an instantaneous-evidence control condition with equivalent levels of support in which the focal hypothesis was self-selected, because it would be an error for a participant to select the lake with 70% fish of the relevant colour as the focal hypothesis.
gradual-evidence condition in terms of Support-for-the-Focal-Hypothesis and for each of its alternatives.

3.4.2 Results & Discussion

All of the participants run were more than 80% accurate in selecting the most probable hypothesis to be the focal hypothesis. None of them were excluded from our analysis. We excluded any trials in which the focal hypothesis was less probable than one of its alternatives, whether it was selected by the participant or by the computer. We excluded an average of 3.8% (SD=1.9%) of trials with self-selected focal hypotheses. The percentages were the same for trials with externally selected focal hypotheses, as accuracy was matched between the self and external conditions. We performed a 2 X 2 ANOVA to check for an interaction of Gradual Evidence Accumulation (whether evidence was gradually accumulated versus all presented instantaneously) with Selection Type (self-selected versus externally selected focal hypothesis). For gradually-accumulated-evidence trials, only the rating made at the end of the trial, once all of the evidence had become visible, was included in this analysis. This was compared to the one rating made on the corresponding instantaneous-evidence trial. As in Experiments 1 to 3, all statistical tests were repeated on rank transformed scores. All effects reported below to be significant in the original data were also significant in the rank transformed data. The data averaged across the Confirmatory and Neutral conditions are portrayed in Figure 3.3. They are reported separately for each type of evidence in Table 3.5.

The ANOVA revealed a significant main effect of Gradual Evidence Accumulation, $F(1,41) = 27.95, p < .001, \eta^2 = .41$, involving a tendency to rate the focal
hypothesis as more probable if evidence was gradually accumulated ($M = 37.7$), than if it
was instantaneously presented ($M = 34.2$). This is consistent with the findings of Chapter
2, in which evidence supporting a given focal hypothesis was seen to support it more
strongly if gradually accumulated than if all presented instantaneously. There was also a
significant self-selection bias in favor of self-selected focal hypotheses, $F(1,41) = 5.95, p$
< .05, $\eta^2 = .13$, as in Experiments 1-3, with higher ratings for self-selected focal
hypotheses ($M = 36.8$) than for externally selected ones ($M = 35.1$). The ratings of self-
selected focal hypotheses were higher for twenty-nine of the forty-two participants.

Figure 3.3. Experiment 4: Ratings of the relative probability that the focal hypothesis,
rather than either of its alternatives, is true.
However, the interaction of Selection Type with Gradual Evidence Accumulation was not significant, $F(1,41) = 2.69, p = .11$. Finally, we found that self-selection bias and the effect of Gradual Evidence Accumulation were not correlated across participants, $r(42) = 0.12, p = .42$. These results do not support the notion that the two effects share a common underlying mechanism, such as repeated activation of mental representations.

3.5 General discussion

In four experiments, we found evidence for a self-selection bias whereby self-selected focal hypotheses were rated as being more probable than externally selected ones. This occurred despite the fact that (1) the two types of focal hypothesis were matched in terms of mathematically normative probabilities, and (2) the overall accuracy of the computer in selecting the most probable hypothesis was matched, within-subjects, to the participant’s accuracy in doing so. These results suggest that the cognitive operations involved in selecting a hypothesis lead to assignment of higher probability to that hypothesis.

Our secondary goal was to explore possible mechanisms by which the cognitive processes involved in selecting a focal hypothesis might lead to higher probability ratings. One of these was that the self-selection bias occurred because extra cognitive effort involved in focal hypothesis selection caused its mental representation to be more salient as a result of increased processing. We examined this possibility in Experiment 3 by manipulating the difficulty of identifying the most probable hypothesis. The results showed that the amount of cognitive effort required to select the focal hypothesis had no significant effect on the magnitude of self-selection bias. Another possible mechanism
was that the self-selection bias occurred because of repeated activation of mental representations, leading to stronger subjective probabilities (a potential mechanism for the effects of gradual evidence presentation which was discussed in Chapter 2). In Experiment 4, we manipulated whether evidence was gradually accumulated, so that evidence supporting the focal hypothesis was processed repeatedly, or was instantaneously presented. We found no correlation between the effect of gradual versus instantaneous evidence and self-selection bias, and thus found no evidence of a common underlying mechanism.

The results present two replicable judgment biases. These are: (1) a tendency to judge a self-selected hypothesis as more probable than one selected by an external source (self-selection bias) and (2) a tendency to weight gradually accumulated evidence more strongly than instantaneously presented evidence. This second bias replicates the results of Chapter 2. Although both appear to be examples of repeated processing effects, whereby repeated processing of information consistent with a given hypothesis causes it to seem more salient and plausible, Experiment 4 suggests that if this is so, the underlying cognitive operations do not overlap.

One alternative interpretation stems from reports that the perceived value of information can be distorted prior to a decision (Bond, Carlson, Meloy, Russo, & Tanner, 2007; Brownstein, 2003; Dekay, Stone, & Miller, 2011; Russo, Carlson, & Meloy, 2006; Russo, Carlson, Meloy, & Yong, 2008), apparently in order to maximize consistency with the initially preferred option (Russo et al., 2008; Simon & Holyoak, 2002; Simon, Krawczyk, Bleicher, & Holyoak, 2008; Simon, Krawczyk, & Holyoak, 2004; Simon, Snow, & Read, 2004). In terms of our paradigm, this means that the perceived strength of
evidence for the preferred hypothesis may have increased prior to focal hypothesis
selection. Another potential interpretation is that the self-selection bias is a manifestation
of the self-affirmation effect studied in social psychology (Brownstein, 2003; Steele,
1988; Steele, Spencer, & Lynch, 1993), whereby dissonance leads individuals to rate an
option as being more desirable after choosing it than beforehand. Of course, pre-decision
and post-decision biases are not mutually exclusive. They might even result from a
common underlying mechanism, with the drive to maximize consistency being an
inherent property of the cognitive system (Russo et al., 2008; Simon & Holyoak, 2002;
Simon et al., 2008; Simon, Krawczyk, et al., 2004; Simon, Snow, et al., 2004).

Finally, an alternative to repeated processing and cognitive consistency
explanations is that the type of repeated processing that is involved in self-selection is
qualitatively different than that involved in straight-forward repetition. When a preferred
hypothesis is self-selected, the choice is a self-generated cognitive event (even though the
hypothesis is not self-generated). It is clear that self-generated cognitive events are
tagged with cognitive qualities that distinguish them from other-generated events
(Johnson, Hashtroudi, & Lindsay, 1993). These qualities may lead to assignment of
higher probability ratings.

Regardless of which of the above possible interpretations might contribute to
selection bias (which will be an interesting direction for future research), the main
contribution of the current work is that we demonstrated a selection effect in a paradigm
with objectively quantifiable evidence. This was not the case with previous studies of
self-selected material (Glockner, Betsch, & Schindler, 2010; Ronis & Yates, 1987; Sieck
et al., 2007; Sniezek et al., 1990), consumer choice (Glockner & Betsch, 2008; Glockner
et al., 2010; Russo et al., 2006; Russo et al., 2008) and legal decision-making (Simon & Holyoak, 2002; Simon et al., 2008; Simon, Krawczyk, et al., 2004; Simon, Snow, et al., 2004). One other recent set of studies has investigated the effect of choice in a paradigm with objectively quantifiable evidence. However, that set of studies involved monetary gambles (Dekay et al., 2011). The current set of studies demonstrates that selection bias is not the result of confounds with individuals differences in personal experience, motivational leanings towards reward seeking and risk avoidance, or ease of memory retrieval. Rather, we demonstrate that some fundamental cognitive mechanism inherent to selecting a preferred focal hypothesis increases its perceived probability.

The direction of our self-selection bias is opposite to some previous experiments (Ronis & Yates, 1987; Sieck et al., 2007; Sniezek et al., 1990), which reported higher confidence in the correctness of other-selected material. However, as mentioned above as the motivation for this study, a number of variables confound the comparison of self-to–other selected trials, such as familiarity with the subject matter, fluency in memory retrieval, or completeness of memory retrieval. Moreover, the ratings made in previous studies were of confidence that the chosen answer had been correct, not probability comparisons as were carried out in the present study. These two processes (i.e., post-hoc confidence ratings versus probability comparisons) would seem to involve different cognitive operations, possibly contributing to the different self-selection effects. Finally, even when comparing our results to those of studies involving probability estimates rather than confidence estimates, we must consider that making a rating by moving a slider on a scale with the labels “definitely true” and “impossible” is not necessarily equivalent to making a numerical estimate of probability.
The findings of selection bias and of overweighting of gradually accumulated evidence in a paradigm requiring no long-term memory retrieval indicates the need to expand existing models of how choice affects confidence. These models describe how confidence ratings depend on fluency of retrieval from semantic and episodic memory (Ratcliff & Starns, 2009; Sieck, 2003; Sieck & Yates, 2001; Thomas, Dougherty, Sprenger, & Harbison, 2008). While there is no retrieval from long-term memory in our paradigm, there seem to be differences in the fluency of visual scene analysis between the self-selected and externally selected conditions. During the rating stage, the visual scene is analyzed more quickly in the self-selected condition than in the externally selected condition. This is presumably because some visual scene analysis was performed during the selection stage. The scene analysis performed during the rating stage is then faster / more fluent because it can build on information persisting in visual short-term memory from the previous scene analysis during the selection stage. Consequently, it may be that the selection bias is the result of more fluent visual scene analysis in the rating stage. An interesting direction for future research would involve adjustment of existing models to account for how the fluency of visual scene analysis is affected by choosing from one of multiple options (as opposed to the yes/no choices made in more basic, speeded perceptual discrimination tasks (Pleskac & Busemeyer, 2010).

A limitation of this study is that, although exclusion of semantic information and memory retrieval processes from our paradigm had the advantage of allowing us to reduce the cognitive confounds when comparing self- to other-selected trials, it may limit the generalizability of our findings, as semantic information and memory retrieval processes are typically involved in opinion formation. Even when interpreting unfamiliar
situations, individuals often make metaphorical comparisons to previous experiences or to semantic knowledge. For the sake of real-world validity, it will be necessary for future research to explore how the biases reported here, and the memory-retrieval effects found in previous research, either compete or interact with each other in everyday belief/opinion formation. Similarly, while the removal of motivational factors involving risks and rewards allows us to establish that selection bias can occur in the absence of those factors, this limits generalizability to real-world situations involving risky decision-making. Future research will be required to establish how selection bias is affected by such motivational factors.

The current studies suggest that the cognitive operations involved in self-selecting a hypothesis lead to assignment of higher probability to that hypothesis, and that this effect is independent of hypothesis selection difficulty and the rate of evidence accumulation. In the case of belief formation, self-selection bias could lead to a tendency to overvalue evidence confirming self-selected hypotheses. This could be a possible mechanism contributing to the holding of beliefs with weak supporting evidence, such as in horoscopes. This implies that difficulty accepting evidence that disconfirms beliefs may be partly due to the nature of the self-selection processes, which plays a role in elevating a hypothesis to belief status.
4 Bias in Favour of Self-Selected Hypotheses is Exacerbated in Delusional Schizophrenia Patients

Delusions in schizophrenia are typically characterized by self-generated, idiosyncratic explanations used to interpret events, as opposed to the culturally normative interpretation (Mullen, 1979). Cognitive accounts of delusions in schizophrenia (reviewed in Bell, Halligan, & Ellis, 2006; Garety & Freeman, 1999) have focused on probabilistic reasoning biases (Garety, Hemsley, & Wessely, 1991; Moritz & Woodward, 2005), theory of mind deficits (Frith, 1994), attributional biases (Bentall, 1994), and incorrect attribution of salience to benign external stimuli and internal percepts (Kapur, 2003; McKenna, 1991; van Os, 2009). However, despite its face validity, whether a cognitive bias towards self-generated hypotheses may be associated with delusions in schizophrenia has not been empirically tested to our knowledge.

In past work on healthy participants it has been noted that a bias toward over-rating the plausibility of one’s own hypotheses, relative to those suggested by others, is a characteristic of healthy human cognition (Koehler, 1994; Ronis & Yates, 1987; Sieck, 2003; Sieck & Yates, 2001; Sniezek et al., 1990). These early studies confounded self-selection with a variety of other material-based cognitive variables (e.g., familiarity of subject matter, fluency in memory retrieval, completeness of memory retrieval), but the results of Chapter 3, obtained using a probabilistic reasoning paradigm, demonstrated that even if self- and externally-selected hypotheses are exactly equated in terms of objectively quantifiable
supporting evidence, self-selected focal hypotheses were judged to be more probable than externally-selected ones. In the current study we extend this work by administering this task to a sample of schizophrenia patients, and comparing their performance to psychiatric and healthy control groups.

The probabilistic reasoning paradigm used here is a variation of the beads-from-a-jar probabilistic reasoning task (Huq, Garety, & Helmsley, 1988; Moritz & Woodward, 2005). The traditional probabilistic reasoning task involves judging the likelihood that a series of beads is drawn from jar A rather than jar B, based on the colours of the beads in jars A and B, and on the colours in the series of beads being drawn. We have developed versions of this task involving a fisherman fishing from one of two lakes (Speechley et al., 2010; Woodward et al., 2009) or downstream jumping fish originating from one of two or more upstream lakes as in Chapters 2 and 3. The version of the task used here involved judging the probability that a single jumping fish originated from one of three lakes, as in Chapter 3. Specifically, participants judged the probability that the fish originated from a given self- or externally-selected lake rather than being drawn from either of the two alternatives. The self- or externally-selected lake is referred to as the focal hypothesis, while the other two lakes are referred to as alternative hypotheses. On all trials, participants were required to indicate the likelihood that the focal hypothesis (rather than the two alternatives) was true. The self-selected hypotheses were tracked, and computer-selected hypotheses were produced that exactly matched the self-selected hypotheses in terms of supporting evidence.

Based on the results of Chapter 3, we predicted a self-selection bias for all participants, whereby probability ratings of the focal hypothesis would be higher if it was self-selected than if it was externally selected. Based on the self-generated nature of
delusions and the centrality of the delusional state to schizophrenia, we expected this bias to be exacerbated in schizophrenia patients relative to healthy and psychiatric controls, and to be correlated with the severity of delusions in the schizophrenia sample.

4.1 Methods

4.1.1 Participants

Thirty-six participants with schizophrenia and 16 psychiatric controls (diagnosed with bipolar disorder) were recruited from psychiatric hospitals and community health agencies in and around Greater Vancouver, British Columbia, Canada. All diagnoses were based on DSM-IV-R criteria American Psychiatric Association (2000). Diagnoses were confirmed with the Mini-International Neuropsychiatric Interview (MINI; Sheehan et al., 1998), which was administered on the date of testing. Psychopathology was assessed using the Signs and Symptoms of Psychotic Illness scale (SSPI; Liddle, Ngan, Duffield, Kho, & Warren, 2002), a schedule gauging symptom severity using 20 symptom items scored 0–4. Item 7 from the SSPI was used to quantify the severity of delusions. The possible values on this item are: 0 (absent), 1 (vague idea which might be delusional; peculiar ideas which do not conflict with evidence in a clear-cut manner), 2 (belief contrary to evidence, but patient has partial insight in the unrealistic nature of the belief), 3 (definite delusions, but the delusional beliefs do not have a pervasive influence on thinking or behaviour), and 4 (definite delusions which have pervasive influence on thinking and/or influence observable behaviour). Any or all of delusions of guilt, grandiose delusions, paranoid delusions, delusions of reference, or Schneiderian delusions can be rated on this item. All bipolar patients had SSPI delusions scores of 0.
Table 4.1. Psychopathological and socio-demographic characteristics of the participants.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Healthy n = 33</th>
<th>Bipolar n = 16</th>
<th>Schizophrenia n = 36</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, yrs</td>
<td>29.70 (9.44)</td>
<td>35.31 (12.14)</td>
<td>34.36 (9.66)</td>
</tr>
<tr>
<td>Sex, male:female</td>
<td>19:51</td>
<td>19:52</td>
<td>19:53</td>
</tr>
<tr>
<td>Education, yrs</td>
<td>15.90 (1.74)</td>
<td>14.19 (2.04)</td>
<td>13.49 (2.63)</td>
</tr>
<tr>
<td>Parental Socioeconomic status</td>
<td>65.88 (20.69)</td>
<td>70.13 (24.91)</td>
<td>80.94 (25.00)</td>
</tr>
<tr>
<td>Quick Test IQ score</td>
<td>98.00 (13.18)</td>
<td>99.00 (9.90)</td>
<td>97.61 (10.15)</td>
</tr>
<tr>
<td>K-BIT IQ score</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vocabulary</td>
<td>102.42 (13.72)</td>
<td>98.93 (11.10)</td>
<td>100.56 (13.54)</td>
</tr>
<tr>
<td>Matrices</td>
<td>110.55 (12.09)</td>
<td>104.00 (13.98)</td>
<td>104.80 (14.74)</td>
</tr>
<tr>
<td>Composite</td>
<td>107.45 (9.62)</td>
<td>101.80 (11.77)</td>
<td>103.06 (14.37)</td>
</tr>
<tr>
<td>Illness duration, yrs</td>
<td>N/A</td>
<td>6.79 (4.63)</td>
<td>11.83 (8.55)</td>
</tr>
<tr>
<td>Delusions</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>1.94 (1.49)</td>
</tr>
<tr>
<td>Guilt or worthlessness</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>0.36 (0.83)</td>
</tr>
<tr>
<td>Grandiose</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>0.75 (1.18)</td>
</tr>
<tr>
<td>Paranoid</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>1.46 (1.56)</td>
</tr>
<tr>
<td>Schneiderian</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>1.06 (1.41)</td>
</tr>
<tr>
<td>Hallucinations</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>1.77 (1.82)</td>
</tr>
<tr>
<td>Thought disorder</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>0.31 (0.79)</td>
</tr>
<tr>
<td>Underactivity</td>
<td>N/A</td>
<td>0.88 (0.81)</td>
<td>1.19 (1.06)</td>
</tr>
<tr>
<td>Poverty of speech</td>
<td>N/A</td>
<td>0.0 (0.0)</td>
<td>0.42 (0.81)</td>
</tr>
<tr>
<td>Flattened Affect</td>
<td>N/A</td>
<td>0.50 (0.89)</td>
<td>1.19 (0.92)</td>
</tr>
</tbody>
</table>

*Unless otherwise indicated, symptom scores are derived from the Signs and Symptoms of Psychotic Illness rating scale.

†healthy v. bipolar p = .01, ‡healthy v. schizophrenia p < .001, §healthy v. schizophrenia p = .01,

¶bipolar v. schizophrenia p < .001, √bipolar v. schizophrenia p < .01, †bipolar v. schizophrenia p < .05.
Participants were excluded if they reported a head injury resulting in a loss of consciousness for 10 minutes or more, and for current and past substance abuse and alcoholism. Substance abuse was assessed by chart review and by interview, and participants were excluded if they met the DSM IV-R criteria for an Axis I diagnosis of a substance-related disorder (e.g., polysubstance dependence). With the exception of two patients, all patients with schizophrenia were stabilized with antipsychotic medications, with 27 on atypical antipsychotics and 9 on typical antipsychotics. Of the 16 patients in the bipolar group, 7 were on antidepressants only, 7 were on antidepressants and atypical antipsychotics, 1 was on antidepressants and typical antipsychotics, and 1 was on typical antipsychotics only. All schizophrenia patients were either currently experiencing delusions, or had in the past. 8/16 bipolar patients had some history of psychotic features.

Thirty-three healthy control participants were recruited via posters on the University of British Columbia campus and in community centers in the greater Vancouver area, and also via postings on electronic bulletin boards. All participants were reimbursed $10 per hour for their time plus parking and transportation expenses. The healthy control group had no history of psychiatric illness as determined by a medical questionnaire. Additional exclusion criteria were the same as those employed for the patient groups.

All participants were fluent in English. Intelligence estimates were made using the Kaufman Brief Intelligence Test (K-BIT; Kaufman & Kaufman, 1997) for verbal and non-verbal intelligence, and the Ammons Quick Test (QUICK; Ammons & Ammons, 1962) for an assessment of current intelligence quotient (IQ). Socioeconomic status was estimated using the Amherst Modification of the Hollingshead-Redlich Two-Factor Index of
Socioeconomic Status (Hollingshead & Redlich, 1958; Watt, 1976) using highest parental occupation and education level.

The probabilistic reasoning task used in this study allows exclusion of data that is characteristic of poor performance, or a lack of understanding of task instructions. Namely, the lake that is chosen as a self-selected hypothesis should be the mathematically most likely origin of the downstream jumping fish. In accordance with our methodology on healthy participants (see Chapter 3), in order to ensure that participants clearly understood the instructions, we excluded their data if their accuracy in selecting the most probable hypothesis as the focal hypothesis was less than 81% (more than 5 errors out of 27 selection trials). As a result, the groups described above consisted of the participants remaining after fourteen of the original ninety-nine participants (one healthy control, two bipolar patients, and eleven schizophrenia patients) were excluded due to evidence that they did not understand the task. In our experience, comprehension in probabilistic reasoning tasks is very important for reducing noise in the dataset (Balzan, Delfabbro, Galletly & Woodward, 2012; Speechley et al., 2010; Moritz and Woodward, 2005), and for interpretation of the measures of interest (in this case the self-selection bias). If a participant is not meeting the basic reasoning requirements, the measured cognitive processes cannot be known.

4.1.2 Materials & Procedure

The probabilistic reasoning task employed here was identical to Experiment 2 of Chapter 3, except that participants completed only one third as many experimental blocks in the current study. Each trial of the task involved a scene depicting four blue lakes (see Figure 4.1), three of which were upstream from the fourth. On all trials participants were required to
rate the relative probability that the focal hypothesis, rather than its alternatives, was true. For the self-selected focal hypothesis trials, participants were required to select the lake that they preferred prior to making the probability rating. In contrast, for the externally-selected trials, the to-be-rated focal hypothesis was selected by the computer. Unknown to the participant, the computer-selected lakes were matched precisely to the self-selected lakes by computerized yoking based on the participants’ pattern of responding. A more detailed description of the methodology follows.

At the start of each trial, a single black or white fish was seen to jump in the downstream lake. The colour of this jumping fish, referred to hereafter as the relevant colour, was randomized across trials. Next, the contents of each of the three upstream lakes became visible. Each contained a mixture of black and white fish (40 fish in total per lake), which remained in view until a rating had been made. Participants were told that the fish in the downstream lake originated from one of the upstream lakes. Thus, each upstream lake corresponded to a hypothesis about the origin of the jumping fish. The upstream lake with the most fish of the relevant colour was the most likely origin of the fish in the downstream lake.

Next, if the trial was in the self-selected condition, participants indicated the lake they deemed to be the most likely origin of the jumping fish by moving the mouse cursor (a red square) over their preferred lake and clicking with the left mouse button. This lake, referred to hereafter as the focal lake, then turned green. If the trial was in the computer-selected condition, the focal lake was selected by the computer to match the choice made by the participant on an equivalent trial in a preceding block with self-selected focal hypotheses.
Figure 4.1. Display presented during a typical trial of this experiment. At the start of each trial, a single black or white fish was shown to jump in the downstream lake. If the trial involved a self-selected focal hypothesis, the participant indicated the upstream lake from which the jumping fish was most likely to have migrated, which then turned green. Otherwise, the green lake was selected by the computer. Next, the participant rated the probability of that fish having migrated downstream from the green lake (the focal hypothesis) rather than either of the blue upstream lakes (the alternative hypotheses).
The focal lake turned green immediately after the fish in the bottom lake jumped, at the same time as the fish in the upstream lakes became visible.

Once the focal lake was selected (self- or computer-selected), participants were required to rate the relative probability that the focal hypothesis, rather than its alternatives, was true. Ratings were made on a vertical scale, with the labels "definitely true" at the top end and "impossible" at the bottom end. Participants used a mouse to move the slider smoothly up and down the scale and clicked the left mouse button when it was in the desired location. The vertical position of the slider, in pixels, was then recorded. In the results section, ratings are reported as a percentage of the total height of the response scale. At the beginning of each trial, the slider was set at the mid-point of the response scale. Trials with self-selected and externally selected focal hypotheses occurred in separate blocks. In total there were six blocks of nine trials each, alternating between blocks in which the focal hypothesis was self-selected and blocks in which it was externally selected. The first block always consisted of trials in which the focal hypothesis was self-selected.

Strength of support for the focal hypothesis was manipulated, as was the strength of support for its alternatives, by manipulating the percentage of fish of the relevant colour in each lake, as in Chapter 3. As the self-selection bias found in healthy individuals does not vary as a function of support for the focal hypothesis or the two alternatives, all analyses in the current paper were collapsed across these factors. We simply assessed the magnitude of the self-selection bias for each group of participants, and assessed whether the bias correlated with the severity of delusions in the schizophrenia group.
4.1.3 Strategy of Data Analysis

We excluded from data analysis any error trials (i.e., trials on which the selected “focal hypothesis” was actually less probable than one of its alternatives). Self-selection bias scores were calculated as the difference between the mean probability rating for self-selected focal hypotheses and the mean rating for externally (i.e., computer) selected ones. Note that, as the objective probabilities were identical in these two conditions, an ideal mathematically normative rater would have a self-selection bias score of zero. Based the findings of Chapter 3, we expected the self-selection bias score to be positive for all groups. For the current study, we hypothesized that the schizophrenia group would show an increased self-selection bias relative to the bipolar group and the healthy control group, and that the selection bias would correlate positively with the present severity of delusions in the schizophrenia group. Each of the statistical tests reported below was also repeated with rank-transformed scores, in order to adjust for potential skew in the data often inherent to ratings made on a probability scale (Conover & Iman, 1981). The rank transformation did not change the significance of any of the reported effects, so is not reported here.

4.2 Results

4.2.1 Patient Demographics

The socio-demographic and psychopathological characteristics of the sample are summarized in Table 4.1. Fisher’s exact tests indicated no significant differences for gender between groups. A t-test comparing the two patient groups also revealed a significantly longer illness duration, \( t(47) = 2.08, p < .05 \), in the schizophrenia group \((M = 35 \text{ years})\) than in the bipolar control group \((M = 14 \text{ years})\). Univariate analyses of variance (ANOVAs)
comparing groups on demographic and IQ measures indicated significant differences between groups on years of education, \( F(2, 82) = 10.45, \text{MSE}=51.23, p < .001 \) and socioeconomic status, \( F(2, 78) = 3.56, \text{MSE}=1936.86, p < .05 \). Post-hoc t-tests based on Fisher’s least-significant difference (LSD) correction were conducted to determine which groups differed significantly from each other and are reported in Table 4.1. Where adjustments were required for unequal variances on t-tests, the conclusions were unchanged.

### 4.2.2 Hypothesis Comparison Task

Contrary to one of our predictions, the ANOVA on the self-selection bias showed no significant effect of Group, \( F(2, 82) = 0.02, \text{MSE}=0.87 \), with the bias being present for schizophrenia and bipolar patients and in healthy controls equally (means = 3.64, 3.88 and 3.48, respectively). However, within the group of schizophrenia patients, self-selection bias was correlated significantly with delusion severity as assessed by the SSPI, \( r(35) = 0.42, p = 0.01 \). The associated scatter plot is displayed in Figure 4.2. The self-selection bias was not correlated with any other SSPI symptom rating scores (all \( p > .09 \)), with the exception of auditory hallucinations, for which a strong correlation was also observed, \( r(35) = 0.52, p < 0.01 \). To assess the possible impact of confounding variables on this correlation, we inspected the correlations between the self-selection bias measure, the delusions item on the SSPI, and each of the characteristics in Table 4.1. None of the correlations were significant, so could not be confounding the relationship between the self-selection bias and delusions (the same was observed when the delusions item was replaced by the hallucinations item).

We also performed an analysis in which the schizophrenia patients were split into a severely delusional group (N=7), with an SSPI delusions score greater than 3, and a less
The severely delusional group had a selection bias that was significantly stronger than that of the less delusional group, \( t(34) = 3.25, p < .01 \), or the healthy control group, \( t(38) = 2.93, p < .01 \), and marginally stronger than that of the bipolar control group, \( t(21) = 1.74, p = .09 \). This pattern is consistent with the selection bias being largest for the severely delusional group (SSPI=4) in Figure 4.2.

Figure 4.2. Self-selection bias as a function of delusion severity within the group of schizophrenia patients.
4.3 Discussion

Delusions are typically characterized by idiosyncratic, self-generated explanations used to interpret events, as opposed to the culturally normative interpretations. In past work on healthy participants, it has been noted that a bias toward over-rating the plausibility of one’s own hypotheses, relative to those suggested by others, is a characteristic of healthy human cognition. In the current study we test whether or not such a bias is exaggerated in schizophrenia patients compared to bipolar patients and healthy controls, and related to delusions. To achieve this, we employed a probabilistic reasoning task for which self- and externally-selected hypotheses were equivalent in terms of objectively quantifiable supporting evidence. On each trial, participants rated their acceptance of a focal hypothesis relative to two alternatives, with the most probable focal hypothesis selected either by the participant, or by the stimulus presentation software. All groups showed an equivalent self-selection bias, but within the schizophrenia group, this bias was correlated with the current severity of delusions. An increased self-selection bias likely contributes to the delusional state in schizophrenia, as delusions are typically based on an individual’s own interpretations of events as opposed to culturally normative interpretations.

Although an overall difference between the groups was not present, within the schizophrenia group severity of delusions and hallucinations correlated with the magnitude of the self-selection biases, suggesting that this bias is a state, rather than a trait aspect of the illness. This apparent discrepancy arose because the asymptomatic schizophrenia patients scored lower than the control groups on the self-selection bias, although this bias increased in a linear manner with symptom severity (M = .96, 1.18, 2.69, 3.11, 10.25; M = .60, .96, 1.70, 5.68, 8.44; for SSPI scores of 0, 1, 2, 3, and 4 on delusions and hallucinations items,
respectively). The sample sizes are small, hampering efforts to carry out analysis of these subsets of patients with specific levels of symptom severity, and future research would be required to determine whether the decreases and increases in the self-selection bias at specific levels of severity are reliable. In the current study, the linear “dose-response” relationship between the self-selection bias and levels of symptoms reached significance, but evidence for a trait-related group difference was absent.

A relatively large number of participants did not understand the task instructions, as they did not select the most plausible lake in the self-selection condition at a rate substantially higher than chance. This rendered the study of a self-selection bias impossible for these participants, as the reasons for why they performed this way can be based on speculation only, but likely reflects some form of reasoning impairment that is not related to the self-selection bias. Exclusion was no more frequent in schizophrenia (23% excluded) than in bipolar disorder (26% excluded), although healthy controls had better comprehension (13% excluded). The excluded and retained subjects for each group did not differ significantly on any demographic variable including IQ. This task may be suboptimal for a general tool for investigation of schizophrenia due to task difficulty, but when the self-selection bias is to be measured, the ability to check for accuracy is important. However, it is possible that the participants who were 'left' in the analyses are unique in some way, and that their results may not generalize to the population at large.

The correlation reported here with auditory hallucinations as well as delusions is not unexpected. Although hallucinations and delusions are clearly different, they are known to co-occur (Liddle, 1987; van der Gaag et al., 2006), so likely share underlying cognitive processes. Examples of what these might be include a greater weighting of self-generated
concepts and percepts, hypersalience of EVH (evidence-hypothesis) matches, an impairment in integrating new evidence, and a BADE, Hallucinations are partially caused by hyperactivity in voice-selective regions of the cortex (Allen et al., 2012; Rapin et al., 2012), but also by a number of more clearly top-down influences, one of which could be hypersalience of a match between evidence (vivid thoughts) and a self-selected hypothesis (I will hear voices). In addition, both delusions and hallucinations are affected by other top-down personalizing factors which must interact with hypersalience, such as expectations, hypervigilance, imagination/fantasy, and memories/trauma (Waters et al., 2012). Thus, an increased self-selection bias could contribute to hallucinations in a top-down fashion; namely, hypersalience of a match between evidence (vivid thoughts) and a self-selected hypothesis (“I will hear voices”).

A potential limitation of this study is that group differences were present on a number of variables such as general cognitive ability and length of illness. However, overall group differences were absent on the self-selection bias measure, suggesting that these confounds did not affect the results. Moreover, in a check for confounds of the association between the self-selection bias and the severity of delusions produced no potential confound for the relationship between self-selection bias and delusions (or hallucinations).

The self-selection bias reported here, and possibly a number of other measurable cognitive biases (e.g., hypersalience of EVH matches, BADE), may contribute to delusion formation and maintenance. This study provides further confirmation that the cognitive biases in delusions extend beyond material congruent with an individual’s specific delusions to neutral, unrelated content, and as such, may reflect a pervasive reasoning deficit predisposing individuals with schizophrenia towards the formation and maintenance of
delusional ideation. Such increased understanding of the cognitive biases underlying delusions is important in light of the clinical applications of this work, where it has been demonstrated that sharing information with patients about the cognitive biases underlying delusions leads to reduction of the severity and impact of these symptoms (Moritz & Woodward, 2007a; Moritz et al., 2011; Moritz & Woodward, 2007b).
5 Functional Connectivity in a Frontoparietal Network Involving the Dorsal Anterior Cingulate Cortex Underlies Decisions to Accept a Hypothesis

As was stated in Chapter 1, effectively judging the validity of a hypothesis is fundamental to success in many aspects of life, such as social interaction, economic decision making, and voter choice. Hypothesis judgment is also essential to more basic cognitive functions, such as memory recognition or interpreting a visual scene. Effectively judging a hypothesis often requires comparing it to at least one alternative. In order to decide whether the hypothesis being judged (the focal hypothesis) is more probable than an alternative, one must assess the strength of evidence supporting each hypothesis, compare those strengths, and decide which hypothesis to accept. In the current study, we used functional magnetic resonance imaging (fMRI) to establish a biological basis for these fundamental aspects of hypothesis judgment.

In order to investigate the functional brain networks involved in judging hypotheses, we used a probabilistic reasoning task with objectively quantifiable evidence (Beach, 1968; Moritz et al., 2007; Ross, Freeman, Dunn, & Garety, 2011; Speechley et al., 2010; Waller, Freeman, Jolley, Dunn, & Garety, 2011). In a typical version of this paradigm, the participant is presented with an item of a given colour (the relevant colour) drawn from one of two lakes. The participant rates the probability that it was drawn from one particular lake (the focal hypothesis) rather than a second lake (the alternative hypothesis). The lake with the most items of the relevant colour is the most probable
origin of the item drawn. An advantage of this paradigm is that it allows precise control over the strength of supporting or refuting evidence.

Judging the validity of a hypothesis ultimately involves a decision to accept a focal hypothesis which is considered more coherent with the available evidence than its alternative (provided that decisions are made accurately). When cognitive representations of evidence-hypothesis information form a coherent mental construct, that construct is considered stable and salient (Köhler, 1929; Metzger, 2006), which may translate to a stronger and more stable pattern of activity in the underlying neural network. In the context of our hypothesis comparison task, such coherence and stability might result in a stronger fMRI signal for the network underlying mental representations of evidence-hypothesis matches.

The decision to accept a focal hypothesis due to sufficient coherence with the evidence could be considered a type of “Aha!” moment. To the extent that this is true, the dorsal anterior cingulate cortex (dACC) could be expected to be active under these circumstances. During insightful problem solving and difficult perceptual recognition tasks, the dACC is shown to be active in response to “Aha!” moments, that is to say, when information relevant to interpreting a problem is reorganized into a gestalt, or coherent mental construct, of the solution. Other brain regions involved include the frontal eye fields (FEF), the dorsolateral prefrontal cortex (DLPFC) and parietal regions including the intraparietal sulcus (IPS) and superior and inferior parietal lobules (Aziz-Zadeh, Kaplan, & Iacoboni, 2009; Kounios & Beeman, 2009; Luo, Niki, & Phillips, 2004; Ploran et al., 2007). In the current study, we assessed functional connectivity
between the dACC and these other brain regions triggered by recognition of a match
between the evidence and the focal hypothesis.

We made two predictions regarding the expected functionally connected
frontoparietal network involving the dACC. First, based on our view of the dACC and
other functionally connected frontal and parietal regions being involved in recognizing
coherence between aspects of an emerging mental construct in an “Aha!” moment, we
predicted stronger activity in the underlying neural network when the focal hypothesis
was accepted (because it was coherent with the evidence) than when it was rejected.
Second, we expected this network to be more strongly activated in the hypothesis
comparison task than the less cognitively complex evidence assessment control task, as
dACC-based brain networks are known to be responsive to cognitive demands (Duncan
& Owen, 2000).

5.1 Material and methods

5.1.1 Participants

Forty-six volunteers (26 females, 20 males) with a mean age of 25.0 years (SD =
5.2) participated in the experiment. They received $10 per hour and were reimbursed for
transportation expenses. All participants were right-handed. Participants were recruited
via posters on the UBC campus and in community centres in the greater Vancouver area,
and via postings on online bulletin boards. Ethical approval was provided by the UBC
Clinical Research Ethics Board. Participants were excluded from participating if they
could not safely undergo an MRI scan, if they had experienced any head injuries resulting
in loss of consciousness for more than 20 minutes, if they suffered from epilepsy,
encephalitis, or meningitis, or if they or an immediate family member who suffered from
a psychotic illness (e.g. schizophrenia or bipolar disorder).

5.1.2 Procedure

On each trial of the task, participants were presented with a scene depicting three lakes, two of which were upstream from the third (as depicted below in Figure 5.1 and Figure 5.2). At the beginning of each trial, an animated series of images was displayed, depicting a single fish, either black or white, breaking the surface, jumping along an inverted U-shaped path

Figure 5.1. The displays presented while ratings were made during the hypothesis comparison task.
Figure 5.2. The display presented while ratings were made during the evidence assessment task.
(parabolic) for 140 ms, then disappearing again below the surface. We will refer to the colour of this jumping fish as the *relevant colour*. The colour of this fish was also specified throughout the remaining duration of the trial within the question adjacent to the rating scale. This ensured that participants would be aware of the current relevant colour even if they had not seen the fish jump. The populations of 100 fish in each of the two upstream lakes then became visible. Aside from the jumping fish, no other fish were ever visible in the downstream lake. The positions of the black and white fish within each lake were randomized over trials, so that any two trials with identical ratios of black to white fish would not be identical in appearance. On hypothesis comparison trials, participants were told that any fish appearing in the downstream lake originated in either the left-hand upstream lake or the right-hand upstream lake. They were required to rate the probability that the jumping fish came from one particular lake (the focal lake) rather than the alternative lake. The assignment of the left-hand and right-hand lakes as focal and alternative hypotheses was randomized across trials. On the evidence assessment trials, participants reported the percentage of fish of the relevant colour in both lakes together.

Each trial allowed 6 seconds for the participant to make a rating. All responses were made by moving a slider up or down a vertical response scale using button presses on a LUMItouch fiber-optic response device (Lightwave Medical, Vancouver, British Columbia, Canada). The entire scale was 160 pixels in length. All responses were made with the dominant (right) hand. The two outer response buttons served to move the cursor either up or down ten pixels (the index finger moved the cursor down), while the two inner response buttons served to move the cursor either up or down two pixels (the middle finger moved the cursor down).
The Evidence Assessment and Hypothesis Comparison tasks were performed in alternating blocks of 14 trials each, with 4 blocks per functional run. There were 7 conditions within the Hypothesis Comparison task, corresponding to different percentages of fish of the relevant colour in the focal and alternative lakes. If the percentage was 20% in the focal lake, it was either 20% or 50% in the alternative lake. If it was 50% in the focal lake, it was 20%, 50%, or 80% in the alternative lake. If it was 80% in the focal lake, it was either 50% or 80% in the alternative lake. Thus, the 7 conditions matched the structure of a Likert scale: the evidence strongly favoured accepting the focal hypothesis (50% focal versus 20% alternative), weakly favoured it (80% focal versus 50% alternative), was neutral (80% versus 80%, 50% versus 50%, or 20% versus 20%), weakly favoured rejecting the focal hypothesis (50% focal versus 80% alternative), or strongly favoured rejecting the focal hypothesis (20% focal versus 50% alternative). There were also 7 conditions in the Evidence Assessment task that used the same visual displays, but these required the participants to rate the percentage of fish of the relevant colour in both lakes combined. For each of those 14 conditions, there were 2 trials per run with an inter-trial interval (ITI) of 2 seconds and 2 trials per run with an ITI of 8 seconds. During the ITI, three empty lakes were displayed, i.e. without fish or a response scale. Halfway through each experimental run, a 30-second rest break occurred, during which the words "Take a 30 second break" were displayed on a dark grey screen. The total duration of each run was 740 seconds (370 scans).

5.1.3 Image Acquisition

Imaging was performed at the University of British Columbia's MRI Research Centre on a Philips Achieva 3.0 Tesla scanner with Quasar Dual gradients (with peak
strength of 80mT/m and maximum slew rate of 200T/m/s). The participant's head was firmly secured using a custom head holder. Functional image volumes were collected with T2*-weighted gradient echo spin pulse sequences (TR = 2000ms, TE = 30ms, flip angle 90°, 36 slices, 3 mm thick, 1 mm gap, sense factor 2, matrix is 80 × 80 reconstructed at 128, FOV = 240 mm × 240 mm × 143 mm, measured voxel is 3mm × 3mm × 3mm, actual bandwidth per pixel is 53.6 Hz) effectively covering the whole brain (143 mm axial extent). Each participant completed one structural scan and two functional runs of 370 scans each.

5.1.4 Image Preprocessing

Functional images were reconstructed offline, and the scan series was realigned and motion corrected using the method implemented in SPM5. Translation and rotation corrections did not exceed 2 mm or 2.5° for any of the participants. Parameters for spatial normalization into the modified MNI space used in SPM5 were determined using mean functional images constructed from the realigned images of each participant and scan series. The normalized functional images were smoothed with an 8 mm full width at half maximum Gaussian filter. Data were normalized to the EPI template using an affine transformation and voxels of 4 × 4 × 4 mm³. Any artifacts resulting from head movement were removed via regression, with the regressors being the six head movement parameters output by SPM5 during image realignment.

5.1.5 Functional Connectivity Analysis

To characterize how the activity of functionally connected networks differed between experimental conditions, we used a multivariate analysis technique that
identifies brain regions showing temporally correlated activation (i.e., functional networks). Constrained Principal Component Analysis for fMRI (fMRI-CPCA) combines multivariate regression analysis and principal component analysis to derive networks from the portion of the BOLD signal that is explained by the timing of task events. CPCA differs from other approaches to examining correlations in activation among regions in that it (1) identifies functional networks that are based on task related covariance/correlation in blood-oxygen level dependent (BOLD) signal, as opposed to being based on any source of covariance/correlation in the time course, (2) estimates the hemodynamic response (HDR) for each network, and (3) quantifies the effect of experimental manipulations on each functional network.

The details of the fMRI-CPCA method are presented elsewhere (Metzak, Feredoes, et al., 2011; Metzak, Riley, et al., 2011; Woodward, Cairo, et al., 2006). Briefly, after variance in the BOLD signal attributable to the task has been separated from that not attributable to the task, the dominant patterns of inter-correlation between voxels over time are used to derive functional networks. For the comprehensive CPCA theory and proofs please see previously published work (Hunter & Takane, 2002; Takane & Shibayama, 1991; Takane & Hunter, 2001). The fMRI-CPCA application is available online, free of charge (www.nitrc.org/projects/fmricpca). We now briefly present matrix equations for the current application of fMRI-CPCA. This application of CPCA involved preparation of two matrices: Z and G.

5.1.6 Preparation of Z

The first matrix, Z, contained the BOLD time series of each voxel, with one column per voxel and one row per scan. Each column contained normalized and
smoothed activations over all scans, at first for each subject separately, but then vertically concatenated to form a final Z matrix comprised of stacked individual Z matrices. Prior to concatenation, linear and quadratic trends over the functional runs were removed from the BOLD signal (to correct for scanner drift) using multivariate multiple regression, as was variance related to head movement parameters.

5.1.7 Preparation of G

The second matrix, G, or the design matrix, contained finite impulse response (FIR) models of the expected BOLD response to the timing of stimulus presentations. Since the model of the BOLD response is applied to scans, the number of rows in G is equivalent to the number of rows in Z. FIR models estimate the increase in BOLD signal at specific post-stimulus scans relative to all other scans. The value 1 is placed in rows of G for which BOLD signal amplitude is to be estimated, and the value 0 in all other rows (“mini boxcar” functions). The time points for which a basis function was specified in the current study were the 1st to 10th scans following stimulus presentation. Since the repetition time (TR) for these data was 2 s, this resulted in estimating BOLD signal over a 20 s window, with the start of the first time point corresponding to encoding stimulus onset. We chose to model a 20 s window because the full HRF can occasionally last up to 20 s in some individuals and some brain regions, although the main peak occurs mostly within the first 10 s post-stimulus (Muthukumaraswamy, Evans, Edden, Wise, & Singh, 2012; Wager, Keller, Lacey, & Jonides, 2005). We wished to be able to clearly describe the entire HRF time-course. Given that we used a FIR model rather than a modeled canonical HRF, the analysis did not force the detection of an HRF lasting a full 20 s.
Rather, the shape of the time-course identified in our FIR regression analysis was data-driven.

In this analysis we created a $G$ matrix that would allow us to estimate subject-and-condition specific effects by inserting a separate FIR basis set for each condition and for each individual subject. The columns in this subject-and-condition based $G$ matrix code 10 post-stimulus time points, 14 experimental conditions (7 conditions within the hypothesis comparison task and 7 matched conditions within the evidence assessment control task), and 46 participants, resulting in 6440 columns ($10 \times 14 \times 46 = 6440$). In the results, the difference between accepting or rejecting the focal hypothesis did not vary as a function of whether the evidence was strong or weak, so all results are collapsed across the strong and weak levels of evidence. Trials on which the evidence for the focal and alternative hypotheses was equated were also excluded from the ANOVAs in the results section. These trials were excluded because they required button pressing in the two thirds of evidence assessment trials but not in the evidence comparison trials, and therefore would have confounded contrasts between the comparison and assessment conditions with motor activity.

5.1.8 Matrix Equations

The matrices of the BOLD time series and experimental design are taken as input, with BOLD in $Z$ being predicted from the FIR model in $G$. In order to achieve this, multivariate least-squares linear regression was carried out, whereby the BOLD time series ($Z$) was regressed onto the design matrix ($G$):

$$Z = GC + E$$  (4)
where \( C = (G'G)^{-1}G'Z \) using least squares regression. This analysis yielded condition-specific regression weights in the \( C \) matrix (i.e., regression weights specific to the experimental conditions as defined by the design matrix). The condition-specific regression weights are often referred to (in conventional fMRI analyses) as beta images. \( GC \) contains variability in \( Z \) that was predictable from the timing of stimulus presentations. For the analysis presented here, the \( G \) matrix was standardized for each run separately.

The next step involved applying singular value decomposition to extract components representing functional networks from \( GC \):

\[
UDV' = GC
\]

(5)

where \( U \) is the matrix of left singular vectors; \( D \) is the diagonal matrix of singular values; \( V \) is the matrix of right singular vectors. Each column of \( V \) can be overlaid on a structural brain image to allow visualization of the neural regions involved in each functional network. In the current application of CPCA, we orthogonally rotated (Metzak, Feredoes, et al., 2011) and rescaled the \( V \) matrix prior to display, so that a rotated loading matrix is displayed.

5.1.9 Predictor Weights

To interpret the components with respect to the conditions represented in \( G \), we produced predictor weights (Hunter & Takane, 2002) in matrix \( P \). These are the weights that would be applied to each column of the matrix of predictor variables (\( G \)) to create \( U \)
(U=G×P). The values in P indicate the importance of each column in the G matrix to the network(s) represented by the component(s), so are essential for relating the resultant components to the experimental conditions of interest represented in G. This approach estimates a HDR shape for each individual and each condition separately.

5.1.10 Statistical Test of Component Reliability and Impact of Experimental Manipulations

As is explained above, predictor weights are produced for each combination of post-stimulus time point, condition, and participant. These weights can be used to statistically test whether the network-based BOLD response differed from zero during post-stimulus time, and to confirm that these values are reflecting a HDR shape (Metzak, Feredoes, et al., 2011; Metzak, Riley, et al., 2011). The impact of the experimental conditions on the network-based estimated HDR can also be tested statistically. Specifically, in this experiment, we sought to test: (1) whether the amplitude of the HDR differed as a function of whether the focal hypothesis was accepted or rejected, and (2) whether it differed between the hypothesis comparison task and the evidence assessment control task. In the first case, this would be reflected by a significant interaction between Time Point (post-stimulus time) and Decision (Accept Focal versus Reject Focal) for the estimated network-based HDR measure (i.e., the predictor weights). Omitting the predictor weight representing the first point of post-stimulus time (which was adjusted to zero in all conditions for the purposes of display and data analysis), this analysis was carried out as a 9 × 2 within-subjects ANOVA for each component, with the factors of Time Point and Decision as within-subject factors. Selecting “repeated” contrasts for the within-subjects factor of Time Point allowed significance tests to be restricted to adjacent
time points, such that complex $9 \times 2$ interactions (e.g., between Time Point and Decision) were broken down into 8 different $2 \times 2$ interactions involving adjacent levels of the Time Point. Inspection of the relative size of the $p$-values for these 8 different $2 \times 2$ interactions can pinpoint the time points responsible for the $9 \times 2$ interactions (e.g., the Accept versus Reject pairwise comparison increases significantly from the 5 s to 7 s post-stimulus time points). Tests of sphericity were carried out for all ANOVAs. Greenhouse-Geisser adjusted degrees of freedom are reported where violations of sphericity affected the interpretation of results; otherwise, the original degrees of freedom are reported.

Since our significance testing is carried out at the level of subject-specific HDR estimates, use of bootstrapping to produce Z-map images is not required; therefore, point estimates (from orthogonally rotating and rescaling the $V$ matrix of component loadings) are overlaid on structural brain images for depiction of the spatial arrangement of the functional networks.

### 5.1.11 Follow-up Analysis of Contributions by Individual Clusters to a Network

#### Time Course

In one functionally connected network for which the strength of the HDR differed between experimental conditions, we performed a follow-up analysis to examine how different regions of the network contributed to that effect. This clarified whether the difference between conditions in that network was simply due to a higher overall level of activation within any single region of the network (e.g., the dACC), or reflected a stronger signal for the functionally connected network as a whole. This involved exploring whether each region of the network showed stronger signal during one condition than during another. It was achieved as follows. The following steps were
restricted to voxels with the most dominant 20% of component loadings (the values overlaid on the brain images, rotated $V$ in Equation 5). For each cluster visible in the network, we multiplied those component loadings for voxels within the cluster of interest by the corresponding predicted scores ($GC$ in Equation 4) to create cluster-specific component scores (one score per functional scan, analogous to rotated $U$ in Equation 5). These were then correlated with the model ($G$ in Equation 4) to estimate cluster-specific predictor weights. ANOVAs performed on these predictor weights provided a post-hoc description of the significant effects identified in the full-network analysis.

**5.1.12 Follow-up Analysis of Contributions by Peak and Off-Peak Voxels to a Network Time Course**

In addition to exploring how individual clusters within a network contributed to the network time course, we also assessed the contributions of peak and off-peak voxels. In this analysis, we included voxels from every cluster within the network, but adjusted the percentage cut-off for the most dominant loadings. We first estimated predictor weights including the top 20% of component loadings for each cluster. The percentage for this cut-off was then lowered in increments of 5% to include more voxels, with the analysis being repeated at each cut-off, until a cut-off was reached for which the effect was statistically significant. Note that the initial analysis on full-network predictor weights, described in the sections above, reflects a percentage cut-off of 100% (i.e., all brain voxels were included, and the contribution of each voxel was weighted by how strongly it loaded onto the component of interest).
Table 5.1. Ratings of the relative probability that the focal hypothesis rather than its alternative is true, expressed as a percentage of the total height of the rating scale.

<table>
<thead>
<tr>
<th>Percentage of Fish of the Relevant Colour</th>
<th>Hypothesis Comparison Task</th>
<th>Evidence Assessment (Control) Task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal Lake (f)</td>
<td>Alternative Lake (a)</td>
<td>Probability Rating: Mean (SD)</td>
</tr>
<tr>
<td>20</td>
<td>20</td>
<td>48.2 (4.2)</td>
</tr>
<tr>
<td>20</td>
<td>50</td>
<td>34.8 (10.5) *</td>
</tr>
<tr>
<td>50</td>
<td>20</td>
<td>63.8 (9.3) *</td>
</tr>
<tr>
<td>50</td>
<td>50</td>
<td>50.5 (3.4)</td>
</tr>
<tr>
<td>50</td>
<td>80</td>
<td>39.1 (11.1)</td>
</tr>
<tr>
<td>80</td>
<td>50</td>
<td>65.4 (11.0)</td>
</tr>
<tr>
<td>80</td>
<td>80</td>
<td>51.8 (3.38)</td>
</tr>
</tbody>
</table>

* indicates a rating deviating significantly from the mathematical norm at \(p < .001\), which remains significant after a Bonferroni correction for multiple comparisons.
5.2 Results

Behavioral responses are displayed in Table 5.1. Most of the ratings in the hypothesis comparison task and percentage estimates in the evidence assessment control task were quite close to the mathematically normative ratings. The exceptions were the ratings made when the focal and alternative lakes contained 20% and 50% fish of the relevant colour, or vice versa. These ratings were significantly closer to the mid-point of the rating scale than were the mathematically normative ratings. The magnitude of the deviation from the mathematically normative rating did not depend, $t(45)=1.58$, ns, on whether the evidence favoured the focal hypothesis, $t(45)=5.58$, $p < .001$, or its alternative $t(45)=4.04$, $p < .001$. Participants were simply more cautious than necessary when presented with strong evidence, regardless of which hypothesis that evidence favoured. As mentioned above, for all analyses of fMRI data, only trials on which the participants moved the cursor on the response scale were included. This allowed us to match the hypothesis comparison and evidence assessment tasks in terms of motor activity.
Figure 5.3. Functional networks identified by CPCA, with the strongest 20% of component loadings shown. Note that predictor weight time courses are based on a whole-brain network, although only the strongest 20% of loadings are displayed here. (a) Component 1. (b) Component 2. Note that predictor weights can be interpreted as correlations, so a strongly positive predictor weight in the time course for Component 2 indicates that the pattern of deactivations in regions of the default mode network is more intense for that post-stimulus time point and experimental condition.
The scree plot of singular values sorted by magnitude suggested extraction of two components (corresponding to two functional networks). The predictor weights associated with each component followed a time course reflecting an HDR shape. Correspondingly, a significant main effect of Time Point was present for each component. The percentages of task-related variance accounted for by the first and second rotated components were 19.3% and 9.8%, respectively. The brain regions comprising each functional network are portrayed in Figure 5.3 and the tables in Appendix 1. Note that only the strongest 20% of loadings are displayed in Figure 5.3, for the sake of clearly displaying the dominant features of the spatial pattern of each component. The strongest 5% of loadings for these components are displayed in Appendix 2. However, all of the predictor weights analyzed below represent a weighted aggregate of activity across 100% of brain voxels, with the only exception being the paragraph describing our follow-up analysis. Component 1 involved activation in a network involving the dACC and bilateral parietal and lateral occipital regions. Component 2 involved deactivation in the precuneus, ventromedial prefrontal cortex, and bilateral middle temporal gyri; areas which overlap substantially with the default mode network (Buckner, Andrews-Hanna, & Schacter, 2008; Fox et al., 2005), as well as activation in lateral occipital clusters. Note that, as Component 2 is dominated by negative loadings, a strongly positive predictor weight for it mostly reflects activation reductions. Specifically, it reflects an aggregate of deactivations in the large number of voxels with negative loadings and concurrent activations in the small number of voxels with positive loadings. Thus, a strongly positive predictor weight for a given condition
and post-stimulus time point reflects strong activation reduction in the default mode network.

5.2.1 Accept Focal versus Reject Focal

In order to investigate how each component varied as a function of acceptance or rejection of the focal hypothesis, we performed $2 \times 9$ ANOVAs with factors of Decision (Accept Focal versus Reject Focal) and Time Point. A Decision × Time Point ANOVA carried out on the Component 1 predictor weights revealed no main effect of Decision, $F(1,45) = 0.15, ns$, a significant main effect of Time Point, $F(8,360) = 96.27, p < .001$, and a significant Decision × Time Point interaction, $F(8,360) = 3.23, p = .001$. The post-hoc analysis examining this significant interaction using only adjacent time points indicated that the pair-wise contrast of Accept > Reject increased substantially from 5 to 7 s post-stimulus ($p=.01$), reflecting a higher HDR peak in the Accept Focal condition relative to the Reject Focal condition. We also tested whether this effect of Decision on the Component 1 predictor weights interacted with Evidence Strength, but found no significant interaction, $F(1,45) = 2.54, ns$.

A Decision × Time Point ANOVA carried out on the Component 2 predictor weights revealed no main effect of Decision, $F(1,45)=0.02, ns$, a significant main effect of Time Point, $F(8,360) = 89.37, p < .001$, and a significant Decision × Time Point interaction $F(8,360)=2.50, p < .05$. The follow-up analysis examining this significant interaction using only adjacent time points indicated that the pair-wise contrast of Accept > Reject increased substantially from 11 to 13 s post-stimulus ($p=.05$), reflecting a slightly right-shifted HDR peak in the Accept Focal condition relative to the Reject Focal condition.
When Components 1 and 2 were entered into a combined analysis, there was a significant Decision × Component interaction, \( F(1,45)=4.24, p < .05 \), reflecting the fact that the mean difference in predictor weights between the Accept Focal and Reject Focal conditions was greater for Component 1 (\( M=.017 \)) than for Component 2 (\( M=.001 \)). As can be seen in Figure 5.3, the predictor weight time course for Component 1 (the dACC-based network) reached higher amplitude in the Accept Focal (evidence-hypothesis match) condition than in the Reject Focal (evidence-hypothesis mismatch) condition. In contrast, for Component 2 (the default-mode network) there was no clear amplitude difference, but there was a slightly right-shifted HDR peak in the Accept Focal condition.

A follow-up analysis was carried out to clarify whether the difference between focal hypothesis acceptance and rejection in the dACC-based network was simply due to a higher overall level of activation within any single region of the network (e.g., the dACC), or reflected a stronger signal for the functionally connected network as a whole. This involved exploring whether each region of the dACC-based network showed stronger signal during focal hypothesis acceptance than rejection. Cluster-specific predictor weights were estimated as described in the methods section. We first performed this analysis including only voxels corresponding to the top 20% of component loadings, as are displayed in Figure 5.3, for each individual cluster. The Decision × Time Point interaction was not significant for any individual cluster, including the dACC, indicating that the significant interaction reported above is not specific to any one particular brain region within the network. We also performed this analysis at the 20% cut-off for all displayed clusters simultaneously and found no significant interaction. We then carried out this analysis including all voxels that passed a threshold increasing by 5% increments
(i.e., 20%, 25%, 30%, etc.) of the dominant loadings. The Decision × Time Point
interaction reached significance, $F(8,360) = 2.42, p = .05$, once the threshold was set at
the dominant 45% of loadings. No new clusters emerged at this threshold; rather, the
newly included voxels formed concentric rings around the existing clusters. It was not
possible to create cluster-specific predictor weights at the 45% cut-off because as the
clusters grew in size their edges met, resulting in one contiguous cluster identified per
cerebral hemisphere.

The above results suggest that a pattern spanning much of the brain, not just the
peaks displayed in Figure 5.3, is important to representing the difference between
conditions. It should be noted that the spatial patterns of positive and negative peaks were
the same for the two components. The difference between them lay in the off-peak
voxels. In Component 1 (the dACC-based network), 95.76% of voxels had positive
loadings. In Component 2 (the default mode network), 80.23% of voxels had negative
loadings. In sum, the off-peak voxels accounted for both the differences in spatial pattern
between brain networks and also for the differences in cognitive processing. These
analyses are congruent with an account holding that the stronger signal during focal
hypothesis acceptance reflects coordinated activity across a network of brain regions, and
emphasizes the importance of the contribution of non-peak brain regions to this effect
(i.e., the shape of the cluster as well as the peak amplitude and location).

5.2.2 Hypothesis Comparison versus Evidence Assessment

In order to compare component activity in the Hypothesis Comparison task to that
in the Evidence Assessment task, we used $2 \times 9$ ANOVAs with factors of Task
(Hypothesis Comparison versus Evidence Assessment) and Time Point (9 time points
displaying how the BOLD response progressed over 2-20 seconds after stimulus presentation). An ANOVA carried out on the Component 1 predictor weights revealed no main effect of Task, $F(1,45) = 0.01, ns$, a significant main effect of Time Point, $F(8,360) = 122.93, p < .001$, and no significant Task $\times$ Time Point interaction, $F(3.71,167.14)=2.08, ns$. A Task $\times$ Time Point ANOVA carried out on the Component 2 predictor weights revealed no main effect of Task, $F(1,45) = 0.51, ns$, a significant main effect of Time Point, $F(8,360) = 119.09, p < .001$, and no Task $\times$ Time Point interaction, $F(8,360)=1.16, ns$. As can be seen in Figure 5.3, the time courses of the two tasks overlap very closely on Components 1 and 2.

5.2.3 Follow-up Analysis Testing for Lateralization Effects

The tasks used in this study involved randomization designed to ensure that the left and right lakes corresponded to the focal hypothesis equally often. However, we felt it prudent to confirm empirically that no left/right imbalances occurred. To this purpose, we compared the cluster-specific predictor weights between left and right hemisphere parietal-occipital clusters. There were no main effects of hemisphere and no interactions of hemisphere with any other factors of interest in either the Hypothesis Comparison task or the Evidence Assessment control task.

5.3 Discussion

In order to understand the neural basis of comparing evidence for conflicting hypotheses, we used a probabilistic reasoning paradigm to investigate functional brain networks engaged in deciding which hypothesis to accept. As these decisions are comparable to “Aha!” moments, when coherence between the correct interpretation and
the available evidence is recognized, we expected a dACC-based network to be involved. As predicted, we found more activity within a dACC-based network when the focal hypothesis was accepted (an evidence-hypothesis match) than when it was rejected (an evidence-hypothesis mismatch). This is consistent with a role for the dACC and its associated functional network in recognizing a coherent mental construct, or triggering recognition of a match between the evidence and the focal hypothesis. However, the results emphasize that the entire dACC-based network is associated with this effect, not only any individual region. There was also a delayed BOLD response in the default-mode network for hypothesis acceptance, but no overall difference in amplitude.

The CPCA method was optimal for identifying the above pattern of increased activity in the dACC-based network during focal hypothesis acceptance. This is primarily because fMRI-CPCA is designed to identify responses to experimental manipulations of task conditions, rather than identifying spontaneous activity. It is the initial regression phase of CPCA that sets it apart from other component extraction methods and makes it advantageous for identifying task-related functional network changes. This regression constrains the analysis to the small portion variance in brain activity attributable to task performance. This ensures that the results of the subsequent component extraction step are dominated by task-related activity rather than spontaneous activity. This order of operations is particularly important in cases where the spatial configuration of a network changes in response to cognitive demands. While CPCA uses regression to predict brain activity (the criterion) from task timing (the predictor), PLS treats both of these as criterion variables and searches for common factors (Metzak, Feredoes, et al., 2011). An advantage of CPCA over seed-based connectivity methods is that the lack of a
requirement to select a seed region makes the analysis more data-driven. Furthermore, PCA identifies the dominant pattern of inter-correlations in a dataset in a more efficient manner than performing a large number of pairwise correlation analyses. In sum, the results of this study demonstrate the efficacy of constraining an analysis to variance attributable to manipulations of interest prior to employing component analysis.

Although we focus here on the role of the dACC in our task, the role of the other regions in the network merits some discussion. The dACC-based network also included bilateral activity in the precentral gyrus. This was stronger in the left hemisphere, which is consistent with the use of the right hand to respond. We also found strong activity in bilateral parietal and lateral occipital clusters, which is consistent with the use of large visual displays in our paradigm. Finally, we found weak right-lateralized DLPFC activity. As other reports of the role of the DLPFC in perceptual decision-making indicate that the left DLPFC plays the dominant role (Heekeren, Marrett, & Ungerleider, 2008; Philiastides, Auksztulewicz, Heekeren, & Blankenburg, 2011; Rahnev, Lau, & de Lange, 2011), our DLPFC activity is unlikely to reflect the same function. As can be seen in Figure 5.3, it also exhibits noticeably weaker loadings than the dACC or other clusters in Component 1. The network formed by all of these regions represents a variant of the ‘Task-Positive Network’ widely reported to be involved in spatial attention, working memory, and a wide variety of other tasks (Fox, Zhang, Snyder, & Raichle, 2009). In the current study we focus on the role of the dACC in this network because it exhibits the strongest loadings outside of visual and motor areas.

Our follow-up analyses suggested that the stronger signal from the dACC-based network in response to evidence-hypothesis matches (Accept Focal) depended on an
interconnected network-wide pattern. In other words, it depended on more cortical regions than only the peak locations and their amplitude. These analyses indicate that the stronger signal during focal hypothesis acceptance reflects coordinated activity across a network of brain regions, rather than increased activity within any individual cluster peak or subset of clusters peaks. They also suggest that activity throughout each network cluster (i.e., cluster shape), rather than only at the peaks, underlies the stronger signal in response to evidence-hypothesis matches. This demonstrates the importance of a functional connectivity approach to fMRI data analysis based on identifying network patterns, in that it may be able to detect condition differences that could be missed with univariate analyses.

A secondary goal was to investigate activity in the hypothesis comparison task over and above that in the evidence assessment control task. As the hypothesis comparison task involves more cognitive steps than the evidence assessment control task, we expected it to recruit the dACC-based network more strongly, given that the dACC-based network is known to be responsive to cognitive demands (Duncan & Owen, 2000). Contrary to our predictions, we found no between-condition differences in network activity. Assuming that a number of cognitive operations do differ between these conditions, we can conclude that our methods were not sensitive to them. That is not to say that differences in brain activity do not exist, as certain cognitive operations clearly present in the experimental condition are absent in the tightly matched control condition. One possibility is that the BOLD signal may simply be too temporally coarse to detect these differences. The hemodynamic response to any single cognitive event takes several seconds to reach its peak (Boynton, Engel, Glover, & Heeger, 1996; Friston et al., 1998).
Therefore the responses to adjacent rapid cognitive events involved in complex cognitive processes, such as those differing between evidence assessment and comparison, may be merged in the measured BOLD signal. Consequently, the fMRI modality may not be sensitive to subtle differences between two series of complex cognitive events, such as those involved in evidence assessment and comparison here. A neuroimaging method with higher temporal resolution might detect those differences more effectively. Interactions between the decision (i.e. to accept versus reject the focal hypothesis) and evidence strength might also become apparent if a method with higher temporal resolution were used.

This study is subject to a number of limitations. As the results are dependent on the analysis of functional networks, they may not replicate across other non-connectivity-based analysis methods. Moreover, it may be that other functional brain networks accounting for smaller portions of variance in the BOLD signal also play a role in hypothesis comparison, but were not detected here. Furthermore, the results depict a correlational relationship between differences in network activity and the experimental manipulations of interest, leaving the question of causality open. Finally, the data are limited by the low temporal resolution of fMRI and slow time course of the BOLD response, and other modalities sensitive to more precise time scales (such as MEG) may be beneficial in this regard.

The results of the current experiment help to clarify the precise role of a dACC-based network in the recognition of the “Aha!” moment, or in triggering recognition of a match between the evidence and the focal hypothesis. A number of other roles have been attributed to the dACC, such as monitoring the environment for conditions that may
require adjustments in control over the course of action (Behrens, Woolrich, Walton, & Rushworth, 2007; Paus, 2001; Woodward, Metzak, Meier, & Holroyd, 2008), detection of conflict (Walsh, Buonocore, Carter, & Mangun, 2011), detection of errors (Carter et al., 1998), or detection of surprise (Egner, 2011; Egner & Hirsch, 2005). The moment a decision is made (i.e., an insightful “Aha!” moment), a given pattern of coherence between aspects of a mental representation is recognized. Thus, these data support a general role for a dACC-based network in recognition that a change in mental set is required (Woodward et al., 2008).

Optimally interpreting our situations and experiences frequently requires comparing the evidence supporting conflicting hypotheses and deciding which to accept, with the final decision stage being comparable to an “Aha!” moment reached during insightful problem solving. The results suggested that this involves a stronger signal for a dACC-based network as a whole, and that functional connectivity between the dACC and other brain regions is a possible mechanism for coherence between components of a mental representation. This helps clarify the role of the dACC in the wide variety of tasks which involve judging and comparing hypotheses, such as social interaction, economic decision making, voter choice, perceptual decisions, and evaluating scientific research.
6 Patterns of Cortical Oscillations Organize Neural Activity into Whole-Brain Functional Networks Evident in the fMRI BOLD Signal

In Chapter 5, we found an effect of whether the evidence supported accepting or rejecting the focal hypothesis. Here, we discuss the neural activity that might underlie that effect by reviewing the neural activity underlying the BOLD signal and patterns of functional connectivity observed in fMRI. It is understood that whereas fMRI can effectively describe the spatial activation patterns of whole-brain networks, it is limited to measuring the delayed hemodynamic response observed in the BOLD signal. This delay limits its ability to describe rapid changes in neural activity underlying the sequential processing stages inherent to any cognitive task. We can obtain much higher temporal resolution from EEG, MEG, or ECoG data. However, due to limitations on the number and location of feasible electrode placements and to difficulties in measuring signals from sub-cortical regions, these methods do not provide complete whole-brain neural activity measures with a spatial precision equivalent to that of fMRI. The above temporal and spatial limitations can be addressed through studies combining fMRI data with simultaneously recorded EEG data, or with co-registered MEG or ECoG data recorded in separate sessions. To best interpret the results of such multimodal studies, one must understand the relationship between the BOLD signal, neuronal activity, and the rapid oscillatory activity measurable with EEG, MEG, and ECoG. Here, we describe how cortical oscillations organize post-synaptic potentials and neuronal firing, functionally connecting activity in disparate regions to form the widespread cortical networks observed in the BOLD signal.
6.1 Neuronal ensembles and local metabolic demand: Co-ordinated neural activity and oscillations

At the local level, several studies have used invasive techniques to simultaneously record action potentials (APs), BOLD signal strength, and cortical oscillations. It should be noted that the BOLD signal might be expected to correspond less closely to APs measured via single-cell recordings than to local field potentials (LFPs), which reflect post-synaptic potentials summed across large numbers of neurons, because a single fMRI voxel typically contains more than a million neurons (Arthurs & Boniface, 2002). Indeed, the BOLD signal is reported to correlate more closely with LFPs than with APs (Arthurs & Boniface, 2002; Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001; Mukamel et al., 2005; Niessing et al., 2005). More specifically, the BOLD signal tends to correspond closely to LFPs oscillating in the high gamma range (approximately 50 to 100 Hz) although the precise range can vary across studies (Arthurs & Boniface, 2002; Logothetis et al., 2001; Mukamel et al., 2005; Niessing et al., 2005; Nir et al., 2007). However, the BOLD signal is coupled to neuronal firing when the firing rates of neighbouring neurons (smoothed across periods of a few hundred milliseconds) are most highly correlated. This coupling between firing and BOLD can depend on whether the type of visual stimulus being presented is an optimal driver of the neurons (Lippert, Steudel, Ohl, Logothetis, & Kayser, 2010). These periods also involve strong coupling between neuronal firing and gamma frequency oscillatory power (Nir et al., 2007). This suggests that, at the local level, the BOLD signal may reflect the coordination of neuronal firing mediated by gamma-frequency oscillations in post-synaptic potentials. These oscillations could facilitate communication between neurons by ensuring that spikes arrive at the moment of peak excitability (Fries, 2005).
Gamma-frequency oscillations in the post-synaptic potentials summed across many neurons are believed to integrate activity between spatially disparate neuronal ensembles. Phase-locking of gamma oscillations is reported to coordinate activity between visual cortical neurons responding to different parts of the same moving object (Gray, Konig, Engel, & Singer, 1989; Gray & Singer, 1989). Distinct sub-frequencies of gamma oscillations are thought to coordinate activity across distinct sets of regions in the hippocampus and parahippocampal cortices. Medium-frequency gamma (~60 Hz) appears to coordinate activity between CA1 hippocampal neurons (deep layer) and medial entorhinal cortex. Low-frequency gamma (~ 40 Hz) appears to coordinate activity between CA1 hippocampal neurons (superficial layer) and CA3 hippocampal neurons (Belluscio, Mizuseki, Schmidt, Kempter, & Buzsaki, 2012; Colgin et al., 2009). While these gamma oscillations coordinate activity between nearby regions, they also play a role in segregating neuronal ensembles involving different layers of CA1. Further evidence of the role of gamma oscillations in segregation involves ‘inhibitory sculpting’ constraining activity to within individual cortical columns (Contreras & Llinas, 2001). In sum, these findings suggest that gamma oscillations dynamically combine local elements into neuronal ensembles while keeping the ensembles distinct from each other.

6.2 **Orchestration: Networks formed from multiple frequencies of oscillations**

While gamma oscillations are effective in combining activity at the local level, it has been suggested that slower oscillations would be more optimal for co-ordinating activity across longer distances between hemispheres or between frontal and posterior regions, which can involve longer, poly-synaptic conduction delays of dozens of milliseconds (Varela,
Lachaux, Rodriguez, & Martinerie, 2001; von Stein & Sarnthein, 2000). Whereas this is consistent with findings of local synchronization in the gamma band, more long-range task-induced synchronization of slower alpha (~10Hz) oscillations between occipital and parietal regions, and frontoparietal synchronization in the theta band (Colgin et al., 2009; Doesburg, Green, McDonald, & Ward, 2009a; Gray et al., 1989; Gray & Singer, 1989; von Stein & Sarnthein, 2000), there are also reports of long-distance EEG gamma-band synchronization between electrodes over frontal and parietal/occipital cortices (Doesburg, Roggeveen, Kitajo, & Ward, 2008). Furthermore, gamma-frequency LFPs are reported to correlate with BOLD signal in distant cortical regions (Schölvinck, Maier, Frank, Duyn, & Leopold, 2010). Thus, spatial co-ordination cannot be simplified to a linear relationship between oscillatory frequency and the distance over which information is organized.

The short-range and long-range organization of neural activity by oscillations of different frequencies depends upon the ways in which those oscillations work in concert. One means by which oscillations are widely reported to work in concert involves the gamma and theta frequency ranges. The amplitude of gamma oscillations can be modulated by the phase of a theta oscillation (Canolty et al., 2006; Doesburg, Green, McDonald, & Ward, 2009b; Jensen & Colgin, 2007). The amplitude of broadband high gamma activity (80 to 150 Hz) is maximal at the trough of 5 Hz theta oscillations in ECoG data collected from a wide region of cortex (Canolty et al., 2006).

This pattern of theta-modulated gamma appears to play an important role in cognitive processing. During binocular rivalry, it connects a frontoparietal network involved in perceptual switching. Immediately prior to a perceptual switch and concomitant response, it dynamically connects inferior temporal and motor cortices to the network (Doesburg et al.,
It has been postulated that the timing of gamma oscillations within a given theta cycle plays an organizational role, with each 40 Hz gamma cycle within a 7 Hz theta cycle corresponding to the neuronal ensemble for one item in a set maintained in working memory (Jensen & Colgin, 2007; Lisman & Idiart, 1995). While empirical data remain inconclusive regarding that particular model of working memory, there is evidence that theta phase distinguishes between neuronal ensembles oscillating at different gamma frequencies. In rats exploring a maze, medium-frequency (50-90 Hz) gamma oscillations in the hippocampus occur at a slightly earlier phase of the theta cycle than slower (30-50 Hz) gamma oscillations (Belluscio et al., 2012). As these different gamma frequencies correspond to different neuronal ensembles, as described in the previous section, this demonstrates how phase-amplitude modulation serves to distinguish between ensembles in neighbouring regions.

In addition to modulating gamma amplitude, theta phase can also modulate gamma phase. Cross-frequency theta-gamma phase-phase coupling occurs in the hippocampus and parahippocampal cortex in the medium (50-90 Hz) and slow (30-50 Hz) gamma ranges (Belluscio et al., 2012). Theta phase can also alter synchrony between gamma oscillations originating in disparate regions. Prior to a change in percept in a binocular rivalry paradigm, both intra-regional gamma band synchronization and inter-regional synchronization between frontal and posterior regions increased. Both types of synchronization were also modulated at the theta frequency (Doesburg et al., 2009b). Thus, gamma oscillations can be phase-locked over long distances, but slower oscillations tend to be the mechanism by which local ensembles oscillating within the gamma range are organized into networks and sub-networks.
6.3 Correspondence between oscillatory networks and fMRI networks

The precise mechanism by which oscillations form functional networks varies with task demands and with the specific cortical regions involved in a given network. If we consider the regions of the dorsal and ventral attention networks often reported in the fMRI literature (Corbetta, Patel, & Shulman, 2008; Fox et al., 2005), we can find corresponding patterns of oscillatory connectivity at a range of frequencies. Alpha (~10 Hz) oscillations are phase-locked between the superior parietal lobule (SPL) and inferior occipital gyrus (IOG) contralateral to attended locations (Doesburg et al., 2009a). Beta (~20 Hz) oscillations are reported to synchronize activity between the frontal eye fields (FEF), the intraparietal sulcus (IPS), and occipitotemporal cortices (Hipp, Engel, & Siegel, 2011). Theta and gamma oscillations are reported to synchronize frontal regions such as the dorsolateral prefrontal cortex (DLPFC) and superior frontal gyrus (SFG) to the precentral gyrus and precuneus (Doesburg et al., 2009b). Slower oscillations (slow cortical potentials or “up/down” states) in EEG / MEG / ECoG data occur at a rate comparable to the spontaneous resting-state oscillations measurable in the BOLD signal (He & Raichle, 2009; He, Snyder, Zempel, Smyth, & Raichle, 2008). In sum, power in no single frequency band can be said to be the signal driving the BOLD response. Instead, several different frequencies of oscillation will likely work in concert to connect the regions belonging to a given fMRI network, particularly if that network involves many regions. This view would be consistent with recent findings that the amplitude and time-course of the hemodynamic response are dependent not only on gamma-frequency power (although gamma power is the strongest predictor of BOLD signal amplitude) but also alpha and beta power (Magri, Schridde, Murayama, Panzeri, & Logothetis, 2012). It is also consistent with recent findings that coherent low-frequency
oscillations were the predominant contributors to inter-regional correlations in BOLD signal in a thalamo-cortical visual network. These slow oscillations modulated local high-frequency (gamma) activity via cross-frequency coupling (Wang, Saalmann, Pinsk, Arcaro, & Kastner, 2012).

The involvement of different oscillatory frequencies in a cortical network varies as a function of cognitive state (Brookes et al., 2011; Doesburg et al., 2009a, 2009b; Doesburg et al., 2008; von Stein & Sarnthein, 2000), and those states often last only a few hundred milliseconds. Given that the hemodynamic response is delayed by several seconds, fMRI cannot distinguish between the neural responses to brief sequential cognitive states. Thus, a given fMRI network configuration might reflect the sum of several oscillatory network configurations, each of which had a brief duration. When interpreting the results of multimodal studies, researchers should expect that each network identified in their fMRI data is likely to decompose into multiple oscillatory network configurations. In addition, they should expect fMRI data reflecting early sensory processing to correspond most closely to evoked responses in EEG/MEG/ECoG data, as much of signal contributing to the event-related averages in these data involves oscillations phase-locked to the onset of sensory stimuli. In contrast, fMRI data reflecting high-level cognitive processing involving cognitive stages with more variable timing should correspond more closely to induced responses in EEG/MEG/ECoG data, as these reflect oscillations not precisely phase-locked to the onset of sensory stimuli. It should be noted that both evoked and induced responses may derive from frequency-dependent changes in phase alignment (Burgess, 2012).


6.4 Directions for future research

Much of the work remaining for future research involves describing cognitive processes in terms of the activities of their underlying brain networks, identifiable both in BOLD signals and in patterns of electrophysiological activity. The combined high spatial and temporal resolution of such multimodal analyses, as well as the potential for identifying complex multi-frequency oscillatory patterns, represents an opportunity for extensive discovery by cognitive neuroscientists. A promising approach to combining the spatial resolution of fMRI with the temporal resolution of EEG or MEG involves identifying oscillatory networks with high spatial correspondence to fMRI networks. The time-course of oscillatory activity can then be described with high temporal resolution, while the fMRI data provide high confidence in the locations of the generators of the oscillatory signals.

There is also a need for more basic research on the generating mechanisms of neuronal oscillations (Burns, Xing, & Shapley, 2011), extending our understanding beyond the hippocampus to a diversity of neocortical and sub-cortical regions. One interesting finding in this area involves patterns of oscillatory connectivity between neocortical layers. Oscillatory activity in V1 appears to be compartmentalized within either infragranular layers, which project largely to thalamic regions, or granular and supragranular layers, which project mainly to other cortical regions (Maier, Adams, Aura, & Leopold, 2010). It would be interesting to investigate whether communication between those compartments was accomplished via the cross-frequency coupling underlying connectivity in thalamo-cortical visual networks (Wang et al., 2012). Finally, understanding how the brain networks evident in multimodal studies are affected by genetic variants and neurotransmitter levels will be integral to understanding clinical etiology and advancing treatment.
6.5 Conclusion

If multimodal studies attempt to identify the electrophysiological metric that best predicts the BOLD signal, they will produce findings of limited generalizability. There is no single oscillatory frequency range, and no single measure of neuronal oscillation or synchronization, that can be said to be the best predictor. Rather, the pattern of correspondence between electrophysiology and hemodynamics will depend upon whether one compares spatial patterns of network activity or network time courses. It will also depend upon whether one compares signal strength at a local level or at a whole-brain level. Finally, it will depend upon whether data are recorded at rest or during performance of a cognitive task, and upon the specific cognitive demands of said task. Converging results obtained using diverse measurements suggest that the BOLD signal strength corresponds well with high frequency oscillatory power at the local level, and that functional connectivity in the BOLD signal across greater distances corresponds well with lower frequency oscillations. It would be more fruitful, however, for researchers to explore how these different oscillatory frequencies work in concert. A particular pattern representing a combination of low and high frequencies (such as when high-frequency amplitude depends upon low-frequency phase) may organize activity at a local level by integrating some signals while segregating others, and simultaneously co-ordinate multiple organized local patterns across much greater distances. These multi-frequency patterns provide an optimal explanation for the mechanisms of cognitive processing because they dynamically change at the same pace as cognition.
7 General Discussion

The general goal of our investigations was to identify cognitive factors affecting hypothesis judgments and underlying brain networks. Specifically, we predicted that judgments would be sensitive to cognitive coherence, as would the activity of underlying functional brain networks. This could be coherence between the initially presented evidence and subsequently presented or re-considered evidence, between the focal hypothesis being judged and the available evidence, or between a self-selected, preferred hypothesis and subsequently presented or re-considered evidence. This bias would result from the corresponding mental representations of the evidence and hypothesis forming a stable, salient gestalt.

7.1 Discussion of behavioural results

Our behavioural investigations identified two cognitive factors affecting hypothesis judgments, despite no effect being predicted by mathematically normative models. The first of these involved a bias towards giving more weight to gradually accumulated evidence than to the same evidence presented instantaneously, as we had expected. Contrary to our predictions, the bias in favour of gradual evidence was not driven by an anchoring effect, was independent of whether the evidence supported or refuted the focal hypothesis, and was independent of the strength of the evidence. Thus, the bias in favour of gradual evidence does not appear to be an effect of cognitive coherence between the evidence and focal hypothesis. Rather, it involves a tendency for the overall salience of unpacked evidence to be greater than that of packed evidence.
The second cognitive bias identified involved judging self-selected focal hypotheses to be more probable than externally selected ones with equivalent supporting evidence. Like the gradual evidence effect, the selection bias effect was not dependent on evidence strength. The bias depended on a categorical choice of hypothesis rather than on the extent to which the relevant evidence was coherent with the preferred hypothesis. While selection bias does not result from coherence, it might be said to cause a coherence effect, in that selecting a preferred hypothesis resulted in a subsequent overestimation of evidence supporting (coherent with) that hypothesis.

As predicted, selection bias was exacerbated in delusional schizophrenia patients. An interesting direction for future research would be to investigate whether this correlated with another effect in that population, in which ‘evidence-hypothesis matches’ were found to be hypersalient while mismatches were not (Speechley et al., 2010). In that case, there was no explicit choice of preferred hypothesis before probability ratings were made. Instead, evidence in favour of an externally selected focal hypothesis was judged to be stronger than objectively equivalent evidence in favour of an alternative hypothesis. In other words, coherence between a hypothesis and the available evidence biases judgments in schizophrenia. It would be interesting to examine whether that bias was related to selection bias.

A limitation of using a probabilistic reasoning paradigm to study selection bias is that it has limited real-world validity, as many hypotheses are not merely self-selected, but rather self-generated. A limitation of paradigms involving self-generated hypotheses is that they would not allow us to control for the strength of the evidence considered. However, the generation (rather than selection) of a preferred hypothesis involves cognitive processes not
included in our probabilistic reasoning paradigm. For this reason, a task involving self-generated hypotheses may have utility for future studies of delusional schizophrenia patients as a result of greater real-world validity.

7.2 Discussion of neuroimaging results

In the neuroimaging study reported here, we found a difference in network activity between evidence-hypothesis matches and non-matches. This was in a network involving the dACC, bilateral parietal cortex, and bilateral occipital cortex. Our results were consistent with the prediction that evidence-hypothesis matches would result in a coherent, stable, salient mental representation (or gestalt) and a correspondingly stronger signal from the brain network underlying that mental representation. Contrary to our expectations, we found no effect of evidence strength on network activity. One possible explanation for that is the poor temporal resolution afforded by fMRI. As we noted in Chapter 6, this could cause the signals associated with subsequent cognitive processes to merge. Future research using the high temporal resolution of EEG or MEG to dissociate between the patterns of activity associated with sequential processes might reveal effects of evidence strength.

One methodological limitation of the neuroimaging study reported here is that the use of a Likert scale for making probability judgments required multiple button presses on the response box. This meant that any direct comparisons between high and low levels of evidence strength would be confounded with the amount of motor activity – specifically, the number of button presses made. If there had been an effect of evidence strength or certainty that did not depend on whether the evidence supported the focal hypothesis that effect would have been confounded with the amount of motor activity (the number of button presses
made). Such confounds could be avoided in future studies via an MRI-compatible trackball mouse. However, the distance traveled by the mouse would still vary as a function of certainty, so confounds with motor activity would only be minimized, not completely eliminated. An alternative would be using the button box to elicit categorical ratings of ‘strongly agree’, ‘agree’, ‘disagree’, and ‘strongly disagree’. However, this would eliminate the option of recording behavioural biases in probability ratings and correlating those with brain activity.

7.3 Conclusions

Before conducting these studies, we predicted one of two distinct effects fitting within the general framework of cognitive coherence. One possibility was that the degree to which the initially presented evidence supported the focal hypothesis would determine the strength of a bias in subsequent judgments. Another way of phrasing this is to say that the magnitude of bias would depend on the magnitude of objectively quantifiable coherence between the evidence and the focal hypothesis. The other possibility was that the presence or absence of a bias would depend on a binary distinction, namely whether the initially presented evidence supported or refuted the focal hypothesis. In this case, the strength of a measured bias would not depend on the level of objectively quantifiable coherence. Instead, a bias would be observed if the evidence supported the focal hypothesis, and absent if the evidence refuted it. This second possibility was most consistent with our results.

Behavioural studies of hypothesis comparison showed that making an initial choice between two or more hypotheses biased later judgments, regardless of whether those later judgements involved new evidence or re-evaluation of the initially presented evidence.
Choosing a preferred focal hypothesis biased later judgements of relevant evidence in Chapters 3 and 4. In contrast, an initial judgment of the relative probability of the focal hypothesis, made on a Likert scale, did not bias subsequent judgments. This was seen in the absence of either an anchoring effect or an effect of repeated judgments in Chapter 2.

We also found that choice affected the activity of a dACC-based functional brain network in our fMRI study. However, that network was not affected by evidence strength. Thus, behavioural and neuroimaging results both indicate some unique processing involved in choosing to accept a hypothesis. Behaviourally, we observed a bias in favour of evidence coherent with a hypothesis the participant had previously accepted. That effect was specific to situations in which a choice was made – situations in which the initial evidence was processed in a binary or categorical manner rather than as a continuous variable. This is relevant to many real-world judgment and decision-making situations in which evidence strength is not objectively quantifiable, and categorical processing, such as that involved in a pro-con list, is the only option. This may be why the cognitive processes underlying hypothesis judgment lack the precision inherent to the mathematically normative judgments. If quantifiable evidence is often unavailable, defaulting to associative processing based on cognitive coherence may be the optimal strategy for avoiding indecision.
References


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### Appendix 1: Clusters and Peak Locations for Networks Identified in fMRI Data

Table A1. Cluster volumes for most extreme 20% of Component 1 loadings, with anatomical descriptions, MNI coordinates, and Brodmann’s area for the peaks within each cluster. Only clusters > 25 mm³ are presented here. All of the loadings for this component were positive.

<table>
<thead>
<tr>
<th>Cortical Regions</th>
<th>Cluster Volume (mm³)</th>
<th>Brodmann’s Area for peak locations</th>
<th>MNI Coordinate (X Y Z) for peak locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1 (Bilateral):</td>
<td>308032</td>
<td></td>
<td></td>
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<tr>
<td>Superior Parietal</td>
<td>7</td>
<td>32</td>
<td>-60</td>
</tr>
<tr>
<td>Middle Occipital</td>
<td>18</td>
<td>-32</td>
<td>-96</td>
</tr>
<tr>
<td>Fusiform Gyrus</td>
<td>18</td>
<td>-28</td>
<td>-88</td>
</tr>
<tr>
<td>Superior Parietal Lobe</td>
<td>7</td>
<td>-24</td>
<td>-68</td>
</tr>
<tr>
<td>Precuneus</td>
<td>7</td>
<td>28</td>
<td>-72</td>
</tr>
<tr>
<td>Inferior Occipital Gyrus</td>
<td>18</td>
<td>32</td>
<td>-92</td>
</tr>
<tr>
<td>Cingulate Gyrus / dACC / Supplementary Motor Area</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Lingual Gyrus</td>
<td>17</td>
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<td>-100</td>
</tr>
<tr>
<td>Middle Occipital Gyrus</td>
<td>19</td>
<td>36</td>
<td>-88</td>
</tr>
<tr>
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<td>Fusiform Gyrus</td>
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<tr>
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<td>-68</td>
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<tr>
<td>Lateral Occipital Gyrus</td>
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<tr>
<td>Cerebellum (Left)</td>
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<td>Supramarginal Gyrus</td>
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</tr>
<tr>
<td>Precentral Gyrus</td>
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<td>-52</td>
<td>8</td>
</tr>
<tr>
<td>Precentral Gyrus</td>
<td>4</td>
<td>-36</td>
<td>-20</td>
</tr>
<tr>
<td>Superior Frontal Gyrus / Supplementary Motor Cortex</td>
<td>6</td>
<td>-4</td>
<td>0</td>
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Cluster 2: 7168  
Right Precentral Gyrus 44 56 12 32

Cluster 3: 5632  
Right Superior Frontal Gyrus / Frontal Pole 46 40 44 28

Cluster 4: 960  
Right Thalamus n/a 12 -16 8
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<th>Brodmann’s Area for peak locations</th>
<th>MNI Coordinate (X Y Z) for peak locations</th>
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<td>-44 28 28</td>
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<td></td>
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<td>32 20 0</td>
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Table A2. Cluster volumes for most extreme 20% of Component 2 loadings, with anatomical
descriptions, MNI coordinates, and Brodmann’s area for the peaks within each cluster. Only
clusters > 25 mm$^3$ are presented here. Positive and negative loadings are presented in the top
and bottom sections of the table, respectively.

<table>
<thead>
<tr>
<th>Cortical Regions</th>
<th>Cluster Volume (mm$^3$)</th>
<th>Brodmann’s Area for peak locations</th>
<th>MNI Coordinate (X Y Z) for peak locations</th>
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<td>Brodmann’s Area for peak locations</td>
<td>MNI Coordinate (X Y Z) for peak locations</td>
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Appendix 2: The Most Extreme 5% of Loadings for

Components 1 and 2 of Chapter 5