The Cognitive and Neural Mechanisms of Curiosity Driven by Visual Uncertainty

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Declaration

I declare that this thesis is my own work under the supervision of Professor Gert Westermann and Dr Katherine Twomey and that it has not been submitted substantially the same for the award of a higher degree elsewhere.

Signed:

Date: 12/12/2022

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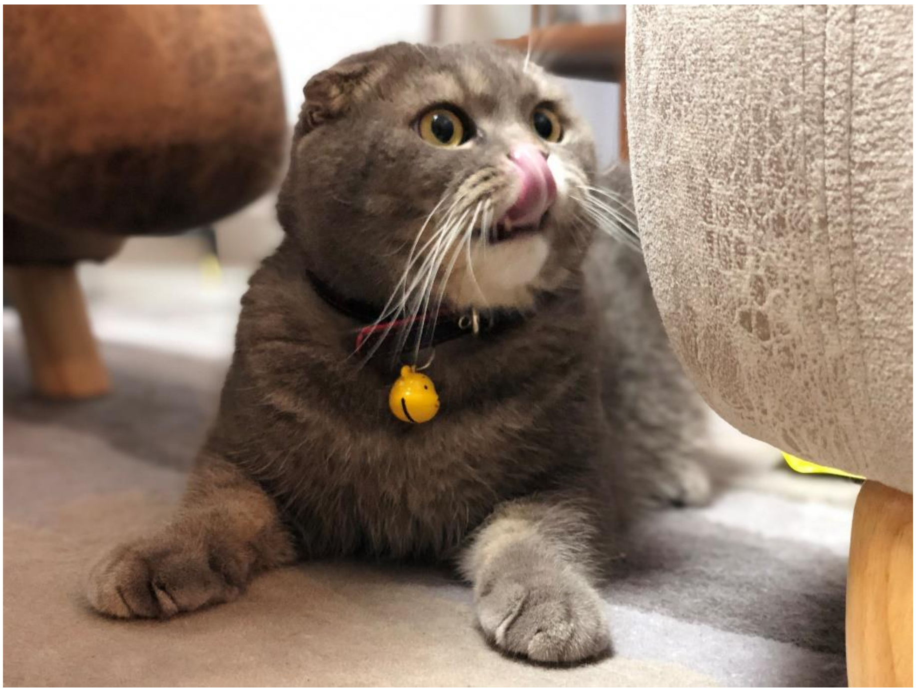
List of Abbreviations

ACC	Anterior Cingulate Cortex
AOI/AOIs	Areas of Interest(s)
ANOVA	Analysis of Variance
CI	Confidence Interval
CLMM	Cumulative Link Mixed-Effects Model
EEG	Electroencephalogram
EGI	Electrical Geodesic Incorporated
ERD	Event-Related Desynchronisation
fMRI	Functional Magnetic Resonance Imaging
GLMM	Generalised Logistic Mixed-Effects Model
NOUN	The Novel Object and Unusual Name Database
OSF	Open Science Framework
VIF	Variance Inflation Factors for collinearity

For Pepper & Max



Thesis Abstract

Curiosity is regarded as one of the most important drives in human cognition, which motivates us to explore the environment and influences our decision-making (Gottlieb & Oudeyer, 2018; Kidd & Hayden, 2015; Loewenstein, 1994). There has been increasing research interest dedicated to studying the biological function, the underlying mechanisms of curiosity and its beneficial effects on learning (Berlyne & Normore, 1972; Fandakova & Gruber, 2021; Gruber et al., 2014; Jepma et al., 2012). Yet, there is still a lack of evidence to uncover a full picture of the underlying mechanisms of curiosity and learning. On the other hand, the majority of currently available curiosity research was conducted with and based on adult participants. Yet, infants and children, especially young infants as curious learners explore their environment actively and seek novelty, and the more nuanced aspects of curiosity in this age group are less researched. Therefore, this thesis seeks to research curiosity-based learning in infants as well as adults using a variety of methods from behaviour, and eye tracking to electroencephalogram (EEG), aiming to provide empirical evidence and new insights into the field.

In Chapter 1, a general background of the literature was first provided with highlights of the most relevant theories and empirical research in both adults and children. In Chapter 2, against the background that curiosity about uncertainty enhances attention, benefiting learning in adults, yet, it is unclear whether this stays true for young infants and what the role of curiosity resolution may play in young children. Two experiments were conducted using eye-tracking method and novel, infant-friendly paradigms to investigate (1) whether curiosity induced by uncertainty enhances object learning in young infants, and (2) whether young infants seek resolution of curiosity over novelty. These two experiments provide supporting evidence that curiosity induction is associated with attentional arousal. However, given the ambiguity about the interpretations of the looking preference paradigm, further investigation

is needed to examine the precise manifestation of attentional arousal during the processing of visual uncertain information. The results from this chapter also give no obvious evidence that young infants would prefer curiosity resolution over novelty, indicating that infants might not have yet developed epistemic curiosity in this age group.

In Chapter 3, an EEG study with adult participants was conducted to investigate neural oscillations in response to curiosity about visual uncertainty, as little knowledge that we know about the neural representation of curiosity driven by visual uncertainty at a cortical level. This investigation provides supporting evidence that curiosity about visual uncertainty is associated with attentional arousal as indicated by increased alpha desynchronisation. As the role of metacognitive ability in curiosity-based learning has been highlighted in the literature, in Chapter 4, an online study was designed to investigate the roles of subjective prior knowledge, confidence and curiosity in learning using a blurred image paradigm with adult participants, allowing for improving and extending the generalizability of research findings in the field.

Overall, the findings of these experimental studies reveal a complex nature of curiosity about visual uncertainty, suggesting a potential developmental trajectory such that curiosity changes from a broader state of attentional arousal in young infants to more goal-directed and metacognitive-based information seeking in adults. The implications of these findings for future research and suggestions are discussed.

Chapter 1

Literature Review: On Curiosity

1.1 General Introduction and Chapter Overview

Curiosity is a basic drive for information and knowledge acquisition that plays a crucial role in motivating learning and influencing our decision-making throughout development. In the last decades, there has been increasing interest in curiosity across wide-ranging disciplines, including cognitive psychology, neuroscience, personality psychology and so on, providing many valuable insights about its nature. Despite these recent scientific advances, there is an absence of a clear definition of curiosity, leading to a rich set of similar notions used in the literature, such as exploratory behaviour (Berlyne, 1950), information-seeking behaviour (Gottlieb et al., 2013), curiosity-driven learning (Twomey & Westermann, 2018), active learning (Deci & Ryan, 1981; Gureckis & Markant, 2012; Saylor & Ganea, 2018) and so on.

Among these broadly interchangeable terms, curiosity is generally viewed as an intrinsic drive (Kidd & Hayden, 2015) that motivates a learner to actively explore, seek and obtain information without obvious external reward (Gottlieb & Oudeyer, 2018; Harlow & McClearn, 1954; Oudeyer & Smith, 2016; Ryan & Deci, 2000). Humans indeed exhibit pervasive intrinsically motivated information-seeking behaviour. For example, young infants play with and explore toys by chewing, throwing and manipulating autonomously, actively and continuously. Adults also spend time reading books, engaging with puzzles and other activities without foreseeable incentives but for fun. Beyond these examples, curiosity, as an inner need for knowledge, not only drives human cognitive development but also has its evolutionary value in expanding the knowledge boundary and inspiring innovation and discovery (Oudeyer & Smith, 2016).

Given the significant role of curiosity in motivating information-seeking and driving knowledge acquisition, it is important to understand what curiosity is and its underlying mechanisms. Hence, this chapter will summarise and evaluate significant theories and approaches to curiosity, offering a general background to the literature. Then, reviews on the current development of empirical curiosity research in adults and infants are introduced respectively. Finally, a general conclusion of this chapter and an overview of the current thesis objectives are presented.

1.2 Theories of Curiosity

There have been surges of curiosity research activities since the 1950s. A few important theories and ideas derived from these activities, from the early conceptualisation of curiosity, have substantially influenced current concepts of curiosity. This section will highlight the drive-arousal theory (Berlyne, 1954) and the information-gap theory (Loewenstein, 1994), as these approaches are closely relevant to the key research questions of this thesis: the relationship between curiosity and arousal (Chapter 2 and Chapter 3) as well as the role of metacognition in curiosity (Chapter 4). More contemporary approaches that emphasise the role of reward in driving curiosity, such as the learning progress theory proposed by Oudeyer and colleagues (2007; 2018) and the reward-learning approach by Murayama and colleagues (2019; 2022) will also be introduced.

1.2.1 The Drive-Arousal Theory: Curiosity is an Aversive and Aroused State

Dating back to the 1950s – 1960s, the first surge of curiosity research activity, led by behaviourists, focused on the psychological basis of curiosity and asked questions such as whether curiosity is a homeostatic drive and what factors influence it. In this drive-arousal theory, curiosity is assumed to be a form of homeostatic drive that is similar to hunger or thirst (Berlyne, 1954). Like other basic drives (e.g., hunger), once aroused, it is thought to create an aversive state which would intensify gradually if not satisfied. As the aroused state is aversive, it motivates organisms' exploratory behaviour to reduce the level of aversive arousal.

Such an aroused state could be induced by different sources, and it has been argued that different sources of curiosity lead to different *types* of curiosity (Berlyne, 1960). For example, curiosity induced by external stimuli that are high in collative[1] properties such as complexity, novelty, surprise and incongruity is referred to as *perceptual curiosity*. Curiosity could also be elicited internally by higher-order motivation such as a desire for gaining information and knowledge acquisition. This *epistemic curiosity* is bound to an individual's internal symbolic representations and is likely to be evoked by existing ideas and concepts in mind. In Berlyne's view (1960, 1966), human adults are more likely to seek "symbolically expressed information" (1966, p32) relative to young children and animals. Most importantly, in his opinion, there are distinct hierarchical differences between perceptual and epistemic curiosity such that epistemic curiosity is a higher level of cognition relative to perceptual curiosity. Additionally, according to the breadth of sources that triggers it, curiosity has also been categorised into *specific curiosity* and *diversive curiosity*[2]. *Specific curiosity* is the desire, triggered by particular sources (e.g., one particular object or event), to seek a particular piece of information about the sources (e.g., the nature of the object or the event). In contrast, *diversive curiosity* does not seek to gain specific information to resolve uncertainty. Rather, it is a general motivation for perceptual or cognitive stimulation and it is likely to be triggered by boredom (Berlyne, 1960).

Although extensive research has been carried out to examine the drive-arousal theory (Berlyne, 1960), the main weakness of this approach is the failure to explain why people would actively expose themselves to curious situations and seek them out, if curiosity is an

[1] Collative refers to features or properties that have a certain arousal potential, such as novelty, complexity, uncertainty or conflict. See p60 in Conflict, Arousal and Curiosity (1960).

[2] In Berlyne's book on Conflict, Arousal and Curiosity (1960), he used specific and diversive exploration.

aversive state. Plausibly, one would assume that it is human nature to avoid situations that cause aversion. In addition, for the two-dimensional categorisation of curiosity (i.e., perceptual vs. epistemic, specific vs. diversive), this theory does not provide a clear specification to account for the differences between the four types of curiosity. In particular, it seems that regardless of the sources (perceptual or epistemic) that excite curiosity, specific (and epistemic) curiosity could be elicited. And when perceptual curiosity is piqued, the relief of perceptual curiosity will ultimately be through specific exploration or epistemic activities (Berlyne, 1960). For example, when hearing a very brief snippet of a familiar song from a podcast, one would experience a sudden urge and be motivated to search for what the song was based on a few words of the lyrics they just heard. In other words, perceptual or epistemic probes of curiosity are often intertwined and hard to disentangle, and whether they are separable remains debated. Furthermore, further work is also required to investigate the relationships between curiosity, arousal and other cognitive functions, especially attention. Attention and arousal closely interact with each other. Attention is the ability to control and allocate cognitive resources and has been divided into alertness, selective attention, and focused/sustained attention (Lindsay, 2020). Arousal is a physiological reaction, elicited by low-level stimulation or higher-level cognition (Coull, 1998), which could be a part of the attention system (i.e., alertness). Although there is a general consensus that curiosity is related to increased arousal, there is very little empirical research investigating what the arousing state of curiosity is like and how it could be related to other aspects of the attention system (e.g., the potential effects of aroused curiosity states on selective attention and sustained attention).

1.2.2 The Information-Gap Theory: Curiosity and Metacognition

Inspired by past theories (Berlyne, 1954; Festinger, 1962; Hebb, 1955; Hunt, 1965), Lowenstein (1994) proposed the influential information gap theory, which exclusively discusses specific epistemic curiosity. In his point of view, curiosity is strictly intrinsically motivated and is a cognitively-induced deprivation that arises from the perception of a gap in knowledge and understanding, highlighting the essential role of metacognition in curiosity. More specifically, it is thought that curiosity arises from an individual's awareness of a gap between what one knows and what one wants to know, indicating at least two prerequisites to trigger curiosity: an estimate of prior knowledge and an identification of a missing piece of specific information for understanding. Similar to the drive-arousal approach, it is assumed that the elicited curiosity is an aversive state and creates a sense of deprivation, which motivates an individual to seek it out. In addition, it assumes that gaining the information for curiosity reduction is rewarding, which overrides the aversiveness derived from curiosity induction, reinforcing and resulting in more voluntary curiosity behaviours. In particular, the degree to which curiosity could be excited depends on the size of the information gap, quantified by the differences between one's current knowledge state and an informational goal. If the information gap is too small or too large, meaning that the potential information gain would not compensate for the aversiveness from the induced curiosity in the first place, an individual would not pay attention to it. Thus, an individual would always seek information that is just above their current knowledge level.

Although this 'just-about-right' knowledge gap perspective has been demonstrated empirically (Baranes et al., 2015; Kang et al., 2009), findings in the literature concerning the relationship between the size of the knowledge gap and curiosity remain inconsistent. For example, it has been found that higher curiosity is related to both smaller and larger knowledge gaps relative to an intermediate gap. Studies using trivia question paradigms to study the associations between a perceived knowledge gap and curiosity about trivia questions found that the closer the participants felt they were to the correct answers (i.e., a smaller knowledge gap), the more curious they were (Litman et al., 2005; Metcalfe et al., 2017; Wade & Kidd, 2019). On the other hand, studies using a lottery paradigm also found that curiosity increases linearly as the unpredictability of the lottery outcome (i.e., a larger information gap) increases linearly (van Lieshout et al., 2018). Overall, these mixed findings reveal that the degree to which the knowledge gap modulates curiosity needs further investigation.

Moreover, the central ideal in this theory is that curiosity requires metacognitive abilities and the awareness of an information gap derived from one's current knowledge base, which fails to explain curiosity in young children who do not have the metacognitive awareness necessary to identify their knowledge gaps. Further work is required to establish the degree to which metacognition affects curiosity and how this effect might change across development.

1.2.3 The Driving Forces of Curiosity: Rewards

A central theme in curiosity research is to understand why curiosity has such motivational power in driving human behaviour for information acquisition. A general consensus on the answer is that curiosity is driven by non-instrumental rewards such as learning itself and information. Here, two approaches will be presented to explain the association between curiosity and these rewards.

1.2.3.1 Learning Progress Approach: Learning as a Reward

The learning progress theory (Oudeyer & Kaplan, 2007) assumes that curiosity is an intrinsic motivation to acquire knowledge, which has two key predictions: (1) learning happens via prediction error reduction, and (2) learning itself is rewarding. Based on these two principles, a learner would always prefer to maximise learning progress and so would maximise rewards by choosing information with a moderate level of predictability, permitting self-directed learning and allowing maximal information gain. The rationale of this selectivity for moderate predictability lies in the assumption that stimuli or situations with such predictability could provide maximal information gain and therefore maximal learning progress and maximal reward. In other words, if a learner focuses on stimuli that are very predictable (small prediction errors), learning progress would be small, and if it focuses on stimuli that are too unpredictable (large prediction errors), it is likely to be trapped in the 'white noise' situation where stimuli are inherently too complex to make learning progress.

Empirical evidence from both infant and adult studies suggests that indeed, both infants and adults have the tendency to allocate their attention to stimuli that could maximise their learning progress (Kidd et al., 2012, 2014; Poli et al., 2020, 2022). In a study with 8-month-old infants, Poli and colleagues (2020) presented infants with stimuli that had different levels of surprise, predictability and learning progress (information gain). They found that infants allocated their attention to the stimuli that offered maximal learning progress. Most importantly, when the progress of learning one stimulus diminished, infants would search for new input that further maximised their information gain. Similar learning patterns were found in adults such that adults would continuously engage with an environment as long as the environment provided learning progress (Poli et al., 2022). When the learning progress decreased, adults looked for a new learning environment. Overall, this approach provides a good explanation for exploratory and information-seeking behaviour, which captures the mechanism of human intrinsic motivation for autonomous, self-directed and curiosity-driven learning.

However, there are some shortcomings of this approach. First, it falls short of explaining cases such as familiarity preference where individuals show a preference for a familiar over a novel stimulus. One of the key predictions of this approach is that a learner would search for new inputs for information gain when the learning progress decreases. Therefore, if a learner already gains enough information from a familiar object, redirecting the attentional resources toward the same, perceived object would likely provide very little information gain or learning progress. In contrast to constantly searching for novel information, a preference for familiar inputs is quite prevalent, especially in young infants

(Houston-Price & Nakai, 2004) and also in adults (Park et al., 2010). Second, supporting evidence is mostly derived from studies employing a tightly-controlled experimental environment, meaning that computational demands were low. However, when in a real-life and highly complex environment, a learner will need to compute and keep track of the expected error rates across various situations and compare them to choose an ideal learning opportunity. This means it would need great computational power to switch between different types of activities as they would have different predictive models, and a large amount of memory storage to deal with multiple activities simultaneously. Although extensive evidence also suggests that people are good at flexibly switching between tasks (Ong & Gupta, 2016), it comes at the cost of decreased performance and increased mental stress (Dzubak, 2008). Finally, the learning progress approach is built to optimise immediate rewards. Thus, it cannot explain problems involving delayed rewards. In other words, it cannot explain cases in which humans would wait to satisfy their curiosity (Mullaney et al., 2014; Rosenbaum & Johnson, 2016). Taken together, future studies on the ecological validity of this approach are therefore recommended.

1.2.3.2 The Process Account: Information as a Reward

Distinct from the discussed theories or frameworks, the process account of curiosity proposed by Murayama (2019, 2022) considers curiosity as a folk concept that does not and need not have a formally standardised definition. This approach regards curiosity, *not* as a constituent element in the framework, but as a subjective experience that emerges during the pursuit of knowledge acquisition. Therefore, this framework prioritises the importance of understanding the process of (autonomous) knowledge acquisition instead of curiosity itself.

In essence, this process account builds upon the information gap theory (Loewenstein, 1994), also upholding the idea that information-seeking behaviour starts from the awareness of a knowledge gap (i.e. a state of uncertainty) in one's existing knowledge base (i.e. prior knowledge). In addition, this account highlights the significance of the expected information that could resolve the identified gap and considers it to be rewarding. Once that information is received and the gap is closed, the learner experiences the feeling of reward, which sustains subsequent information-seeking behaviour and knowledge-acquisition activities. Moreover, there are several factors such as personality traits, the magnitude of a perceived knowledge gap, the emotional valence of the expected information and so on, emphasised in this framework that could influence the process of knowledge acquisition and the experience of curiosity.

Overall, this process account offers a unique perspective with regard to the relationship between information-seeking behaviour and curiosity. It illustrates how knowledge acquisition in general could be intrinsically incentivised as long as learning and information gain are ongoing. The experience of curiosity emerges during this process, i.e. *'I am learning so I become curious.'*. This account reveals the reason why the exact concept of curiosity is so difficult to pinpoint – as curiosity is simply the experience or psychological state that appears in the process of knowledge acquisition. Such an approach offers new insights into the field, positing the idea that knowledge itself is the ultimate goal of information-seeking behaviour regardless of its motives, revealing the core of knowledge acquisition – information gain.

However, the major limitation of this approach is that viewing curiosity as an experience that emerges during the learning process poses a challenge to investigating it empirically. For instance, if curiosity indeed is an experience, how and in what way could it be measured and studied? Without a precise definition, it is impossible to do so. On the other hand, the central idea of this framework is that information-seeking behaviour is driven by the reward value of information in general. Therefore, learners would actively approach information that fills a knowledge gap as they would feel rewarded once they receive the information. Yet, people also actively avoid being exposed to information such as spoilers of a film (Hertwig & Engel, 2016; Rosenbaum & Johnson, 2016), which could not be explained by this approach, indicating an issue of underspecification. Most importantly, it is not specified in this framework whether this feeling of reward is related to and to what extent it is associated with the experience of curiosity.

Another concern is that, like the earlier information gap approaches, the process account hinges closely on a learner's metacognitive ability in identifying a knowledge gap and their prior knowledge base. As a result, it excludes a wide range of information-seeking behaviours particularly in young children and those behaviours of seeking novelty and surprise, i.e. *'I am curious so I would like to learn.'*. In other words, these behaviours are against the core idea that curiosity emerges during the process of knowledge acquisition because they are instances in which curiosity occurs before learning happens. Last but not least, a few factors mentioned earlier could influence the process of knowledge acquisition, such as the personality trait of a learner and confidence in estimating a knowledge gap (Durik et al., 2015; Murayama et al., 2016). It is unclear how these factors would impact the learning process and interact with the experience of curiosity.

Taken together, there are still many unanswered questions about the role of curiosity in knowledge acquisition according to this process framework. For example, if curiosity indeed is an experience that emerges during information seeking, in what way will this experience manifest? Could it be attentional arousal as Berlyne predicted or an emotional experience? If the reward value embedded in information is indeed the driving force of knowledge acquisition, what is the relationship between reward and curiosity? Would differences in perceived reward have an impact on the experience of curiosity? For a full understanding of the process account and its predictions, further studies which take these questions into account will need to be undertaken.

1.2.4 Interim Summary: Theories in Relation to the Current Thesis

This section summarised the key theories of curiosity in the literature that are most relevant to the current thesis, providing multiple perspectives on what curiosity is and why we are so curious. Overall, curiosity is the pursuit of information, which could manifest in various ways (e.g., a state of arousal, exploratory, information-seeking behaviour or a form of experience) with diverse goals (e.g., novelty seeking, closure of a knowledge gap or information gain). These theories have provided rich and nuanced explanations of curiosity, which help establish the foundation for empirical research and open up many new questions for future investigation. On the other hand, this section also raises intriguing questions regarding the nature and extent of curiosity in relation to arousal, metacognition, information-seeking behaviour and reward learning. Therefore, in this investigation, this thesis set out to investigate two key themes (1) the relationships between curiosity, arousal and attention, (2) the relationships between curiosity, metacognition and learning.

1.3 Current Research in Curiosity

Empirical research in curiosity has yielded many fruitful outcomes in the past few decades, revealing the underpinning causes of curiosity from multiple disciplines. This section aims to provide brief reviews on the current development of curiosity research in both adults and children, with the main focus on the literature that is most relevant to this thesis.

1.3.1 Current Research in Adult Curiosity

This section will focus on introducing the current development of curiosity research in adults from three aspects. First, paradigms that have been used frequently in empirical studies will be introduced, centring on the questions of *how* curiosity is operationally defined and measured. Second, as a central theme in the literature and this thesis, the roles of uncertainty in the literature of curiosity and its relation to metacognition will be discussed. Finally, summaries of findings about the boosting effect of curiosity on learning will be provided.

Paradigms of Curiosity Studies

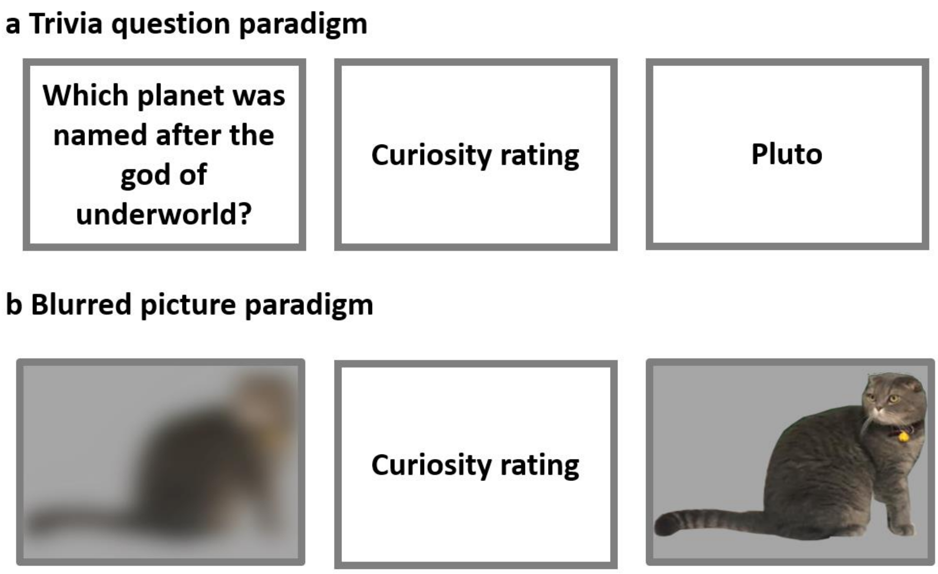
To operationally measure curiosity in the laboratory, several paradigms with different experimental materials (e.g., trivia questions, blurred images and lottery tasks) and designs have been developed to investigate the state of curiosity. The core idea of these designs lies in using these materials to moderate states of curiosity including induction and reduction of curiosity. This section summarises three paradigms that have been frequently applied to investigate different aspects of curiosity: trivia question paradigms (Kang et al., 2009), uncertain picture paradigms (Berlyne & Normore, 1972; Nicki, 1970) and lottery tasks (Kobayashi et al., 2019; Van Lieshout et al. 2018).

To begin with the most frequently used paradigm, the trivia question paradigm (Figure 1a), the central idea behind this paradigm is largely based on the information gap theory (Loewenstein, 1994) such that experiencing a sense of lack of information associated with one's prior knowledge base induces states of curiosity. Thus, in this paradigm, a set of trivia questions as partial or incomplete information are shown to participants to induce their curiosity. Participants are asked to answer questions such as '*What is the ninth most poisonous animal in the world?*' and '*What was the name of the first probe to send back pictures from Mars?*'. Then, participants answer self-reported questions about the level of curiosity about the answer to each trivia question (i.e., "How curious are you about the answer?"). Finally, the answer to the trivia question is revealed to resolve the elicited curiosity. For uncertain picture paradigms (Figure 1b), the main idea is based on the drive-arousal theory which suggests that being exposed to a stimulus high in uncertainty induces curiosity. Therefore, in this case, distorted pictures (e.g., blurred, scrambled) are presented to participants who are then asked to identify the displayed objects and evaluate how curious they are about the identity of the pictures. Finally, the clear corresponding picture to the uncertain picture is revealed to resolve the induced curiosity.

Another frequently used paradigm is lottery tasks, which are based on the idea that both uncertainty and reward from information gain modulate curiosity and its associated decision-making behaviour. In these tasks, a lottery task in which both outcome uncertainty (e.g., the likelihood of a certain lottery outcome) and expected reward of the outcome (e.g., whether the lottery outcome is revealed or not) are manipulated independently, allowing for disentangling the relationships between curiosity, uncertainty and reward of information. Participants indicate their curiosity by answering "*How curious are you about the outcome?*" or "*Do you want to see the outcome?*" when they are about to see the outcome of the lottery. These tasks usually are used to study neural circuits related to curiosity, uncertainty and reward (Kobayashi et al., 2019; Van Lieshout et al. 2018).

Taken together, this summary shows that different paradigms of curiosity studies have different theoretical viewpoints and various research purposes. Depending on the objectives of the research, additional changes are made to the 'prototype' paradigm to fit the research need. Generally speaking, these paradigms usually attempt to investigate research questions about the induction of curiosity ("*What makes us curious?*"), the reduction of curiosity ("*What are we curious about?*") and the role of curiosity in learning. The following section therefore will introduce current research with regard to these questions.

Figure 1 *Curiosity paradigm: a. an example of the trivia question paradigm; b. an example of a blurred picture paradigm*



Curiosity and Uncertainty

The role of uncertainty in eliciting curiosity has been noted in both theoretical and empirical studies. It is been suggested that situations that are high in perceptual (Berlyne, 1954) and epistemic uncertainty (Loewenstein, 1994; Golman & Loewenstein, 2018) are aversive and related to an increase in arousal, which provokes curiosity, motivating an individual to seek out the uncertainty. Different empirical studies have also provided supporting evidence for this view (Nicki, 1970; Jepma et al., 2012; Kang et al., 2009; Gruber et al., 2014; Kobayashi et al., 2019; van Lieshout et al., 2018). Findings from neuroimaging studies have demonstrated curiosity driven by perceptual uncertainty led to greater responses in brain structures such as the anterior cingulate cortex (ACC) and the striatum that are sensitive to aversiveness and arousal (Jepma et al., 2012) and are associated with the processing of conflicts and uncertainty (White et al., 2019). In addition, it has also been shown that curiosity evoked by epistemic uncertainty led to greater activation in the brain areas that are associated with reward anticipation. In a trivia question study, greater activations in the nucleus accumbens and the midbrain were found when high-curiosity trivia questions were presented, relative to low-curiosity questions (Gruber et al., 2014). These findings suggest that curiosity induction is an anticipatory state for uncertainty resolution and rewarding information (Kidd & Hayden, 2015; Kang et al., 2009; Kobayashi & Hsu, 2019).

Overall, these findings reveal the relevant neural basis of curiosity induction, suggesting that curiosity induction indeed involves sensory arousal and the anticipation of information for uncertainty resolution (Cervera et al. 2020). However, it remains unclear how curiosity driven by uncertainty is related to the recruitment of specific cognitive functions, especially attention and metacognition, and whether there are differences in these cognitive functions recruited between curiosity elicited by perceptual and epistemic uncertainty. Of the two, it seems that perceptual uncertainty is relevant to a general state of sensory arousal in relation to attention (Berlyne, 1960), whereas epistemic uncertainty is associated with a higher level of goal-directed cognitive processing in relation to metacognition (Loewenstein, 1994; Goupil & Proust, 2022). Against this background, one of the objectives of this thesis is to investigate the extent to which curiosity elicited by visual uncertainty would modulate attention and examine its relationship with metacognition.

On the other hand, despite research efforts, results from behavioural data regarding the relationship between uncertainty and curiosity remain unclear due to mixed findings in the literature, with the relationship appearing approximately linear (Wade & Kidd, 2019; Sander et al., 2021; van Lieshout et al., 2018) or following inverted U-shape trajectory (Nicki et al., 1970; Cohanpour et al., 2022; Kang et al., 2009). In these studies, uncertainty is manipulated in either a direct or an indirect way. The direct way is to manipulate the degree of uncertainty of the physical properties of stimuli (e.g., blurredness and distortion; Nicki et al., 1970) or to vary the likelihood of the outcome uncertainty (e.g., lottery outcome; van Lieshout et al., 2018). The indirect way is to measure uncertainty via confidence such that intermediate confidence is associated with high uncertainty and high curiosity (Cohanpour et al., 2022;

Kang et al., 2009; Wade & Kidd, 2019). These inconsistencies and variations may be explained by the variation in the paradigms and task materials across studies.

For example, one possibility is that these inconsistencies are due to the differences in the manipulation of uncertainty. For studies that used blurred picture paradigms, Nicki (1970) measured uncertainty in a direct way, whereas Sander et al. (2021) and Cohanpour et al. used an indirect way. Yet, both Nicki and Cohanpour found the inverted-U-shape relationship between uncertainty and curiosity, whereas Sander found a linear relationship. It is also possible that these inconsistent results might lie in the order of questions asked. In Sander's design, curiosity was measured before confidence as well as a prediction made by the participant, whereas in Cohanpour's design, curiosity was evaluated after a prediction was made and confidence was evaluated. In other words, having a clear prediction is unlikely to bias the evaluation of curiosity or confidence. However, when using the same order of questions as Cohanpour's design, Wade and Kidd (2019) used a trivia question paradigm and found a linear pattern, indicating that task materials also contribute to this inconsistency. As a result, further work is required to establish the association between uncertainty and curiosity to advance our understanding of curiosity. Therefore, another objective of this thesis is to examine the relationship between curiosity and objective and visual uncertainty manipulated in either a direct (i.e., varying the physical properties of stimuli, Chapter 3) or indirect way (i.e., confidence, Chapter 4) while keeping the materials consistent.

Curiosity Resolution and Metacognition

One intriguing question to researchers is what people are curious about. In general, an accumulation of studies indicates several objectives of curiosity with particular emphases on uncertainty resolution and reward of information (Kidd & Hayden, 2015; FitzGibbon et al., 2020). Uncertainty is associated with a state of arousal and deprivation, which motivates an individual to seek the uncertainty out, whereas information in and of itself has a reward value, incentivising information-seeking behaviour for knowledge acquisition.

Extensive research indeed shows supporting evidence for this view. For example, when curiosity elicited by uncertainty is not resolved, it is related to more negative emotions such as disappointment and unhappiness, relative to when the uncertainty is resolved (van Lieshout et al., 2018, 2021; Jepma et al., 2012). When provided with options either to resolve the uncertainty or not, participants showed a systematic preference for uncertainty resolution (Nicki, 1997). These studies suggest that resolving uncertainty has motivational value and indeed is one of the goals of curiosity. In addition, empirical research on information-seeking behaviour and reward showed that both animals and adults were willing to pay a certain cost in exchange for non-instrumental information (Brydevall et al., 2018; Lau et al., 2020) and advanced information (Cabrero et al., 2018; Wang & Hayden, 2019), revealing the fact that information in and itself has high motivational value. Moreover, the reward pathways that are associated with primary rewards are found to overlap with the ones associated with information rewards (Bromberg-Martin & Hikosaka (2009). Supporting evidence regarding the involvement of reward circuits in encoding information is also found in recent imaging studies with adults (Gruber et al., 2014; Kobayashi et al., 2019; Lau et al., 2020).

It is noticeable that under the influence of the information gap theory (Loewenstein, 1994), most studies in the field highlight the role of metacognition in the process of seeking curiosity resolution, especially when curiosity is associated with an information gap. It is assumed that recognising such a knowledge gap requires metacognitive abilities in evaluating one’s prior knowledge and identifying the information that is needed to resolve the gap. Moreover, due to the sought information being rewarding, it is, therefore assumed that individuals would tend to maximise information gain by seeking out an intermediate knowledge gap relative to a small or large gap. This is because such information is more likely to align with the existing knowledge base, helping learners to update their world model (Gottlieb & Oudeyer, 2018; Kidd & Hayden, 2015; Metcalfe et al., 2020; Kang et al., 2009). However, as the information gap theory exclusively discusses specific epistemic curiosity, it is less unclear the extent to which metacognition would impact sensory perceptual curiosity. For example, would curiosity about perceptual information be triggered and driven by a recognised knowledge gap? In addition, much uncertainty still exists about the relationship between the size of a knowledge gap and curiosity due to mixed findings in the literature. Moreover, much less is known about the role of the development of metacognition in curiosity and information-seeking behaviour. Thus, this thesis seeks to address some of these research gaps by assessing whether and the extent to which metacognition may play a role in curiosity induced by perceptual uncertainty.

The Boosting Effect of Curiosity on Learning

There is ample evidence suggesting that curiosity boosts learning and enhances memory, not only for task-relevant information (Jepma et al., 2012) but also for task-irrelevant information (Gruber et al., 2014) and for long-term retention of information learned during a high state of curiosity (Fastrich et al., 2018; Stare et al., 2018). Imaging studies so far highlight the additional roles of brain areas such as the hippocampus and parahippocampal gyrus, which are involved in learning and memory (Kang et al., 2009; Gruber et al., 2014; Jepma et al., 2012), in this beneficial effect on memory encoding and consolidation. In a trivia question study by Gruber and colleagues (2014), when participants were anticipating the answer to a trivia question, incidental information (i.e., an image of a human face) was presented briefly before the answer was given. Afterwards, participants completed a surprise recall test in which they were asked to recall the trivia answers and to recognise the incidental faces. Results showed that activation of the hippocampus during a high curiosity state predicted better retention not only for the trivia answers but also for incidental information.

Furthermore, evidence also suggests that curiosity elicitation is associated with increased activities in the dopaminergic pathways, especially in the midbrain and nucleus accumbens (Gruber et al., 2014). These findings highlight the possibility that curiosity, especially the induction of curiosity, activates critical brain regions associated with encoding upcoming information, leading to memory enhancements for the encoded information (Kang et al., 2009; Gruber et al., 2014). Additionally, information embedded in curiosity resolution is intrinsically rewarding, which activates the reward circuitry and hippocampal areas that facilitate memory retention and consolidation (Fandakova & Gruber, 2019; Jepma et al., 2012; Kang et al., 2009; Ligneul et al., 2018; van Lieshout et al., 2018).

Taken together, these studies indicate a bi-directional feedback loop between curiosity and learning. Curiosity induction is related to anticipation of rewarding information. This anticipation prepares critical learning and memory regions of the brain for upcoming information encoding, leading to enhanced memory. On the other hand, curiosity reduction is associated with the activation of reward pathways which in turn, enhances the processing and learning of the received information. Although extensive research has been carried out on the effect of curiosity on learning, it has been mostly restricted to adult participants using limited materials (i.e., trivia questions), limiting the generalisability of existing findings. Further investigation is needed with different task materials and design to expand existing findings.

1.3.2 Current Research in Infant and Child Curiosity

Despite ample evidence showing that children are curious learners, the majority of the available curiosity research has focused on adults. More recently, there has been an increase in research interest in studying curiosity in children, which begins to shed light on the role of curiosity in child development and learning.

Seeking Something New: Novelty Preference in Early Development

Curiosity for novelty is thought to be a fundamental function of supporting the acquisition of new knowledge and expanding the knowledge base for humans (Kidd & Hayden, 2015; Wittmann et al., 2008). From early on, young children are “well-equipped” with great perceptual competencies and sensitivities across different sensory modalities such as touch, vestibular, smell, hearing and vision (Haith, 1986; Aslin & Smith, 1988). For example, young infants from one week to 14 weeks of age are sensitive to detecting visual patterns that are high in perceptual similarity (Fantz, 1961, 1963). Even newborns demonstrate certain levels of sensitivities in perceiving visual patterns varied only in simple configuration or form (Fantz & Miranda, 1975) or, in 3- to 4-month-old infants, in subtle features (Quinn et al., 1993, 2001, 2004). These perceptual sensitivities enable children to detect the changes in the environment efficiently (Aslin & Smith, 1988), forming a fundamental basis for navigating their exploration of the environment.

Indeed, extensive research has shown that young children demonstrate a great sensitivity in detecting novelty and show a strong preference for novel information (Hunt, 1970; Spelke, 1985). For example, infants’ visual attention at the age of one week to 15 weeks decreases as a result of repeated presentation of the same stimuli using visual preference paradigms (Fantz, 1964). When newborn infants have gained familiarity with the stimuli in a short period (Friedman, 1972), they shift their visual preferences towards new, novel or unexpected stimuli (Hunt, 1970; Spelke, 1985). This shift from familiarity to novelty preference is widely studied and found to be associated with age, the amount of familiarisation time, task difficulty as well as the complexity of the stimulus of interest (Hunter & Ames, 1988; Hunter et al., 1983). This flexibility in allocating cognitive resources from familiar information to novel information (Johnson, 1998; Slater 2004; Cao et al., 2022) might suggest novelty preference as an indicator of curiosity in early child development, highlighting children’s active roles in information sampling to acquire new information.

On the other hand, novelty preference and perceptual curiosity are not completely identical concepts. Different from novelty looking, perceptual curiosity elicited by novelty also implies a desire to resolve the novelty by seeking it out. Although there has been extensive research on novelty preference for many decades, this research does not fully encapsulate the relationship between novelty and curiosity. For example, it is not clear whether infants would seek out the novelty if given the opportunity to do so (e.g., longer sustained attention or hand manipulation). Therefore, further research is needed to study the continuum of novelty-driven information-seeking behaviours in infancy. A good example would be Stahl and Feigenson's study (2015) where 11-month-old infants were provided with opportunities to explore objects that were associated with novelty. Alternatively, more work could be done to review the extensive literature of novelty preference to establish the extent to which perception of novelty leads to a desire to seek out the novelty.

Active and Curiosity-driven Learning in Children

Considering the finite cognitive resources we possess, and yet the seemingly unlimited amounts of information in the surrounding environment, young children seem to navigate and structure their learning and acquire useful information from the noisy environment efficiently. Curiosity-driven learning approaches suggest that children being active learners is the key to this learning efficiency through selective information sampling and making inquiries about the environment (Saylor & Ganea, 2018).

Indeed, from early on, children actively select and choose *what* to engage with from the environment (children at 17 and 19 months of age, Smith et al., 2011). Importantly, much evidence suggests that children are intrinsically motivated to seek information that could provide an optimal learning opportunity but are less interested in those stimuli that are above or below the optimum (Hunt, 1965; Dember & Earl, 1957; Oudeyer & Kaplan 2007). For example, young children prefer information with an intermediate level of complexity or predictability across sensory modalities (Kidd et al., 2012; 2014). Using a look-away paradigm, Kidd and colleagues (2012, 2014) presented 7- to 8-month-old infants with visual and auditory sequences with various probabilistic structures. They found infants allocated their attention to the sequences with intermediate predictability and were more likely to look away from the highly predictable and highly unexpected sequences. Such a "Goldilocks effect", as in a preference for intermediate rates of information representing optimal complexity, has been reported by many other researchers (Piaget, 1970; Hunter & Ames, 1988; Kinney & Kagan,1976; Roder et al., 2000), with the idea that they avoid the learner allocating cognitive resources to already known or overly difficult information that cannot be parsed. Relatedly, it has been suggested that infants as young as 8 months old tailor their attention to stimuli that could maximise their learning progress (Poli et al., 2020). In this study, infants were presented with sequences containing different informational structures in surprise, predictability and informativeness. The results showed that infants allocated attention towards the stimuli that offered maximal learning progress. Most importantly, when the learning progress of one stimulus diminished, infants would search for new input that further maximised their information gain.

In addition, recent literature on active learning also highlights the significant role of *autonomy* in controlling children's own learning progress, benefiting the learning outcomes. For instance, children's self-produced, visual-manual exploration plays an essential part in object learning (Johnson, 2010). Even in preverbal infants at 11 to 12 months of age, self-produced babbling was found to be associated with enhanced attention to objects, resulting in better learning of the objects (Goldstein et al., 2010). Moreover, much research using active and yoked learning designs showed that by giving children active control over *which* information to learn from and *when* to learn, this active control on information sampling improves children's performance across different tasks (Patridge, 2015; Ruggeri et al., 2019).

In these studies, an active condition allowed children from 3 to 11 years-old to control the content, pace and sequence of learning, whereas a yoked condition involved children passively observing the learning experience of others (Markant et al., 2016). The beneficial effect of active learning could be related to greater engagement with and increased attention to the information during learning. Moreover, active learning involves monitoring and planning, allowing the learner to tailor their pace to meet their actual needs (Markant et al., 2016).

Children also actively make inquiries and know *whom* to solicit reliable information from (Chow et al., 2008; Rakoczy et al., 2008; Bazhydai et al., 2020) and *when* to be flexible to choose from different informants depending on the reliability and credibility of an informant (Jaswal & Neely, 2006). For example, 2- to 3-year-old children are more likely to view adults as knowledgeable informants and to follow instructions and elicit or use the information provided by an adult relative to others (Kachel et al., 2021; Wimmer et al., 1988; Southgate et al., 2007). However, 3- to 4-year-old children are also able to flexibly sample information from more reliable sources with very little contradictive evidence (Jaswal & Neely, 2006). Children know *how* to request information from others via different means such as babbling (Goldstein et al., 2010), social referencing (Bazhydai et al, 2020), pointing (Begus & Southgate, 2012) and asking questions (Ronfard et al., 2018). They also actively direct others to provide them with information that they are interested in (Begus et al., 2014; Lucca & Wilbourn, 2016).

Taken together, this summary demonstrates that children actively navigate and construct their learning and this active learning may lead to learning improvement. However, much of the research in children mentioned above involves less mechanistic explanations relative to curiosity research in adults, posing challenges to our understanding of the nature of curiosity in children as well as the generalisability of adult curiosity theories. Therefore, further theoretical work is needed to map curiosity in children and more empirical investigations are needed to examine the extent to which curiosity in children could be explained by existing adult curiosity theories.

Developmental Changes, Curiosity and Learning

Although curiosity is regarded as a booster of learning, literature on children has emerged that offers new insights into this claim, suggesting a developmental change in the effect of curiosity on learning (Walin et al., 2016; Fandakova & Gruber, 2021; Liquin et al., 2021). Overall, extensive research has demonstrated curiosity indeed is associated with improved memory. However, this enhancement is modulated by influences such as age differences in attention, memory and metacognitive abilities.

To examine the extent to which curiosity would facilitate learning of both task-relevant and incidental information in children, Fandakova and Gruber tested 10- to 12-year-old children and 13- to 14-year-old adolescents using a trivia question task. Similar to the adult study (Gruber et al., 2014), children were presented with a trivia question to induce curiosity and were asked to rate their curiosity. During the anticipation period before answering, a neutral face image was presented, followed by the actual answer. After the presentation of the answer, children were asked to rate their feeling of interest in the answer. They found that high states of curiosity predicted enhanced memory for the trivia answers in both age groups. However, the effect of post-answer interest on recall accuracy was greater than the effect of curiosity, especially in older children, highlighting again age differences as well as other factors such as surprise about received feedback on curiosity-based learning. Moreover, the enhanced effect on incidental information in adults was absent in both groups in this study, suggesting an age difference in the development of memory and attention. For example, children might be more attentive to the trivia questions and might have fewer cognitive resources to encode the incidental information as well as to remember them, compared to adults.

On the other hand, evidence suggests that the role of metacognitive abilities in curiosity-driven learning differs between adults and children, suggesting age is a modulator in the relationship between curiosity and metacognition. Walin and Xu (2016) used child-appropriate trivia questions to induce 7- to 8-year-old children's curiosity and examined the effect of induced curiosity on learning the trivia answers. In this study, children were provided with a set of six trivia questions related to different contents and were asked to rank these questions in order from 1 (not curious at all) to 6 (very curious). These questions were prescreened to make sure that the child did not know the answers. After ranking the questions, the children then learned the answers. Children were then tested on these questions to see if they remembered the answers. Results suggested that only in the 8-year-old group, children's curiosity predicted the recall performance such that the more curious children were about a question, the more likely they could recall the answer correctly. However, this effect was absent in the 7-year-old group, raising an important question about the extent to which children's metacognitive skills in identifying a gap would influence curiosity-based learning. In other words, the 7-year-old group and younger children might not have the metacognitive awareness necessary to recognise a gap, thus the associated curiosity might not effectively influence learning.

Although increasing research on the topic begins to shed light on the role of curiosity in child development and learning, unlike curiosity research with adults, research on child curiosity is mostly empirical investigation. Future work on summarising these empirical findings and building theoretical frameworks is much needed to move the field of child curiosity forward. So far, the few existing frameworks such as the neurocomputational approach (Twomey & Westermann, 2018) and the learning progress approach (Oudeyer et al., 2007) highlight factors concerning curiosity-based learning, such as novelty, the discrepancy between learning history (prior knowledge) and expected learning opportunities, as well asneural plasticity. The PACE (Prediction-Apprisal-Curiosity-Exploration) approach inspired by adult neuroimaging studies emphasises the roles of cognitive modalities such as attention and memory in the enhanced effect of curiosity on learning (Gruber & Ranganath, 2019; Gruber & Fandakova, 2019). In addition, empirical evidence supports the bi-directional relationship between language development and curiosity. Curiosity facilitates language acquisition (Ackermann et al., 2019; Twomey & Westermann, 2019) whereas the acquisition of language also motivates curious behaviours from environmental exploration (e.g., object manipulation) towards exploitation (e.g., explanation-seeking behaviours) in childhood (Oudeyer & Smith, 2016). Moreover, social influences such as knowledgeable informants (Bazhydai et al., 2019; Jaswal & Neely, 2016), the popularity (Bern et al., 2010) and the utility of information (Dubey et al., 2021) are found to have positive impacts on curiosity. Therefore, further work is required to establish the roles of these factors in the developmental changes of curiosity-driven learning in children.

1.4 General Conclusion and Thesis Objectives

In summary, curiosity, as a potent motivator for learning, seems to be a fundamental element of cognition. Whilst theories and frameworks intend to provide a unifying account of curiosity, they do not seem sufficient in mapping the whole scope of curiosity. Factors such as novelty, uncertainty and other metacognitive variables have been identified in predicting curiosity, but the extent to which and under what contexts these factors influence curiosity remains ambiguous due to mixed findings in the literature. Moreover, these accounts and empirical research predominantly centre on adult curiosity. While young children are undeniably active and curious and are ideal candidates for studies of curiosity, curiosity research with infants and children remains relatively scarce. This imbalance of research between adults and children hinders our understanding of developmental changes of curiosity across the lifespan. Thus, there is a need in the literature for more empirical research to evaluate existing curiosity theories across the lifespan.

Against this background, this thesis sets out to investigate curiosity about visual uncertainty and its effect on memory and learning in both young infants and adults. Chapter 2 reports two eye-tracking experiments: one aimed to investigate the role of curiosity induction in encoding incidental information in young infants (8-month-old); the other to examine whether young infants, like adults, would seek curiosity resolution. This was the first empirical study to explore how states of curiosity affect object encoding in infants and the role of curiosity resolution in this process.

Chapter 3 aims to investigate the neural correlates of visual uncertainty and curiosity using a blurred picture paradigm and EEG with adults. More specifically, this study investigates whether curiosity induction is associated with attentional arousal reflected by alpha desynchronisation and whether curiosity reduction is related to learning enhancement indicated by theta synchronisation.

Chapter 4 aims to disentangle the extent to which curiosity in adults is modulated by metacognitive abilities and prior knowledge using a modified blurred picture paradigm. Moreover, the roles of these variables and curiosity in predicting learning are also examined. As previous studies primarily applied trivia question paradigms to study the relationships between metacognitive abilities, curiosity and learning, this online study was the first study to explore such questions using a different paradigm. Using various materials and paradigms under different environments to investigate similar research questions may improve ecological validity and extend the generalizability of research findings in the curiosity field.

Finally, Chapter 5 provides a summary of the critical findings of the current thesis as well as a discussion about potential implications. Critical evaluations of curiosity theories and suggestions for future research and investigation are also discussed.

Chapter 2

Curiosity Enhances Object Encoding in 8 Months Olds Infants

Despite the fact that children are undeniably curious, with curiosity research disproportionately centres on adult curiosity, there is a need in the literature for more empirical research to investigate the underlying cognitive mechanism of curiosity in young children. Inspired by curiosity research in adults (Gruber et al., 2014; Jepma et al., 2012) and the information-gap theory (Loewenstein, 1994), this chapter presents two eye-tracking experiments to explore how states of curiosity affect object encoding in infants and the role of curiosity resolution in this process. More specifically, these experiments aim to examine 1) the role of curiosity induction due to visual uncertainty in encoding incidental information in 8-month-old infants; 2) whether young infants, like adults, would seek for curiosity resolution.

Text as it appears in Chen, X., Twomey, K. E., Westermann, W. (2022). *Curiosity enhances object encoding in 8 months olds infants.* Journal article in press on *the Journal of Experimental Child Psychology*.

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Abstract

Recent research with adults indicates that curiosity induced by uncertainty enhances learning and memory outcomes and that the resolution of curiosity has a special role in curiosity-driven learning. However, the role of curiosity-based learning in early development is unclear. Here we presented 8-month-old infants with a novel looking time procedure to explore: 1) whether uncertainty-induced curiosity enhances learning of incidental information; and 2) whether uncertainty-induced curiosity leads infants to seek uncertainty resolution over novelty. In Experiment 1, infants saw blurred images to induce curiosity (Curiosity sequence) or a clear image (Non-Curiosity sequence) followed by presentation of incidental objects. Despite looking equally to the incidental objects in both sequences, in a subsequent object recognition phase, infants looked longer to incidental objects presented in the Non-Curiosity than in the Curiosity condition, indicating that curiosity induced by blurred pictures enhanced the processing of the incidental object, leading to a novelty preference for the incidental object shown in the Non-Curiosity condition. In Experiment 2, a blurred picture of a novel toy was first presented, followed by its corresponding clear picture paired with a clear picture of a new novel toy side-by-side. Infants showed no preference for either image, providing no evidence for a drive to resolve uncertainty. Overall, the current studies suggest curiosity has a broad attention-enhancing effect in infancy. Taking into account existing studies with older children and adults, we propose a developmental change in the function of curiosity, from this attentional enhancement to more goal-directed information seeking in older children and adults.

2.1 Introduction

Curiosity – the intrinsically motivated search for information – has a long history of research but has recently re-entered the focus of scientific investigation. Curiosity has been described as a drive evoked by events of complexity, uncertainty and novelty (Berlyne, 1954, 1960, 1966) that promotes exploratory behaviours leading to knowledge acquisition or improved perception of the environment (Loewenstein, 1994). Different theories have been put forward to explain how curiosity motivates exploratory behaviours, such as the drive to close a knowledge gap (Loewenstein, 1994), generation of predictions that are then evaluated (Gruber & Ranganath, 2019), or reduction of experienced uncertainty (Berlyne, 1960; Berlyne & Normore, 1972; Jepma et al., 2012). In experimental studies, the two most frequent paradigms used to induce curiosity are asking participants trivia questions and presenting them with blurred images.

Different studies have shown how curiosity can be elicited by uncertainty (Berlyne, 1954; Gruber et al., 2019; Kang et al., 2009; Loewenstein, 1994; Nicki, 1970; Kobayashi et al., 2019; van Lieshout et al., 2018). For example, in a seminal study, Nicki (1970) presented adult participants with a series of images with low, medium and high degrees of blur to induce uncertainty, followed by the option to press one of two keys, with one revealing the clear corresponding image of the blurred image and the other an unrelated clear image. Participants' key presses leading to the clear corresponding images increased across trials. Moreover, participants' ratings of the blurred images indicated that they showed highest subjective uncertainty (and consequently, highest degree of curiosity) when stimuli were at a medium level of blurredness. In related work, Jepma and colleagues (2012) presented participants with (intermediate-degree) blurred images and used neuroimaging to study the brain regions involved in processing this information. They found that first, participants self-reported high curiosity for the blurred images (mean 4.11 on a 1-5 scale), and second, that the blurred images activated brain regions associated with autonomic arousal and aversive experience. When the participants were subsequently shown clear versions of the blurred images, they showed activation of brain regions linked to reward processing. Together, these studies suggest that in adults, blurred images (especially when blurred at an intermediate degree) reliably elicit strong curiosity, that participants seek to resolve this uncertainty, and that this resolution is intrinsically rewarding.

A core question in research on curiosity has been whether it supports learning. Overall, results using trivia questions or blurred picture paradigms have shown that both adult and child participants recalled information better when they were curious about it than when not (Berlyne & Normore, 1972; Fandakova & Gruber, 2021; Gruber et al., 2014; Jepma et al., 2012; Kang et al., 2009), suggesting that higher curiosity levels enhance attention and facilitate task-relevant information encoding. More recently, research has begun to investigate the extent to which curiosity enhances learning more generally, that is, whether enhanced learning is restricted to the object of curiosity, or whether a state of curiosity more generally facilitates learning of information that is encountered in this state. This work so far has led to mixed results. In one study, Gruber and colleagues (2014) presented adults with a sequence of trivia questions and asked them to rate their level of curiosity about each question. Then, before the answer was revealed, a face image as task-irrelevant information was presented. An immediate and a one-day delayed recall test showed that participants' recall of not only the task-relevant information (trivia question answers) but also the task-irrelevant information (faces) encountered during a high state of curiosity was enhanced relative to information learned during a low state of curiosity. However, contrasting with these results, in a study with children and adolescents using a similar paradigm, Fandakova and Gruber (2021) found that higher states of curiosity enhanced learning of task-relevant more pronouncedly than task-irrelevant information. More specifically, although no group effect of curiosity on learning enhancement for task-irrelevant information was found, further exploratory analysis suggested that children who showed better learning of task-relevant information also learned task-irrelevant information better when contrasting high and low curiosity conditions.

A second question of interest concerns the role of uncertainty resolution in curiosity. As discussed above, theories of curiosity often see the resolution of uncertainty as the main objective of curiosity-driven exploration. Evidence from adults suggests that uncertainty resolution is indeed implicated in curiosity; for example, when curiosity was triggered by blurred images, participants preferred to see a resolution over a novel image (Nicki, 1970), and participants reported higher disappointment when they were provided with a novel image instead of a resolution image after viewing blurred images (Jepma et al., 2012).

Whereas the study of curiosity in adults has a relatively long tradition, only recently has research begun to address the role of curiosity and active exploration in infants' knowledge acquisition (Kidd & Hayden, 2015; Oudeyer & Smith, 2016; Poli et al., 2020; Smith et al., 2018; Twomey & Westermann, 2018). This early work suggests that infants are curious learners who actively navigate and structure their own learning, allocating their attention to the resources that allow them to maximise information gain to learn rapidly (Poli et al., 2020). This work has suggested intrinsically motivated exploration as a powerful mechanism to drive infants' learning and cognitive development, characterizing infants as active explorers instead of mere recipients of environmental information.

However, the mechanisms and effects of curiosity on learning and exploration in infancy are not well understood. Here we therefore addressed two questions in two experiments. First, guided by the idea that curiosity modulated by uncertainty facilitates learning in adults and older children (Fandakova & Gruber, 2021; Gruber et al., 2014; Jepma et al., 2012), we asked whether in 8-month-old infants' curiosity supports learning globally beyond the specific object of curiosity. Second, we investigated whether infants, like adults, show a drive to resolve uncertainty by asking whether they prefer uncertainty resolution over novelty.

Curiosity here is not conceptualised as a metacognitive awareness of ‘not knowing’ (e.g., as in Loewenstein, 1994), but as arousing a state of uncertainty that leads to further exploration (see e.g., Berlyne, 1954, 1960, 1966). It is well-known that animals and humans explore and seek information to reduce uncertainty (Berlyne, 1966; Bromberg-Martin & Hikosaka, 2009; van Lieshout et al., 2018). Given that blurred stimuli induce strong curiosity in adults and since trivia questions are not suitable for use with infants, we used blurred stimuli as uncertain information to induce curiosity in the infant participants. Curiosity in older children and adults is assessed by self-report (e.g., answering the question ‘how curious are you about this stimulus?’) which is not possible with infants. While therefore we cannot be certain that the blurred images did induce curiosity in the infants, we believe so based on the literature showing that adults report high curiosity for such images, that blurred images represent uncertainty, and that uncertainty elicits exploratory behaviours even in non-human animals (Berlyne, 1966; Bromberg-Martin & Hikosaka, 2009; Daddaoua et al., 2016). This uncertainty can be framed on a metacognitive level (“I don’t know what this is.”) but equally on a perceptual level (the information is hard to learn or represent and to link to existing knowledge), suggesting that metacognitive awareness of a knowledge gap is not a necessary precondition for curiosity to arise (Twomey & Westermann, 2019).

Infants show considerable perceptual sensitivities and competencies from a very young age (Aslin & Smith, 1988). They are sensitive to perceptual overlap between visual patterns (Fantz, 1958) and subtle changes in features of visual stimuli as early as the first three months of life (Quinn et al., 1993, 2001). Even newborn infants show certain levels of sensitivity to visual patterns differing only in configuration or form (Fantz & Miranda, 1975). By 8 months of age, visual sensitivity develops rapidly to reach adult levels (Norcia & Tyler, 1985; Skoczenski & Norcia, 1998). We reasoned that on this basis, 8-month-old infants should be able to perceive the blurred stimuli. Moreover, given infants' sensitivity to perceptually overlapping stimuli (Quinn et al., 2001), we also presented the clear version of the blurred images to enable resolution of curiosity.

To investigate the breadth of learning facilitated by curiosity (Experiment 1), we presented infants with two sequences of images representing a Curiosity sequence and a Non-Curiosity sequence. The Curiosity sequence consisted of a blurred image of a novel object to induce curiosity, followed by a different novel (clear) object image serving as incidental information not related to the object of curiosity, which was then followed by a clear version of the initial blurred picture. The Non-Curiosity sequence was similar to the Curiosity sequence except that the first image was always clear and not blurred. Immediately after infants saw these two sequences, we presented them with a preferential looking test in which the two incidental objects were shown side-by-side. We hypothesised that, if infants encoded the incidental objects encountered while in a state of curiosity (after seeing the blurred picture in the Curiosity sequence) or not (after seeing the clear picture in the Non-Curiosity sequence), they should show systematic preferences for either of the incidental objects at test.

To explore infants' resolution of uncertainty (Experiment 2), we presented them with a blurred image, followed by a preferential looking trial in which the clear corresponding image was paired with a new, clear image. We were interested in whether infants would show a looking preference to the clear corresponding image to resolve their curiosity over the novel image. Since Experiment 2 was substantially shorter than Experiment 1 (approximately one minute versus approximately seven minutes), we conducted Experiment 2 before Experiment 1 to maximise data quality for both experiments.

2.2 Experiment 1: The Breath of Learning in Curiosity

2.2.1 Method

Participants

Thirty-nine typically developing 8-month-old infants (*Mage* = 7 months, 28 days; *SD* = 9.68 days; range 7 months 17 days - 8 months, 16 days) and their caregivers were recruited from a database of parents who had indicated an interest in taking part in developmental research. This sample size was large enough to reach sufficient power (0.95) to detect an effect size of 0.7. All infants were born full-term and had no reported hearing or visual deficits. Caregivers' travel expenses were reimbursed, and infants were given a storybook as a gift for their participation. Informed consent was provided by the caregivers. The study was approved by the University's research ethics committee. Data from two infants were excluded for this experiment due to not contributing enough data for the final analysis (see *Data processing and analysis* below for exclusion criteria).

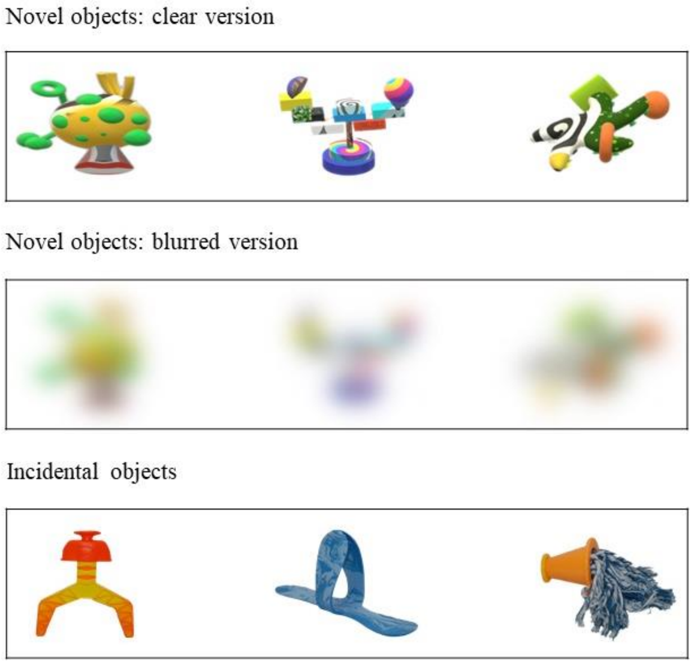
Stimuli

A total of 20 novel images were generated with Microsoft Paint 3D, which were then filtered with a 35-degree blur using a Gaussian filter in MATLAB (R2016b), resulting in 40 images with 20 blurred images and 20 corresponding clear images (see Figure 1 for sample images). All images were adapted to a similar rectangular size of approximately 450 by 350 pixels and placed on a grey background using Gimp (Version 2.10.8). No infant saw the same stimulus in more than one trial in this experiment.

Images were converted into videos with sound and animation effects at the onset of presentation for 700 ms in order to maintain infant engagement. Videos were produced on Microsoft PowerPoint by adding in-built animation effects with four different sound effects (cash register, laser, hammer and whoosh) and one animation effect (fly in from the top of the screen). Sound effects were counterbalanced across trials and participants. Additionally, 20 images of incidental, novel objects were selected from the NOUN database (Horst & Hout, 2016). All images of novel objects were adapted into a similar rectangular size of approximately 450 by 350 pixels and placed on a grey background.

Each pair of incidental objects selected from the NOUN database was matched based on a similar novelty score (%) provided in the database. An unpaired *t*-test showed that the novelty score for objects in each pair was not significantly different (M_1 = 76.90%, SD_1=11.47%; M_2 = 78.60%, SD_2 = 12.04%, $t(9)$ = -0.50, p = .627), suggesting that each pair of the incidental objects chosen was equally novel.

Figure 1. *Sample images of stimuli. Top: Clear novel objects; Middle: Blurred, clear, novel objects; Bottom: Incidental novel objects.*

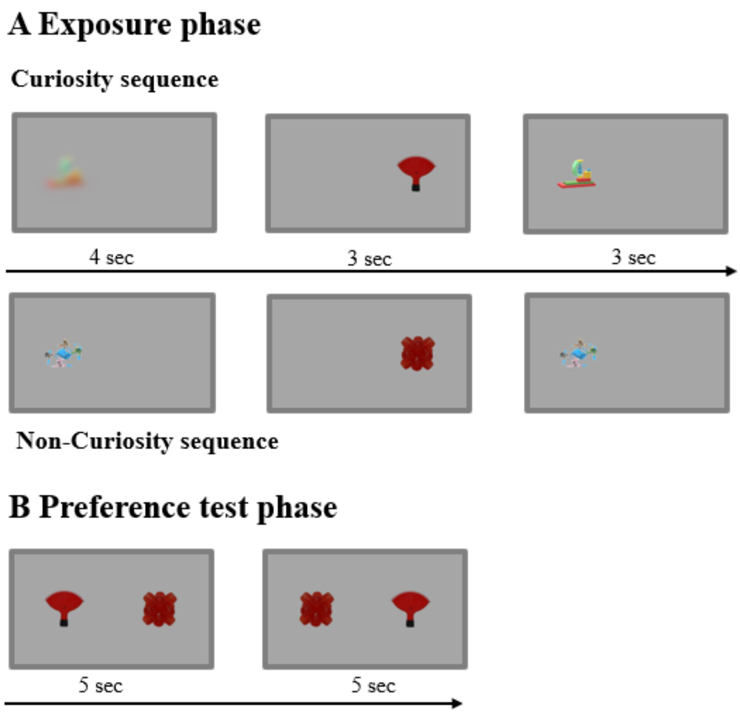


Design

The experiment consisted of 10 trials, each lasting 34 s and comprising an exposure phase (22 s) and a preferential looking test phase (12 s). In each exposure phase, infants saw a Curiosity sequence and a Non-Curiosity sequence, counterbalanced across trials and between infants. In the Curiosity sequence, a blurred image was first presented on one side of the screen for 4 s to induce infants' curiosity, followed by a novel object image as incidental information for 3 s on the opposite side to the blurred image. Then, the clear corresponding image of the blurred image was presented on the same side as the blurred image for 3 s. The Non-Curiosity sequence was similar to the Curiosity sequence except that the first image was always clear and not blurred. At the beginning of and between the two sequences, a central attention getter was presented for 1 s to maintain attention. The order of novel incidental objects was randomised across sequences and infants.

The exposure phase was followed by a preferential looking test phase in which images of the two incidental objects shown in the exposure phase were presented side by side for 5 s, followed by the same objects on reverse sides for further 5 s to account for potential orientation bias. The side on which the image from the Curiosity sequence was displayed first was counterbalanced across trials. Figure 2 presents an example of stimulus presentation order. Overall, the timing decisions were made based on the supervisors' expertise, experience from pilot testing and previous literature on adults (Gruber et al., 2014; Jepma et al., 2012).

Figure 2 *An example of stimulus presentation order in Experiment 1: A) Exposure phase with two counterbalanced sequences (Curiosity and Non-Curiosity sequence) presented sequentially. B) Preferential looking test phase: two incidental objects presented in the learning phase immediately following the exposure phase.*



Data processing and cleaning

Raw eye tracking data were exported from Tobii Studio (Version 3.4) and imported to RStudio (Version 1.1.456) for cleaning and analysis. Rectangular areas of interests (AOIs) with a size of 550 x 410 pixels were defined for the left and right AOI for both phases. AOIs were centred on the objects' stationary locations. The margin between the left and the right AOI was 200 pixels. Analysis was conducted from 700 ms, at which point the stimuli stayed stationary.

Data pre-processing was trial-based with 374 trials collected in total. Across all trials, 70 trials were removed due to the eye tracker failing to reliably detect an eye. Trials were excluded when infants looked for less than 100 ms at each AOI in the exposure phase and the test phase (n = 41). A window size of 80 ms has been defined as a minimum fixation duration (Wass et al., 2011) in previous research. Considering that infants have slower processing speed, we expanded this window size to 100 ms. In other words, these criteria will make sure that infant did look at each stimulus at least once. As a result, 37 of 39 infants contributed 263 trials for further analysis. Given that only 24.04% of trials for the second test image pair were valid, only the first pair was analysed in this experiment.

2.2.2 Results

Exposure phase

To understand infants' looking behaviours during the exposure phase, we conducted three paired *t*-tests (two tailed) on the mean looking time to each stimulus across the two sequences. First, infants looked significantly longer to the first clear stimulus in the Non-Curiosity sequence (M = 2247 ms, SD = 482 ms) than to the blurred stimulus in the Curiosity sequence (M = 1010 ms, SD = 428 ms, d = 2.56; $t(36) = -15.57$, $p < .001$). An estimated Bayes factor of $BF_{01} < 0.01$ using a Cauchy distribution with width of .707 was computed, suggesting very strong evidence for the alternative hypothesis that infants looked longer at the first clear stimulus in the Non-Curiosity sequence (BayesFactor package; Jarosz & Wiley, 2014; Rouder et al., 2009). Second, there was no evidence for a difference in looking to the two incidental objects in both sequences (Curiosity objects: M = 1532 ms, SD = 344 ms; Non-Curiosity objects: M = 1594 ms, SD = 324 ms, d = 0.19 ; $t(36) = -1.14$, p = .26). The Bayes factor BF_{01} was 3.11, which was substantially in favour of the null hypothesis that infants did not preferentially fixate either of the two incidental object images in this exposure phase. Third, there was no significant difference in looking to the final objects in the Curiosity sequence (M = 1583 ms, SD = 346 ms) and Non-Curiosity sequence (M = 1500 ms, SD = 356 ms; d = 0.25; $t(36) = 1.49$, p = .14). Results from the Bayes Factor analysis (BF_{01}= 2.05) suggested anecdotal evidence for the null hypothesis over the alternative.

Preference test phase: Total looking preference

Next, and crucially, to examine the effect of curiosity on the processing of incidental information, we calculated a one-sample *t*-test (two tailed) against chance (0.5) on the proportion looking to each of the two incidental objects on the first test trial. Overall, infants showed a significant preference for the incidental objects presented in the Non-Curiosity sequence (M = 0.56, SD = 0.10, d = 0.60; $t(36) = 3.58$, p = .001; see Figure 3). A Bayes factor of BF_{01}= 0.03 suggested very strong evidence for the alternative hypothesis that infants preferred the incidental objects presented in the Non-Curiosity sequence. We also examined changes in proportion looking across the time course of each trial. A bootstrapped cluster-based permutation analysis using the eyetrackingR package (Dink & Ferguson, 2015) against chance (0.5) was conducted on proportion target looking collapsed into 200 ms time bins. From 400 ms to 1200 ms, infants' looking to the Non-Curiosity incidental object was significantly above chance (p = .02), with looking preference not reaching significance after this interval (see Figure 4).

Figure 3. *A violin plot of the total proportion looking to the Non-Curiosity object: The purple diamond represents the mean proportion looking time to Non-Curiosity incidental objects. Dashed line represents chance (0.5). **p = .001, two tailed.*

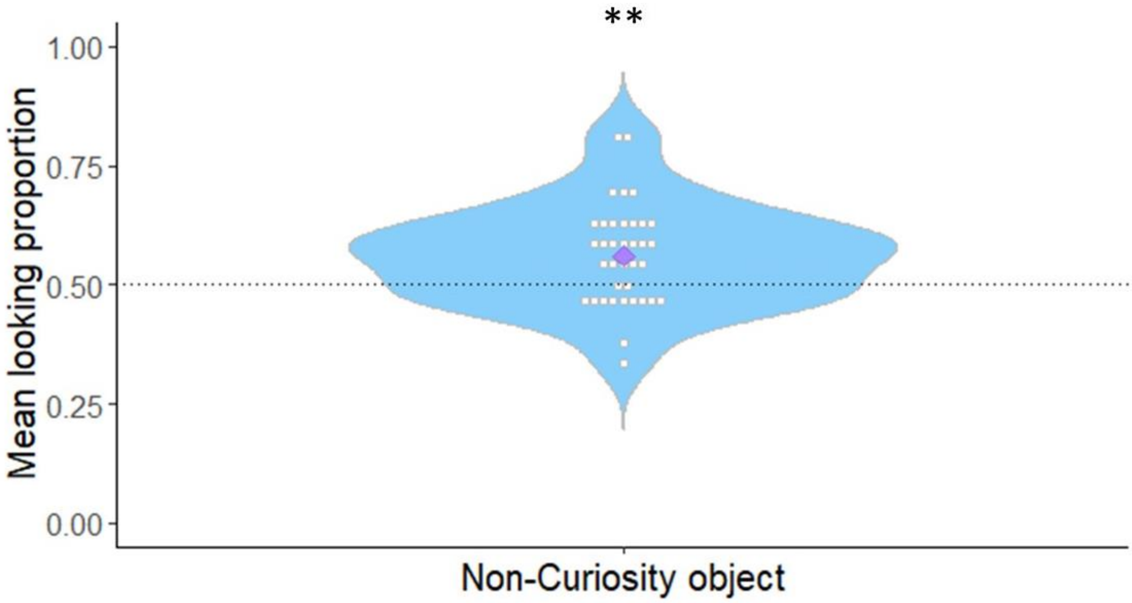
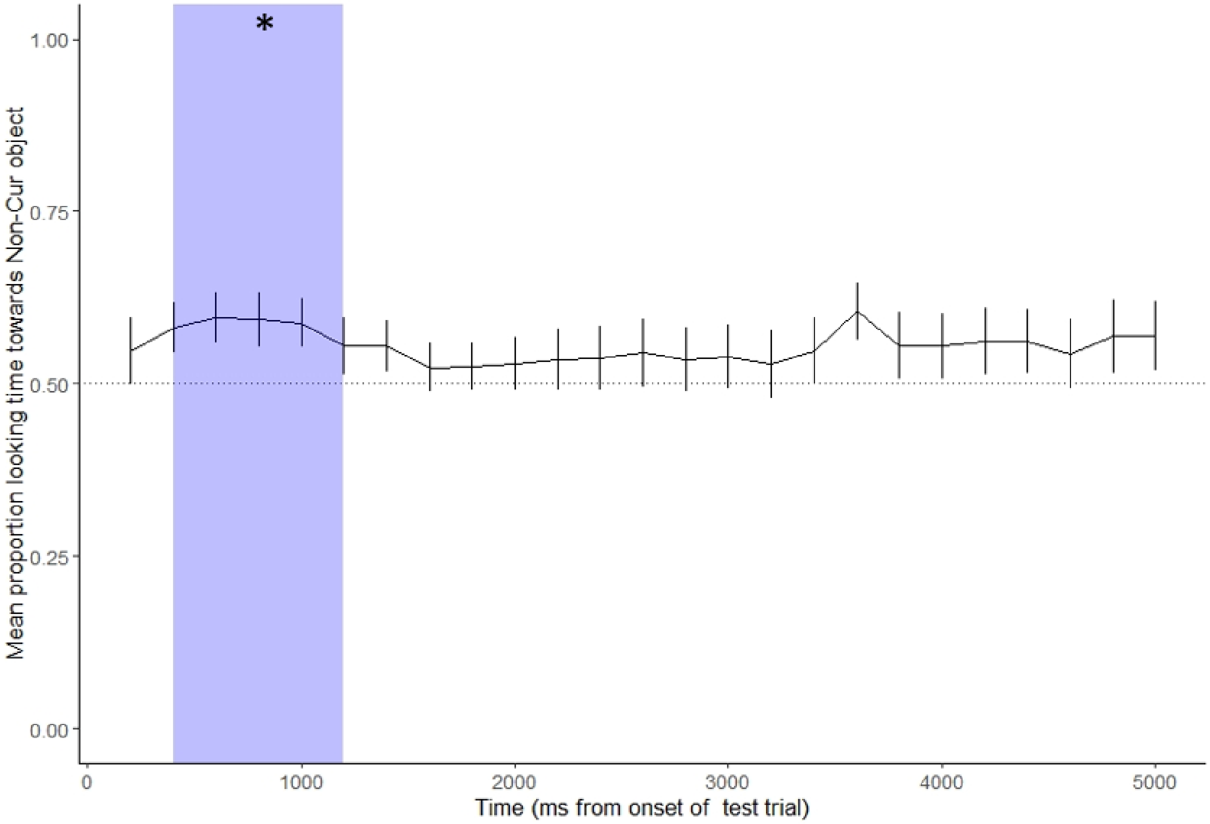


Figure 4. *Time course of looking at each of the incidental objects during test: The purple area indicates where the mean proportion looking towards Non-Curiosity objects was above chance (0.5). Dashed line represents chance. *p < .05, two tailed.*



2.2.3 Discussion

Results from Experiment 1 support the argument that curiosity induced by blurred stimuli enhances infants' processing of subsequent incidental information. Infants spent equal amounts of time looking at the incidental objects in both sequences during the exposure phase. At test, however, infants preferred the Non-Curiosity objects over the Curiosity objects. It is well-known that at this age, patterns of selective looking in infants are likely to be influenced by the novelty of visual stimuli (Ruff & Rothbart, 2001). A preference for one of the two stimuli is taken to indicate that the other stimulus is more fully processed (Reynolds, 2015). Our findings suggest that the encoding of the incidental objects in the Curiosity sequences was more robust than that of objects in the Non-Curiosity sequences, resulting in a novelty preference for the Non-Curiosity item in the later test trials.

As infant looking can indicate both a preference for novelty and familiarity (Hunter & Ames, 1988), an alternative explanation of our results could be that infants showed a familiarity preference for the Non-Curiosity object, which would suggest that they had processed this object more deeply than the Curiosity object. While we cannot definitely exclude this possibility, we believe it to be unlikely due to the prevalence of novelty preference at this age (Hunter et al., 1983) and evidence showing a persistent decrease in familiarity preference before the age of 6 months (Fisher-Thompson, 2014; Fisher-Thompson & Peterson, 2004). Hunter and colleagues (1983) examined the effects of familiarisation time and complexity of stimuli on infants' familiarity-novelty preference, and found that only when the habituation to a stimulus was interrupted and only when the stimulus was complex, would 8-month-old infants show a familiarity preference. In our study, infants spent an equal amount of looking time at either of the incidental objects with the same level of complexity during familiarisation without being interrupted. These findings suggest that in our study infants did show a novelty preference at test.

Another alternative explanation for our results might be that infants did show a novelty preference and had encoded the Curiosity object more deeply, but not because they were in a state of curiosity induced by the blurred image, but because the blurred image had required less processing capacity so that more capacity was left to process the subsequent incidental image. As discussed above, we cannot say with certainty that viewing the blurred image had aroused curiosity in the infants, but adults' self-report of strong curiosity about blurred images and the evidence that perceptual uncertainty elicits exploratory behaviour in infants and even in animals, supports this view. Furthermore, the alternative explanation assumes that a fixed amount of attention is available to be distributed across a number of subsequent stimuli, but to our knowledge no evidence exists for this theory. To the contrary, infant studies usually contain 'attention getters' to re-orient infants to the screen and 'refresh' their attention for the subsequent experimental stimuli.

We found that infants spent less time looking at the blurred image in the Curiosity sequences compared to the first clear image in the Non-Curiosity sequences. It is well established that infant looking time is driven both by stimulus novelty (i.e., how it relates to infants' prior knowledge) and stimulus complexity (the amount of detail; e.g., Cohen et al., 1975; Fantz & Nevis, 1967; Hunter et al., 1983). In the current study, the blurred images contained less detail and were less perceptually complex than the clear images, resulting in infants spending less time processing them compared with the clear images. However, a second result of interest in our study is that infants spent equal amounts of time looking at the final images in the Curiosity and Non-Curiosity sequences in the exposure phase, despite the former representing a resolution of curiosity and the latter, not. This result is in contrast with studies in which older children, adolescents and adults showed preferences for resolving curiosity (Fandakova & Gruber, 2021; Jepma et al., 2012; Nicki, 1970).

In Experiment 2 we aimed to explore whether infants would likewise seek resolution of curiosity without intervening incidental information. Infants first saw a blurred image, followed by a pair of two clear images, one of which was the clear version of the blurred image and the other, a novel image. We tested whether infants would preferentially look at the clear version of the blurred picture over the novel image and thus indicate a preference for the satisfaction of curiosity by uncertainty resolution.

2.3. Experiment 2: Resolution of Uncertainty

2.3.1 Method

Participants

The same infants (N = 39) who participated in Experiment 1 took part in this experiment.

Stimuli

Forty new image stimuli were generated according to the method described in Experiment 1, resulting in 20 blurred images and 20 corresponding clear images. All the stimuli were presented in the form of pictures. No infant saw the same stimulus in more than one trial in this experiment.

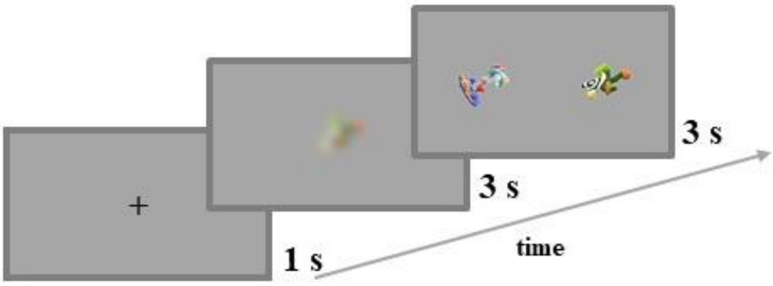
Design

There were 10 trials, each lasting 7 s. On each trial, a blurred object was presented in the centre of the screen for 3 s to induce infants' curiosity. Following this, its clear corresponding image paired with another clear, new object were presented side-by-side for 3 s. Infants' eye movements were recorded throughout each trial. The location of the paired clear images was counterbalanced across participants. Figure 5 presents an example of stimulus presentation order. In addition to the decisions made in Experiment 1, the timeline for Experiment 2 was made also based on the entire study duration. Therefore, the time of the testing trial (3 s) was shorter than the one in Experiment 1 (5 s).

Procedure

The experimental set-up was the same as for Experiment 1.

Figure 5. *An example of stimulus presentation order in Experiment 2*



Data processing and analysis

For the central AOI of the blurred images we defined a rectangular AOI of 550 x 410 pixels, and for the left and right AOIs we defined two rectangular 550 x 410 pixel AOIs. The margin between the left and the right AOI was 200 pixels. Data pre-processing was trial-based with 390 trials collected in this experiment. Across all trials, 12 were removed due to the eye tracker failing to reliably detect an eye. We excluded 12 further trials due to experimenter error, and 102 trials with less than 100 ms looking time at each AOI, leaving 39 participants contributing 264 trials in total for further analysis.

2.3.2 Results

Experiment 2 investigated whether infants, after seeing a blurred object, show more interest in the corresponding clear object (target) or in a novel, clear object (distractor).

We submitted proportion target looking (target looking / (target + distractor looking)) to a two-tailed one-sample *t*-test against chance (0.5). Overall, proportion target looking (M = 0.50, SD = 0.09, d = 0.01) was not significantly different from chance ($t(38) = -0.09$, $p = .93$, Figure 6), indicating no preference for either the target or the distractor object. In order to understand the changes in proportion target looking across the time course of the test trials, we collapsed timestamps into 200 ms time bins. A bootstrapped cluster-based permutation analysis using the eyetrackingR package (Dink & Ferguson, 2015) was performed on the averaged target looking proportion in each bin against chance (0.5). Infants' proportion target looking was not different from chance at any point in the trial (see Figure 7). In order to determine whether this result provided evidence for the null hypothesis, we computed an estimated Bayes factor with Cauchy distribution with a width of .707 (the BayesFactor package; Jarosz & Wiley, 2014; Rouder et al., 2009). This result suggested that the data were 5.77:1 in favour of the null hypothesis that infants did not preferentially fixate either of the two images.

Figure 6. *A violin plot of proportion target looking: The central blue dot represents the mean proportion looking time to target objects. Dashed line represents chance (0.5).*

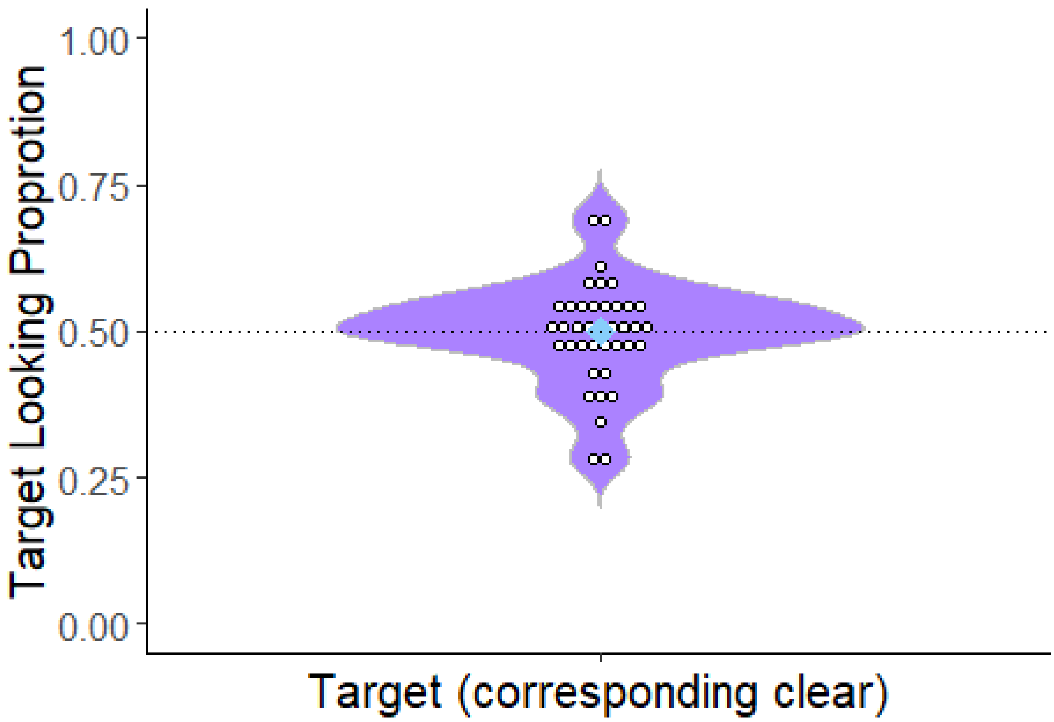
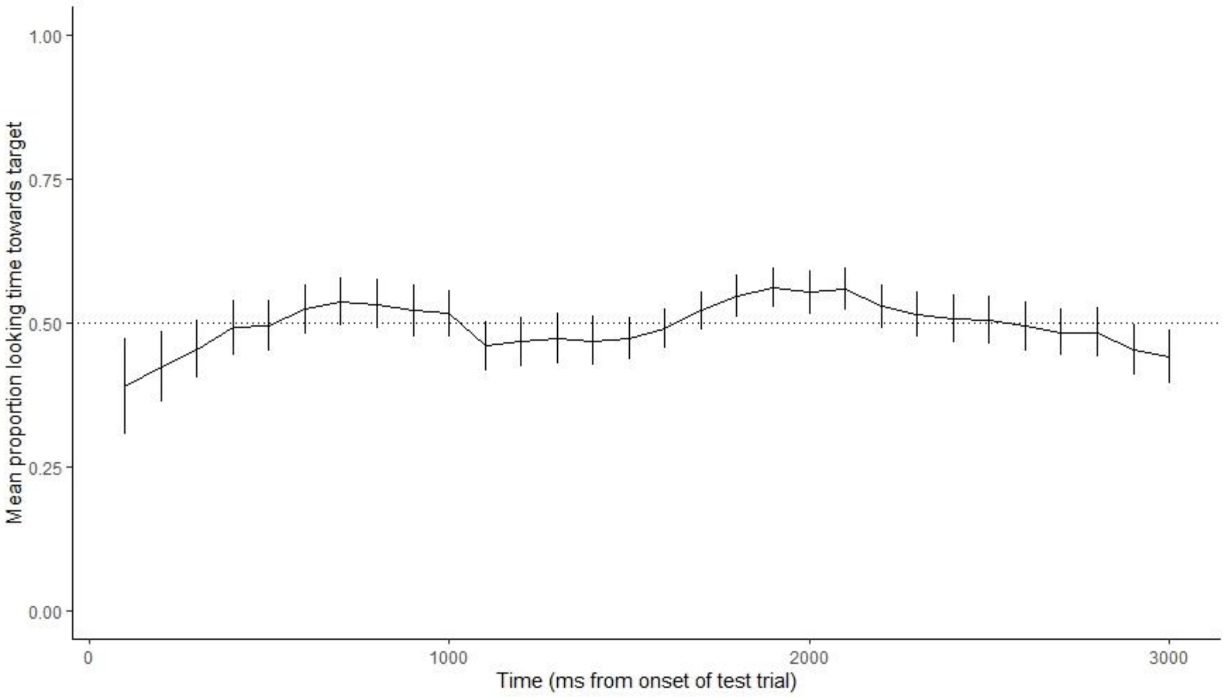


Figure 7. *Time course of target looking proportion during test: Infants' proportion target looking was not different from chance (0.5) at any point in the trial. Dashed line represents chance.*



2.3.3 Discussion

Experiment 2 revealed that after seeing a blurred object, infants did not preferentially look at the clear version of this object compared with a new, equally clear object. These results are in conflict with previous studies with adults where participants showed preferences for information that could resolve their curiosity (Nicki, 1970). Therefore, our results provide evidence against a similar preference for resolving curiosity over novelty seeking in infants.

These results suggest that the role of curiosity resolution varies from infants to adults developmentally. In particular, it is possible that the curiosity resolution effect in adults stems from adults' ability to explicitly reason about their curiosity and deliberately attempt to resolve it. Evidence for this assumption comes from the finding that adults are more curious about missing information when they have a hypothesis about what this information is (Wade & Kidd, 2019). In contrast, young infants are unlikely to be capable of this level of meta-cognition.

Another possible account of these null findings is the competition between a drive for curiosity resolution and infants' novelty preference. In Experiment 2, infants were not only shown a resolution object but also a new object. Given that infants often show a novelty preference in looking tasks it is possible that the novelty of the new object attracted infants' attention, masking any drive to resolve their curiosity. We note that although in Nicki's (1970) paradigm participants had to choose, through a key press, between revealing the clear version of a blurred image and a new image, they did not see the competing images side-by-side. It is possible that in adults too, the presence of a novel competitor would reduce the drive for curiosity resolution.

2.4 General Discussion

The current studies explored how states of curiosity modulated by visual uncertainty affect object encoding in 8-month-old infants, and whether infants prefer resolution of uncertainty over novelty in curiosity-driven processing. In Experiment 1, we asked whether uncertainty-induced curiosity enhances learning of incidental information. In Experiment 2 we asked whether infants' curiosity induced by blurred images leads them to seek resolution of uncertainty over experiencing novelty. Consistent with previous research with adults (Gruber et al., 2014) but different from similar work with older children (Fandakova & Gruber, 2021), Experiment 1 suggested that curiosity induced by blurred images indeed enhanced incidental object processing in 8-month-old infants. Contrary to theories of curiosity in the adult literature, however, Experiment 2 found no evidence that infants showed a drive for uncertainty resolution.

Our results suggest that in young infants, curiosity has a broad, attention enhancing effect that is not specific to the object of curiosity. Infants showed enhanced learning for unrelated information encountered while they were in a state of curiosity, and they showed no preference for resolving their curiosity. Taking into account existing studies with older children and adults (Gruber et al., 2014; Fandakova & Gruber, 2021), these results point to developmental change in the role and function of curiosity. In contrast to infants, in adults curiosity is more focused, and exploration aims to resolve the uncertainty that elicited the curiosity. This strategy is in line with the information gap theory, which postulates that curiosity is triggered by a perceived gap in knowledge (such as the answer to a trivia question, or the identity of a blurred object; Loewenstein, 1994). Perceiving an information gap, however, presupposes metacognitive awareness that is lacking in young infants.

At the same time, information sampling is also affected by developmental change in working memory (Cowan, 2016), and it is possible that enhanced memory capacity in adults enables them, but not older children, to retain incidental information despite a focus of curiosity on the information triggering the curiosity. In other words, these results raise the possibility of a U-shaped developmental trajectory for curiosity-induced memory enhancement for incidental information, with infants and adults, but not older children, showing this effect. In infants, curiosity might induce a more general, unspecific state of arousal which enhances learning generally but which narrows to more specific goal-directed information seeking in older children and adults. With progressive memory development (Ofen, 2012; Cowan, 2016) adults, unlike children, may however become better able to recall incidental information despite the more focused curiosity. Older children's inability to learn incidental information would then occur at a developmental stage in which curiosity is already more focused, but memory is not developed enough to also retain information outside this focus.

Another possible explanation for the discrepancy between our results and those for older children and adults is that the focus of curiosity and the learning of incidental information might vary between different types of information. Whereas in the current study we used blurred images to induce curiosity, the studies testing curiosity-based learning of incidental information with older children and adults have used trivia questions (Fandakova & Gruber, 2021; Gruber et al., 2014). Both blurred images and trivia questions have been shown to induce epistemic curiosity with a drive to reduce uncertainty about the nature of the blurred object and the answer to the trivia question, respectively. However, in contrast with seeing blurred images, being asked to answer trivia questions explicitly triggers the search for an answer, which could lead to a greater focus on this answer than for clear images following their blurred version. In order to investigate the effect of different types of information, future work should replicate the trivia question results from incidental learning in older children and adults with blurred images. Additionally, in these studies the incidental information on which participants were tested was faces whereas in the current study it was novel objects. As faces are processed differently from other information such as objects and words (Inamizu et al., 2020; Martin, 2007) it is not clear how enhanced memory for faces relates to that for other information. Thus, further delineating how the breadth and individual difference of curiosity-driven learning changes across development is an important avenue for future research, considering the profound role of curiosity in motivation and learning.

References

Aslin, R. N., & Smith, L. B. (1988). Perceptual development. *Annual Review of Psychology*, *39*, 435–473. https://doi.org/10.1146/annurev.ps.39.020188.002251

Berlyne, D. E. (1954). A thoery of human curiosity. *British Journal of Psychology. General Section*, *45*(3), 180–191. https://doi.org/10.1111/j.2044-8295.1954.tb01243.x

Berlyne, D. E. (1960). *Conflict, arousal, and curiosity.* McGraw-Hill Book Company. https://doi.org/10.1037/11164-000

Berlyne, D. E. (1966). Curiosity and Exploration. *Science*, *153*(3731), 25–33. https:// doi: 10.1126/science.153.3731.25

Bromberg-Martin, E. S., & Hikosaka, O. (2009). Midbrain dopamine neurons signal preference for advance information about upcoming rewards. *Neuron*, *63*(1), 119. https://doi.org/10.1016/J.NEURON.2009.06.009

Cohen, L. B., DeLoache, J. S., & Rissman, M. W. (1975). The effect of stimulus complexity on infant visual attention and habituation. *Child Development*, *46*(3), 611. https://doi.org/10.2307/1128557

Cowan, N. (2016). Working Memory Maturation. *Perspectives on Psychological Science*, *11*(2), 239–264. https://doi.org/10.1177/1745691615621279

Daddaoua, N., Lopes, M., & Gottlieb, J. (2016). Intrinsically motivated oculomotor exploration guided by uncertainty reduction and conditioned reinforcement in non-human primates. *Scientific Reports 2016 6:1*, *6*(1), 1–15.

https://doi.org/10.1038/srep20202

Dink, J. W., & Ferguson, B. (2015). eyetrackingR: An R library for eye-tracking data analysis.

Fandakova, Y., & Gruber, M. J. (2021). States of curiosity and interest enhance memory differently in adolescents and in children. *Developmental Science*, *24*(1), e13005. https://doi.org/10.1111/DESC.13005

Fantz, R. L., & Miranda, S. B. (1975). Newborn infant attention to form of contour. *Child Development*, *46*(1), 224–228. https://doi.org/10.2307/1128853

Fantz, R. L., & Nevis, S. (1967). Pattern preferences and perceptual-cognitive development in early infancy. *Merrill-Palmer Quarterly of Behavior and Development*. https://www.jstor.org/stable/23082720

Fantz, R. L. (1958). Pattern vision in young infants. *The Psychological Record*, *8*(2), 43–47. https://doi.org/10.1007/BF03393306

Fisher-Thompson, D. (2014). Exploring the emergence of side biases and familiarity-novelty preferences from the real-time dynamics of infant looking. *Infancy*, *19*(3), 227–261. https://doi.org/10.1111/INFA.12051

Fisher-Thompson, D., & Peterson, J. A. (2004). Infant side biases and familiarity-novelty preferences during a serial paired-comparison task. *Infancy*, *5*(3), 309–340. https://doi.org/10.1207/S15327078IN0503_4

Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of curiosity modulate hippocampus-dependent learning via the dopaminergic circuit. *Neuron*, *84*(2), 486–496. https://doi.org/10.1016/J.NEURON.2014.08.060

Gruber, M. J., & Ranganath, C. (2019). How Curiosity Enhances Hippocampus-Dependent Memory: The Prediction, Appraisal, Curiosity, and Exploration (PACE) Framework. *Trends in Cognitive Sciences*, *23*(12), 1014–1025. https://doi.org/10.1016/j.tics.2019.10.003

Hunter, M. A., & Ames, E. W. (1988). A multifactor model of infant preferences for novel and familiar stimuli. *Advances in Infancy Research* , *5*, 69–95. https://psycnet.apa.org/record/1988-98065-003

Hunter, M. A., Ames, E. W., & Koopman, R. (1983). Effects of stimulus complexity and familiarization time on infant preferences for novel and familiar stimuli. *Developmental Psychology*, *19*(3), 338–352. https://doi.org/10.1037/0012-1649.19.3.338

Inamizu, S., Yamada, E., Ogata, K., Uehara, T., Kira, J. ichi, & Tobimatsu, S. (2020). Neuromagnetic correlates of hemispheric specialization for face and word recognition. *Neuroscience Research*, *156*, 108–116. https://doi.org/10.1016/j.neures.2019.11.006

Jarosz, A. F., & Wiley, J. (2014). What Are the Odds? A Practical Guide to Computing and Reporting Bayes Factors. *The Journal of Problem Solving*, *7*(1). https://doi.org/10.7771/1932-6246.1167

Jepma, M., Verdonschot, R. G., van Steenbergen, H., Rombouts, S. A. R. B., & Nieuwenhuis, S. (2012). Neural mechanisms underlying the induction and relief of perceptual curiosity. *Frontiers in Behavioral Neuroscience*, *6*, 5. https://doi.org/10.3389/fnbeh.2012.00005

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T., & Camerer, C. F. (2009). The wick in the candle of learning. *Psychological Science*, *20*(8), 963–974. https://doi.org/10.1111/j.1467-9280.2009.02402.x

Kidd, C., & Hayden, B. Y. (2015). The Psychology and Neuroscience of Curiosity. *Neuron*, *88*(3), 449–460. https://doi.org/10.1016/j.neuron.2015.09.010

Kobayashi, K., Ravaioli, S., Baranès, A., Woodford, M., & Gottlieb, J. (2019). Diverse motives for human curiosity. *Nature Human Behaviour*, 1. https://doi.org/10.1038/s41562-019-0589-3

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*(1), 75–98. https://doi.org/10.1037/0033-2909.116.1.75

Martin, A. (2007). The representation of object concepts in the brain. *Annual Review of Psychology*, *58*, 25–45. https://doi.org/10.1146/annurev.psych.57.102904.190143

Nicki, R. M. (1970). The reinforcing effect of uncertainty reduction on a human operant. *Canadian Journal of Psychology/Revue Canadienne de Psychologie*, *24*(6), 389–400. https://doi.org/10.1037/h0082875

Norcia, A. M., & Tyler, C. W. (1985). Infant VEP acuity measurements: analysis of individual differences and measurement error. *Electroencephalography and Clinical Neurophysiology*, *61*(5), 359–369. https://doi.org/10.1016/0013-4694(85)91026-0

Ofen, N. (2012). The development of neural correlates for memory formation. *Neuroscience and Biobehavioral Reviews*, *36*(7), 1708. https://doi.org/10.1016/J.NEUBIOREV.2012.02.016

Oudeyer, P.-Y., & Smith, L. B. (2016). How Evolution May Work Through Curiosity-Driven Developmental Process. *Topics in Cognitive Science*, *8*(2), 492–502. https://doi.org/10.1111/tops.12196

Poli, F., Serino, G., Mars, R. B., & Hunnius, S. (2020). Infants tailor their attention to maximize learning. *Science Advances*, *6*(39), eabb5053. https://doi.org/10.1126/sciadv.abb5053

Quinn, P. C., Eimas, P. D., & Rosenkrantz, S. L. (1993). Evidence for representations of perceptually similar natural categories by 3-month-old and 4-month-old infants. *Perception*, *22*(4), 463–475. https://doi.org/10.1068/p220463

Quinn, P. C., Eimas, P. D., & Tarr, M. J. (2001). Perceptual Categorization of Cat and Dog Silhouettes by 3- to 4-Month-Old Infants. *Journal of Experimental Child Psychology*, *79*(1), 78–94. https://doi.org/10.1006/JECP.2000.2609

Reynolds, G. D. (2015). Infant visual attention and object recognition. *Behavioural Brain Research*, *285*, 34–43. https://doi.org/10.1016/j.bbr.2015.01.015

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*(2), 225–237. https://doi.org/10.3758/pbr.16.2.225

Ruff, H. A., & Rothbart, M. K. (2001). *Attention in early development : themes and variations*. Oxford University Press.

Skoczenski, A. M., & Norcia, A. M. (1998). Neural noise limitations on infant visual sensitivity. *Nature*, *391*(6668), 697–700. https://doi.org/10.1038/35630

Smith, L. B., Jayaraman, S., Clerkin, E., & Yu, C. (2018). The Developing Infant Creates a Curriculum for Statistical Learning. *Trends in Cognitive Sciences*, *22*(4), 325–336. https://doi.org/10.1016/J.TICS.2018.02.004

Twomey, K. E., & Westermann, G. (2018). Curiosity-based learning in infants: a neurocomputational approach. *Developmental Science*. https://doi.org/10.1111/desc.12629

Twomey, K. E., & Westermann, G. (2019). Building the Foundations of Language. *International Handbook of Language Acquisition*, 102–114.

https://doi.org/10.4324/9781315110622-6

van Lieshout, L. L., Vandenbroucke, A. R., Müller, N. C., Cools, R., & de Lange, F. P. (2018). Induction and Relief of Curiosity Elicit Parietal and Frontal Activity. The *Journal of Neuroscience, 38*(10), 2579–2588. https://doi.org/10.1523/jneurosci.2816-17.2018

Wade, S., & Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psychonomic Bulletin and Review*, *26*(4), 1377–1387. https://doi.org/10.3758/s13423-019-01598-6

Wass, S., Porayska-Pomsta, K., & Johnson, M. H. (2011). Training Attentional Control in Infancy. *Current Biology*, *21*(18), 1543–1547. https://doi.org/10.1016/j.cub.2011.08.004

Chapter 3

Neural Correlates of Visual Uncertainty and Curiosity

Evidence from cognitive neuroscience of curiosity suggests that curiosity elicited by uncertainty is associated with certain attention enhancement and arousal mechanisms, whereas curiosity resolution is associated with reward processing that enhances learning. However, it is unclear how these processes may happen at a cortical level. Thus, the purpose of this investigation is to investigate the neural correlates of visual uncertainty and the association with curiosity using EEG and a blurred picture paradigm.

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Abstract

Evidence from cognitive neuroscience of curiosity research suggests that the induction of curiosity about uncertainty is related to enhancement of attention, whereas curiosity reduction of uncertainty promotes better learning outcomes. However, it is still unclear how these processes relate to attention and learning at a cortical level. Thus, this chapter set out to investigate the neural correlations of visual uncertainty and how it relates to curiosity using EEG. In this blurred image paradigm, visual stimuli with different degrees of blurredness were used to induce curiosity. Then, the corresponding clear stimuli were presented to examine the neural activities to the curiosity reduction. We were interested in examining 1) the extent to which curiosity was modulated by visual uncertainty; 2) whether the induction of curiosity was associated with alpha desynchronisation – an index of enhanced focused attention, and 3) whether the reduction of curiosity was related to increased theta activities – the learning rhythm. Overall, we found a quadratic relationship between curiosity and visual uncertainty such that curiosity increases as visual uncertainty increases and curiosity peaks when visual uncertainty is high. We found stronger alpha desynchronisation for Med and High Blur conditions than Clear and Low Blur conditions over the posterior midline areas. Stronger alpha desynchronisation was also found on the left temporal occipital areas relative to the right temporal occipital areas. However, we did not find strong evidence with regard to increased theta activities as an indicator of enhanced learning over the frontal region for high curiosity resolution images relative to low curiosity resolution images.

3.1 Introduction

Curiosity is viewed as an intrinsic motivation to explore and acquire information from the environment, which plays an essential role in cognition (Gottlieb et al., 2013; Kidd & Hayden, 2015). Considerable research shows an interlocked relationship between curiosity and uncertainty (Berlyne, 1960; Gottlieb & Oudeyer, 2018; Ligneul et al., 2018; Nicki, 1970; van Lieshout et al., 2018), suggesting curiosity is an arousing state in response to a stimulus or a situation that varies in uncertainty. The subsequent exploratory behaviours are motivated by a desire to reduce the uncertainty that prompts them (Bromberg-Martin & Hikosaka, 2009; Jepma et al., 2012; Kalnins & Bruner, 1973; Nicki, 1970). According to the information gap account of curiosity (Loewenstein, 1994), the extent to which curiosity is evoked is also related to the degrees of uncertainty one experiences and perceives. Either very high or very low uncertainty is unlikely to evoke high curiosity as the associated, perceived knowledge gap would either be too big or too small to address (Loewenstein, 1994). A large knowledge gap would mean the desired information is too difficult to learn or too much to obtain, whereas a small knowledge gap represents a learner who is likely to have already possessed the information. Conversely, an intermediate level of uncertainty represents a 'just-about-right' knowledge gap that would pique curiosity for optimal learning (Metcalfe et al., 2020).

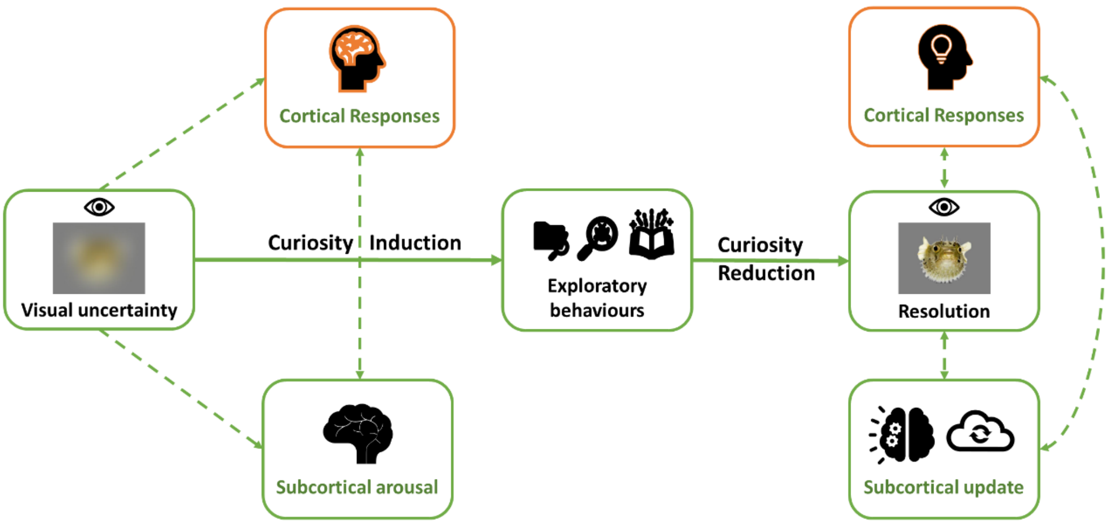
Although this intermediate knowledge gap perspective has been demonstrated empirically (Baranes et al., 2015; Kang et al., 2009), the relationship between the degree of uncertainty in relation to the knowledge gap and curiosity remains ambiguous due to mixed findings in the literature. For example, it has also been found that higher curiosity is associated with both smaller and larger knowledge gaps compared to an intermediate gap. Studies using trivia question paradigms found that participants rated their curiosity higher to the questions that they felt they knew the answers (i.e. the *'feeling-of-knowing'*) relative to the questions they felt otherwise. The '*Feeling-of-knowing*' represents a smaller knowledge gap with less uncertainty, which induces higher curiosity (Litman et al., 2005; Metcalfe et al., 2017; Wade & Kidd, 2019). On the other hand, studies also found that situations that are high in outcome uncertainty increase curiosity linearly (van Lieshout et al., 2018). Overall, these mixed findings could be due to variations in task design and materials (i.e., trivia questions or blurred pictures) applied across studies. Moreover, whether participants were asked to make an explicit guess (i.e., prediction) and when they were asked to provide a curiosity rating (i.e., the order of the questions asked) during the task also substantially contribute to this inconsistency. For example, two studies (Van de Cruys et al., 2021, Wade & Kidd, 2019) that required participants to provide a specific guess found a linear relationship between curiosity and uncertainty, suggesting that having a specific prediction might influence curiosity. Taken together, the degree to which uncertainty modulates curiosity remains an open question that needs further investigation. Hence, in this chapter, we first set out to examine how curiosity is modulated by different degrees of uncertainty using both behavioural and electroencephalogram (EEG) measurements. More specifically, we varied uncertainty by blurring images of everyday objects, creating four different levels of visual uncertainty that allowed us to study its association with curiosity.

Blurred images are often used as uncertain information to study different aspects of curiosity (Berlyne & Normore, 1972; Jepma et al., 2012; Kalnins & Bruner, 1973; Nicki, 1970). At a behavioural level, uncertainty induced by blurred images was found to have motivational value, which reinforces information-seeking behaviours. When presented with a silent colour film and the clearness of the images in the film was controlled by a pacifier, infants' sucking rate increased significantly in the "suck-for-clear" condition as the more sucking, the clearer the image would be. In contrast, the sucking rate decreased in the "suck-for-blur condition" as more sucking resulted in blurring the images (Kalnins & Bruner, 1973). Interestingly, infants spent more time looking at the cleared pictures in the "suck-for-clear" condition but not the “suck-for-blur” condition, indicating that blurredness indeed has impacts on infants’ subsequent preferences for information sampling. Similarly, when presented with blurred images, adult participants preferred to press a certain key that was associated with the corresponding clear images than a key associated with a novel image (Nicki, 1970). In addition, a neuroimaging study using blurred images to investigate subcortical mechanisms of curiosity revealed that when seeing blurred images, brain regions sensitive to conflict and arousal such as the anterior insula and anterior cingulate cortex were activated (Jepma et al., 2012). In sum, these studies indeed showed that being exposed to blurred images creates an arousing state which induces curiosity and motivates exploratory behaviours for uncertainty resolution.

The aroused state of curiosity is associated with enhanced attention, leading to improvement in information processing (Gottlieb et al., 2013). Moreover, a series of behavioural studies by Berlyne and Normore (1972) also demonstrated the beneficial effects of visual uncertainty induced by blurred images on incidental learning, highlighting the role of curiosity reduction in learning enhancement. In these studies, to manipulate the induction and reduction of curiosity about visual uncertainty independently, participants were shown combinations of blurred and clear images. In one condition, a blurred stimulus was used to induce curiosity, followed by the corresponding clear stimulus to reduce curiosity. In a second condition, a blurred stimulus was used to induce curiosity, followed by an unrelated clear stimulus, meaning that the curiosity was not resolved. In a third condition, a clear stimulus followed by the corresponding blurred stimulus was presented, meaning no curiosity induction or reduction was involved. Participants were then asked to recall the stimuli they had seen. It was found that recall performance was the best for the first condition only when the curiosity was relieved. A similar study by Jepma and colleagues (2012) revealed activations of hippocampal and striatal areas during the reduction of curiosity, suggesting the associated learning enhancement might happen during the reduction of curiosity.

Taken together, these studies point to the hypotheses that the induction of curiosity about blurred images is associated with certain attentional arousal enhancement mechanisms setting a ready-to-learn state, whereas the reduction of curiosity about blurred images promotes better learning outcomes. Thus, the current study aims to investigate whether these hypotheses (Figure 1) hold true at a cortical level using a blurred picture paradigm and EEG. As curiosity often is a fleeting phenomenon, neuroimaging methods such as functional magnetic resonance imaging (fMRI) with low temporal resolution have limitations in capturing these swift temporal dynamics. In contrast, EEG has a high temporal resolution, providing an ideal way to do so.

Figure 1 *Demonstration of the current research gaps: it remains unclear what the cortical responses and representations (orange) would be with regard to the induction and reduction of curiosity modulated by uncertainty.*



EEG measures sum synchronised, electrical activities in populations of cortical neurons from the scalp. These synchronised (or desynchronised) and rhythmic activities reflect the performance of cortical information processing, exhibited in waveforms with a wide range of frequencies over the scalp (Hu & Zhang, 2019; Klimesch, 1999). Of particular interest here are the alpha frequency bands ranging from 8 Hz to 13 Hz and the theta frequency bands ranging from 4 Hz to 8 Hz. EEG rhythmic oscillations as well as the spectral changes at different frequency bands fluctuate largely dependent on tasks to tasks. In event-related tasks, increased EEG rhythmic activities are referred to as event-related synchronisation (ERS), whereas decreased EEG rhythmic activities as event-related desynchronisation (ERD; Pfurtscheller & Lopez da Silva, 1999). Different frequency bands and rhythmic oscillations are associated with certain functions and psychological states. Here we focused on the alpha and theta rhythmic oscillations and investigated their relationships to visual uncertainty and curiosity.

Alpha oscillation has unique roles in cognitive information processing given its sensitivities in reflecting changes in psychological states. It is well-known that alpha amplitude over the occipital cortex increases when a subject closes their eyes (the “Berger effect”; Berger, 1931), or when a subject is at a resting state (the ‘idling rhythm’; Pfurtscheller & Aranibar, 1977). Interestingly, alpha amplitude becomes suppressed when a subject opens their eyes regardless of actual visual inputs/simulations, and when a subject is engaged in a task (Adrian & Matthews, 1934; Feige et al., 2005; Klimesch, 1999; Klimesch et al., 2007). This decrease in power in relation to events (also called ERD) has been suggested to be associated with the inhibition of task-irrelevant information, which in turn improves the focused attention on the task (Foxe et al., 1998; Klimesch, 2012; Suffczynski et al., 2001). Moreover, alpha decreases as the cognitive demands of a task increase, such as for a task that requires retrieval of increasingly complex information (Klimesch, 1997; Klimesch et al., 2007, 2011), revealing its role in cortical excitation and active information encoding (Klimesch, 2012). On the other hand, evidence suggests that curiosity modulates attention by increasing arousal, faster orientation and improving focused attention towards desired information. For example, in a trivia question study, participants were presented with trivia questions and asked to rate their curiosity about the questions with their eye movement and pupil size tracked. The answer was then presented on the left side of the screen with a delay. It was found that for high-curiosity questions, participants' saccades oriented towards the answer location faster before the answer was revealed. When the answer was revealed, participants also looked longer at the answer, relative to low-curiosity questions (Baranes et al., 2015). Moreover, pupil responses as a measure of attentional arousal were found to ramp up significantly right before the answers to high-curiosity questions were revealed compared to low or medium-curiosity questions (Brod & Breitwieser, 2019; Kang et al., 2009). Taken together, given these features and functions of alpha desynchronisation in relation to attention, these studies provide a possibility to use alpha desynchronisation as a cortical index of focused attention, creating an ideal window to look into the relationships between curiosity and attention.

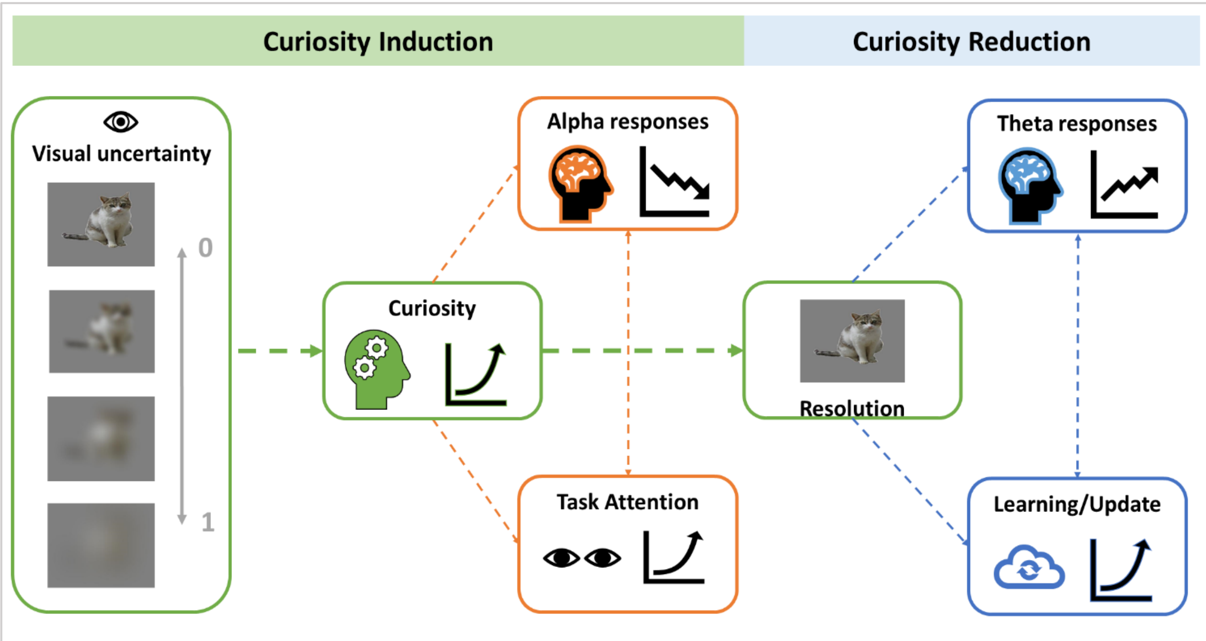
Another well-studied frequency band, theta oscillation (also referred to as 'the learning rhythm') is thought to be an index of active cognitive engagement, context updating and learning (Begus & Bonawitz, 2020; Cavanagh & Frank, 2014; Makeig et al., 2004). A series of studies by Klimesch and colleagues (Klimesch, 1996, 1999; Klimesch et al., 2008) showed that increased theta, especially over the frontal and posterior scalp electrode sites, during information encoding predicts better incidental recall performance. Similarly, in a word learning task, enhanced synchronisation at the theta band between the anterior and posterior brain regions was found for successfully learned words in comparison to unlearned words (Weiss et al., 2000). These findings highlight the role of theta in more efficient information encoding and memory formation (Begus & Bonawitz, 2020; Klimesch, 1999; Lega et al., 2012; Solomon et al., 2017; Weiss et al., 2000). Moreover, theta activities are also closely related to curiosity and active learning. In a free exploration study, infants explored objects freely with EEG recording. Enhanced theta activities over the frontal regions were found during the active object exploration, and most importantly, this enhancement in theta was found to modulate later object recognition (Begus et al., 2015). This work reveals a possibility that theta oscillations could be a suitable tool for studying the underlying mechanisms of curiosity and active learning.

Taken together, given the characteristics of alpha oscillation in modulating focused attention and selective, active information encoding, as well as the representative roles of theta oscillation in cognitive updating and memory formation, this study set out to examine the manifestations of alpha oscillations during the induction of curiosity and theta oscillations during the reduction of curiosity using a blurred picture paradigm. In this task, images with four degrees of blur (i.e., clear, low, medium and high; Figure 2) of everyday objects were used to evoke curiosity and then the clear corresponding images were presented to reduce the curiosity.

Previous evidence suggests that various degrees of blur trigger different levels of curiosity. In particular, it has been found that images with an intermediate level of blur triggered the highest subjective uncertainty and motivated participants' desires to see the corresponding clear images the most (Nicki, 1970), revealing a non-linear relationship (an inverted U-shaped relationship) between curiosity and blurredness. On the other hand, a recent study suggested the relationship between uncertain pictures (i.e., Mooney images) and curiosity is linear such that a higher degree of uncertainty is associated with higher curiosity (Sander et al., 2021). These inconsistent findings reveal the fact that the degree to which uncertainty modulates curiosity remains unclear. Thus, to first establish to what extent curiosity was induced by certain degrees of blur in this study, we asked independent raters to rate their curiosity about the images in a separate online study. Meantime, we investigated whether alpha as an index of attention was modulated by curiosity about images with various degrees of blur using the same stimuli. Given that alpha decreases as a function of focused attention and active information encoding, we hypothesised that alpha decreases as curiosity about the images increases during the induction of curiosity. We focused on occipital alpha based on a similar object recognition task where a series of four images with different levels of distortion (from high to low) were presented consecutively (Freunberger et al., 2008). The spatial frequency of these images was controlled given its influence on alpha activity. This study suggested that alpha over the right temporal occipital areas was reduced significantly up to the start of object recognition. As for theta oscillation, considering its roles in cognitive effort and learning (Begus & Bonawitz, 2020; Freunberger et al., 2008), we predicted that theta amplitudes over frontal areas would be higher for resolution images that rated as high curiosity as effort to reduce the uncertainty, compared to the images rated with low curiosity.

In summary, this chapter intended to investigate three hypotheses. The first aim was to examine the extent to which curiosity was modulated by various degrees of blur. As the existing literature that used uncertain picture paradigms (Cohanpour et al., 2022; Nicki, 1997; Van de Cruys, 2021) revealed either a linear or a U-shaped relationship between curiosity and uncertainty, we predicted that likewise, curiosity would either be in a linear or a U-shaped relationship with blurredness in the current study. The second aim was to investigate whether alpha desynchronisation as an indication of increased global arousal and focused attention (Klimesch, 1997; Klimesch et al., 2007, 2011, 2012) would be associated with increased curiosity during the induction of curiosity, given that a high state of curiosity is associated with increased attention relative to a low state of curiosity (Gottlieb et al., 2013; Kang et al., 2009). Finally, this chapter examined whether increased theta activities as an index of enhanced learning would be related to high curiosity resolution images relative to low curiosity resolution images (Begus & Bonawitz, 2020), based on the beneficial effect of curiosity on learning found in previous studies (Gruber et al., 2014). Figure 2 shows a demonstration of the hypotheses.

Figure 2 *Demonstration of the hypotheses for the current study. Left (green): the induction of curiosity is modulated by visual uncertainty; Middle (orange): alpha decreases (desynchronisation) is associated with increased curiosity; Right (Blue): increased theta oscillation is associated with high-curiosity resolution images.*



3.2 Methods

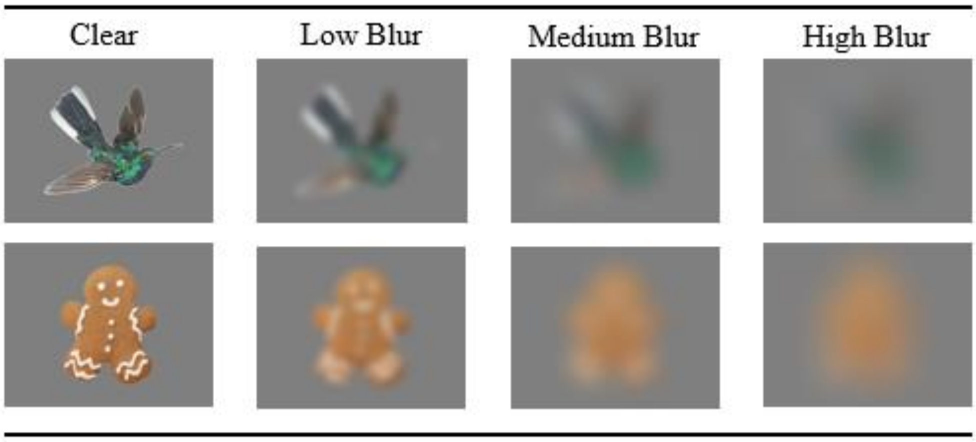
Participants

A total of 27 university students were recruited from Lancaster University. The sample size was pre-determined with a 0.31 effect size, 0.05 as alpha and 0.95 as power using G*power (version 3.1.9.6). One participant was excluded due to experimental error, resulting in 26 participants (M_{age} = 18.69, SD_{age} = 0.84; 20 female, 5 male, 1 non-binary) in the final analysis. Participants received either university credits or monetary rewards based on the standard payment rate. Study information was given to participants and informed consent was obtained before data collection. The study was approved by the University's research ethics committee.

Stimuli

A total of 380 clear object images (320 in the learning phase and 60 as foil images in the recognition phase) were adopted from the Bank of Standardised Stimuli database (BOSS, Brodeur et al., 2014), Moreno-Martínez and Montoro (2012) as well as self-sourced online (copyright free). These images were objects of animals, food, instruments, furniture, utensils and vehicles. All were resized to a rectangular size of 450 by 350 pixels and placed in the middle of a grey background. The 320 images used in the learning phase were blurred with three different degrees (10, 25, 40) of Gaussian filters in MATLAB (R2016b), resulting in three sets of blurred images (see Figure 3) and four conditions (Clear, Low Blur, Medium Blur and High Blur).

Figure 3 *Stimulus examples for four blur levels*



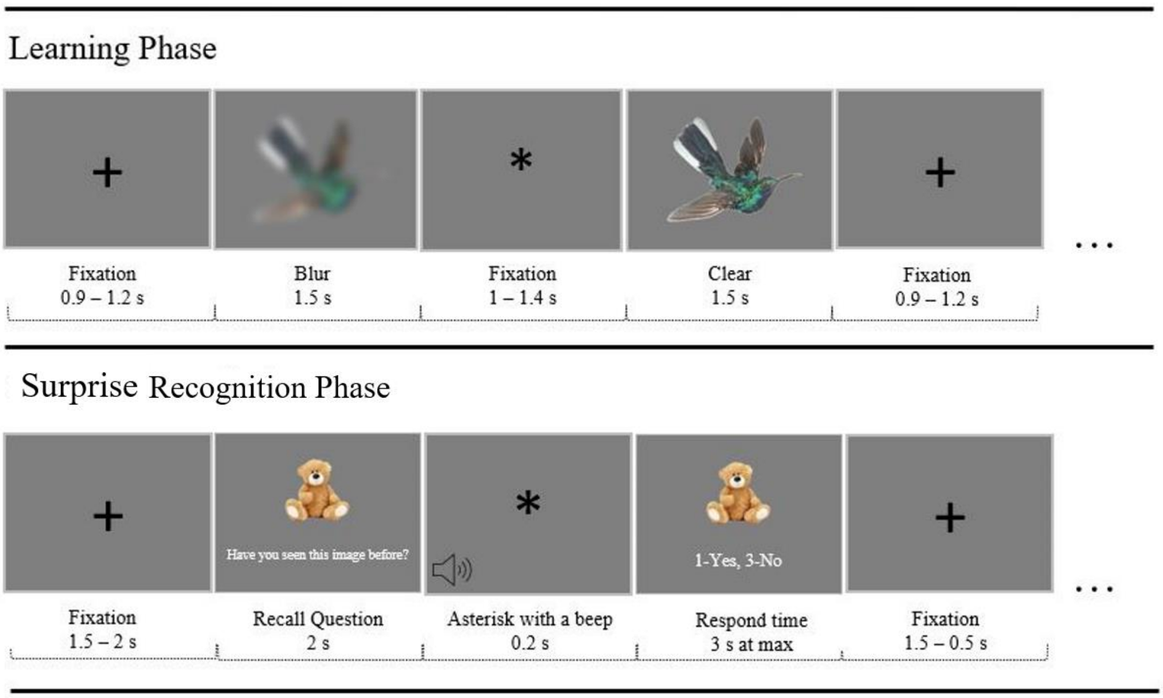
Note: Medium Blur is referred to as 'Med Blur' below.

Design

Electroencephalography (EEG) Experiment

The electrical signal was recorded using 128-channel Electrical Geodesic Incorporated (EGI) nets in Net Station (5.4), 10-20 systems and 1000 Hz sampling rate. The experiment was programmed in MATLAB (R2016b) and presented on a monitor. A small numeric keypad was used in the recognition phase. The experiment consisted of two phases (see Figure 4 for the experimental design): a learning phase and a surprise recognition test phase. In the learning phase, there were three blur conditions (Low, Med, and High Blur) and a non-blur, clear control condition. In each condition, there were 80 trials, resulting in 320 trials in the learning phase. Each trial started with an inter-trial fixation cross ranging from 0.9 s to 1.2 s. Then an image with a different degree of blur was shown in the middle of the screen for 1.5 s, followed by an inter-stimulus fixation asterisk ranging from 1 s to 1.4 s. The corresponding clear image to the blurred one was presented at the end of the trial for 1.5 s. The orders of images, trials and conditions were randomised and separated into five blocks with 64 trials in each block. No image was seen by each participant more than once. Automatic breaks were implemented between blocks and participants could take a break depending on their tiredness or their other needs. A four-second buffer was implemented at the beginning of the experiment as well as before and after a break to ensure obtaining a clear baseline.

Figure 4 *Illustration of the design. Top: Learning phase; Bottom: Surprise recognition phase*

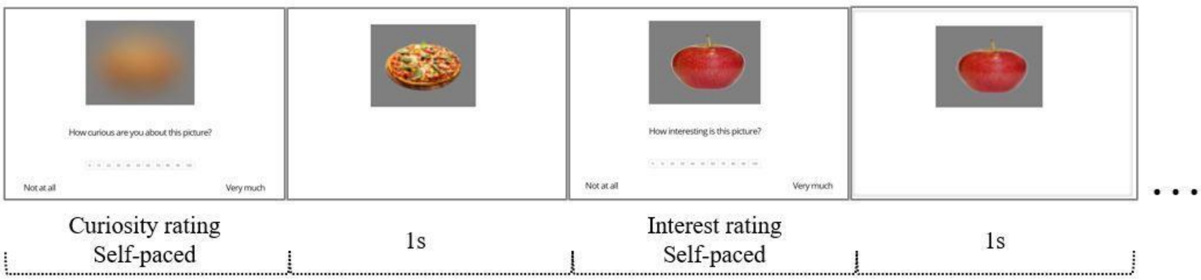


Immediately after the learning phase, a surprise recognition test was conducted where clear versions of the seen images from the learning phase as well as new, clear, foil images were mixed and displayed one at a time to participants. Participants were asked to respond to each image whether they have seen it during the learning phase by pressing 1 (Yes) or 3 (No) on a numeric keypad. There were 120 trials in total in the recognition phase including 60 seen images (clear) and 60 foil images (clear). The 60 seen images were randomly extracted from each condition evenly (15 Clear, 15 Low Blur, 15 Med Blur and 15 High Blur) from the learning phase. For each trial, a fixation cross was presented for 1.5 s to 2 s, followed by a clear image with the question 'Have you seen this image before?' on the screen for 2 seconds. An asterisk as fixation with a beep sound was presented briefly for 0.2 s to indicate participants to respond as soon as they heard the beep. The clear image was presented again for 3 s at maximum with key press instructions on the screen. The trial automatically proceeded to the next trial as soon as the participant responded, or when there was no response gathered within the 3-second limit.

Curiosity Ratings of Stimulus

Independent of the EEG experiment, curiosity and interest in the four sets of stimuli (Clear, Low Blur, Med Blur and High Blur) was rated by 54 independent raters online in Gorilla (www.gorilla.sc). Blurred stimuli were shown to participants once at a time. Participants were asked ‘*How curious are you about this picture?*’ and to rate from 0 (Not at all) to 100 (Very much). The clear corresponding image was then shown for 1s. For clear stimuli, participants were asked ‘*How interesting is this picture?*’ and to rate from 0 (Not at all) to 100 (Very much). As all the images were everyday objects that participants already knew, no uncertainty could be induced. Therefore, we adapted an approach similar to Fandakova and Gruber’s (2021) study by asking participants how interested they felt in the image. Figure 5 shows a scheme of the design. Images with different degrees of blur as well as their presenting orders were counterbalanced and randomised between raters. For each stimulus, the clear, low, medium or high blurred versions were rated by different raters. No rater saw the same stimuli in more than one trial. Trials automatically proceeded as soon as participants responded. A progress bar was shown at the top of the screen.

Figure 5 *A scheme of the curiosity and interest rating design*



Procedure of the EEG Experiment

Participants were invited to a soundproof, dim-lighting room and were seated approximately 120 cm away from a presenting screen, facing the centre of the screen. A short instruction that this was a study about object perception was given. Participants were not told about the surprise recognition test. After obtaining consent from a participant, an experimenter measured the participant's head size and put an EEG cap of suitable size on the participant's head. The impedance of electrodes was measured and made sure it passed a good threshold before starting EEG recording such that the impedances at each electrode should be less than 50 K Ohms (Picton et al., 2000) except for obviously broken electrodes.

At the beginning of the experiment, participants were asked to relax and the resting state of EEG was recorded until signals were stable. After that, the learning phase started and participants viewed the stimuli while their EEG was recorded at the same time. After the learning phase, participants were told about a surprise recognition test and were given a numeric keypad to respond to the test while their EEG was recorded. Only after participation participants were informed about the purpose of the recognition test.

Data Analysis

Filtering and Segmenting

Electrical signals were filtered offline using a 0.01 Hz high pass filter and a 30 Hz low pass filter. The continuous EEG signal was then segmented into epochs with a time window of 1500 ms before and 2500 ms after stimulus onset. Epochs were first sorted into two types of stimuli according to the design: Blurred images and Clear images (see Blur and Clear in Figure 4 Learning Phase). For the purpose of convenience, epochs of the Blurred images were referred to as *Prime* images whereas epochs of the Clear images were as *Target* images. Epochs of Prime and Target were then categorised into four conditions.

Time Window for Wavelet Transformation

EEG signals vary with time and consist of different frequencies. It is suggested to use an adaptive and variable time window for time-frequency analysis. A short time window is useful for high frequencies and a long-time window is for low frequencies (Hu & Zhang, 2019). As we were interested in alpha frequency bands (9 Hz-13 Hz) of the *Prime* epochs and theta frequency bands (4 Hz-8 Hz) of the *Target* epochs, different lengths of the time window for wavelet transformation were used.

A time window of 500 ms before and 1800 ms after the stimulus onset of *Prime* epochs was chosen. For the *Target* epochs, a time window of 700 ms before and 2000 ms after stimulus onset was initially chosen. However, due to many artefacts existing in the time window of 1700 ms after stimulus onset (during the cross fixation where participants were instructed to blink if it was needed), using a time window of 700 ms before and 2000 ms after stimulus onset resulted in a boundary effect that masked the lower frequencies. Boundary effects in wavelet transformation are likely caused by artefacts at the beginning and/or the end of the epochs (Hu & Zhang, 2019; Lilly, 2017; Nobach et al., 2007). Thus, we used a time window of 700 ms before and 1700 ms after stimulus onset for the *Target* epochs in the final analysis. Although this might affect the last 500 ms of the outcomes of the wavelet transformation (Hu & Zhang, 2019; Lilly, 2017), it would not affect our results and the corresponding interpretations. This is because we were interested in the theta activities in the early time window of stimuli (from the onset of the stimulus to 1000 ms after the stimulus onset), and the affected time window was not included.

Artefact Removal

Automatic artefact detections were conducted on the selected time windows of each epoch of *Prime* and *Target* to clear out bad segments due to eye blinks, eye movements, and bad channels. Bad channels and eye movements were rejected if the differences in amplitude exceeded 150 µV and 55 µV respectively within a moving time window of 80 ms. Manual inspection on each epoch was conducted after the automatic artefact detection to ensure clean data. Epochs with eye blinks, eye movements or more than 12 bad channels were excluded.

Five participants were excluded due to contributing less than 50% of *Prime* epochs. Twenty-one participants were included in the final analysis for *Prime* and on average, contributed to 52 out of 80 epochs per condition (*Min* = 31; *Max* = 72). All participants (*N* = 26) contributed to the *Target* on average with 63 out of 80 epochs (*Min* = 38; *Max* = 74) per condition.

EEG Frequency Analysis

The artefact-free epochs were subjected to time-frequency analysis to investigate stimulus-induced oscillatory responses using a toolbox of MATLAB (R2016R), the EEGLAB (Delorme & Makeig, 2004; version 2020.0) and custom scripts, the WTools (Parise & Csibra, 2013). Complex Morlet wavelets were computed for the frequencies 4-20 Hz with 1 Hz resolution. Total-induced oscillations were calculated using a continuous wavelet transformation of all the epochs utilising the convolution of each wavelet and taking the absolute amplitude value of the results. Transformed epochs were averaged for each condition separately. To remove the distortion due to the convolution, we chopped out 300 ms from both edges of the *Prime* epochs and 500 ms from both edges of the *Target* epochs. As a result, all segments are 1700 ms long and each segment has 200 ms before and 1500 ms after stimulus onset. The average amplitude of the 200 ms pre-stimulus window was used as a baseline by subtracting it from the entire epoch at each frequency (Parise & Csibra, 2013).

Behavioural Responses of the Surprise Recognition Test

Raw behavioural data were imported and analysed in R Studio (2021.09.2). Trials without responses were excluded, resulting in 3029 trials (97% response rate) in the final analysis. Proportions of accuracy for each condition (number of correct responses/ (number of correct responses + number of incorrect responses)) were calculated. A one-way repeated measures ANOVA was performed to compare the effect of different degrees of blur on recognition accuracy.

Curiosity Rating

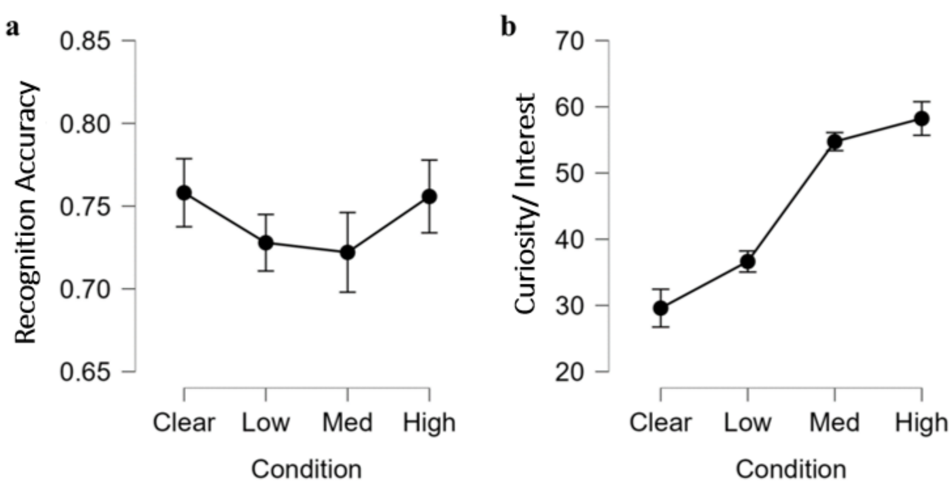
Curiosity rating data were extracted from Gorilla and input in R Studio (2021.09.2) for data cleaning and analysis. One participant was excluded as the same ratings were provided for the clear images, resulting in 53 participants in the final analysis. A one-way repeated measures ANOVA was performed to compare the effect of different degrees of blur on curiosity rating. A Bonferroni posthoc analysis was computed to further examine the significant main effects.

3.3 Results

Behavioural Results

Results of the one-way repeated measures ANOVA showed that there was no significant effect of different degrees of blur on recognition accuracy (F(3, 75) = 0.78, p = .507, η_p^2 = .03; see Figure 6a).

Figure 6 *Line plots of **(a)** the recognition accuracy and **(b)** curiosity/interest ratings across four conditions*



Curiosity Rating

Overall, curiosity ratings were the highest for the High Blur condition and the lowest for the Clear condition (see the descriptive statistics in Table S1 in supplementary materials). As Mauchly's Test of Sphericity indicated that the assumption of sphericity had been violated (p < .001), the Greenhouse-Geisser correction was applied (ε = 0.493). The results showed that curiosity rating was significantly different between at least two conditions, $F(1.48, 76.92) = 40.59$, $p < .001$, $\eta_p^2 = .44$ (see Figure 6b). A Bonferroni post-hoc analysis indicated that the curiosity rating of the High Blur condition ($M = 58.23$, $SD = 27.36$) was significantly higher than that of the Clear condition ($M = 29.60$, $SD = 16.21$, $t = 9.30$, $p < .001$) and the Low Blur condition ($M = 36.64$, $SD = 16.84$, $t = 7.02$, $p < .001$). The Med Blur condition ($M = 54.74$, $SD = 21.59$) was also significantly higher than the Clear condition ($t = 8.17$, $p < .001$) and the Low Blur condition ($t = 5.88$, $p < .001$). However, there were no significant differences between the Clear condition and the Low Blur condition ($t = -2.29$, $p = .141$), or between the Med Blur condition and the High Blur condition ($t = -1.13$, $p = 1.00$).

To further confirm the relationship between curiosity and the degrees of blurredness, based on the shape of the line plot in Figure 6b, we fitted the rating data to a simple regression model and compared it against a quadradic model using the lme4 package (Bates et al., 2022) in R. We first transformed the categorical variable Condition to a numerical variable, Blur (i.e., Clear = 1, Low = 2, Med = 3, High = 4) which was then converted to percentages. The curiosity ratings were standardised. The numerical variable Blur as the fixed factor was fitted to a simple regression model and a quadradic model to predict curiosity ratings. The two models were then compared. Results of the model comparison revealed that the quadradic model is better than the simple regression model in predicting the curiosity rating data ($F = 7.66$, $df = 1$, $p = .006$).

Simple regression model structure:

model01 = lm(Curiosity ~ Blur)

Quadradic model structure:

model02 = lm(Curiosity ~ poly(Blur, 2))

Induced Alpha Responses to Prime

To decide the scalp areas, time window and frequency band for the alpha band EEG analysis, we first located left and right centrotemporal and parietal occipital areas with frequency bands of 10 to 12 Hz based on a previous similar study (Freunberger et al., 2008). Next, we plotted time-frequency plots with 4 to 20 Hz from -200 ms before stimulus onset to the end of the stimulus at 1500 ms for each sensor, which revealed a wider alpha frequency band in our data. We then plotted scalp maps with 9-13 Hz frequency bands at every 100 ms interval from the onset of the stimulus to 1000 ms post-stimulus (see Figure 7) to inspect the time window and sensors. As the temporal occipital regions are the main areas of interest, we first based on the scalp maps, identified sensors on the left (E58, E59, E65, E66) and right temporal occipital (E84, E90, E91, E96) areas from 200 to 600 ms.

We then inspected the scalp maps for other potential regions of interest. As depicted in Figure 7, the scalp maps also indicated differences in alpha responses between conditions over frontal (E5, E18, E10, E11, E12, E16) and posterior midline areas (E62, E72, E75) from 300 ms to 600 ms. Also see Figure 8 for channel locations. We then plotted the averaged time-frequency plots (Figure 9) based on the identified regions and corresponding sensors separately across conditions to refine the frequency bands and time windows. Finally, we measured the induced alpha activity from 9 Hz to 13 Hz over the channels specified above over the frontal area from 200 ms to 600 ms, posterior midline area from 300 ms to 600 ms, and left and right temporal occipital area from 200 ms to 600 ms.

Prior to the statistical analyses, extreme outliers were checked, resulting in the exclusion of Subject 22 (Table S2). The assumptions of the normality using Shapiro-Wilk's method were tested. Also, see the qqplots in Figure S1 in the supplementary material.

Figure 7 *Scalp maps of Prime (alpha response) with 9-13 Hz frequency bands at every 100 ms interval from the onset of the stimulus to 1000 ms post-stimulus*

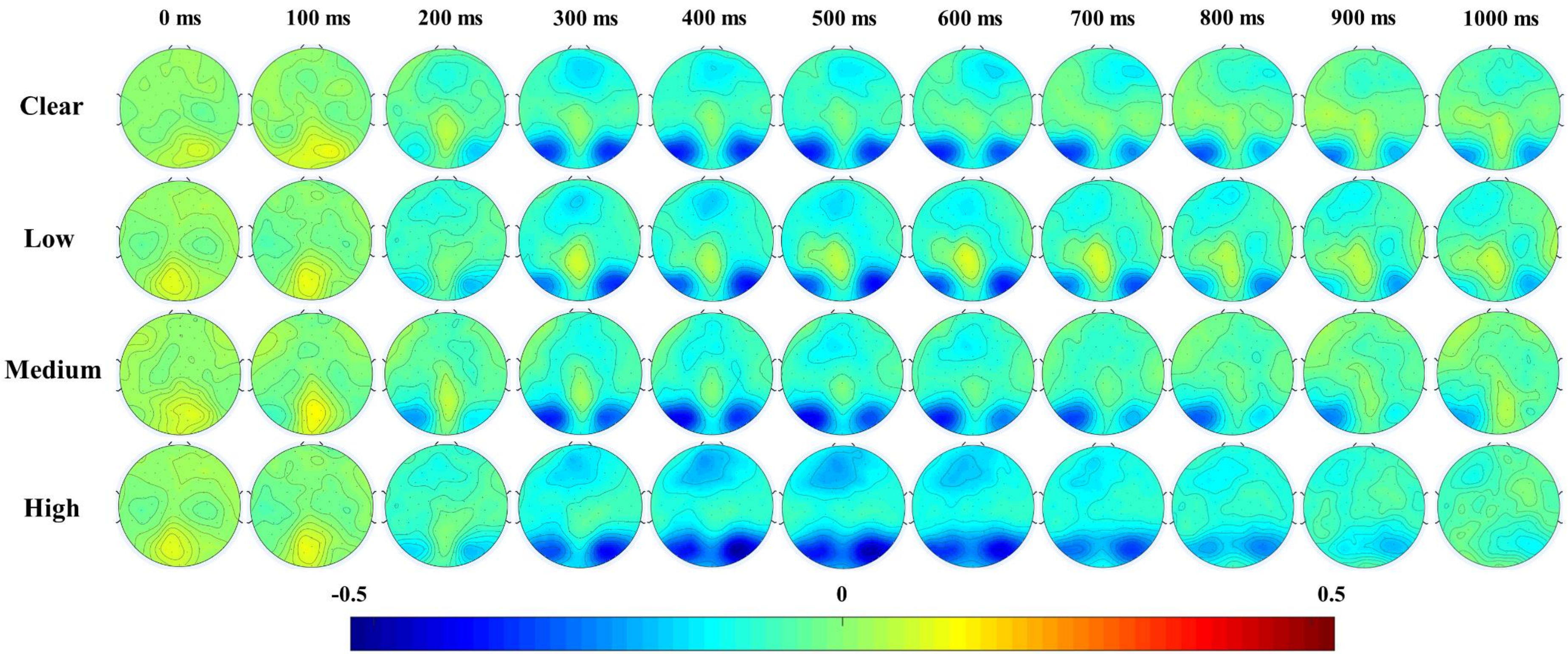


Figure 8 *The averaged channels for Prime (alpha response) over the frontal (green), the left temporal occipital (yellow), the right temporal occipital (purple) and the posterior midline regions (blue)*

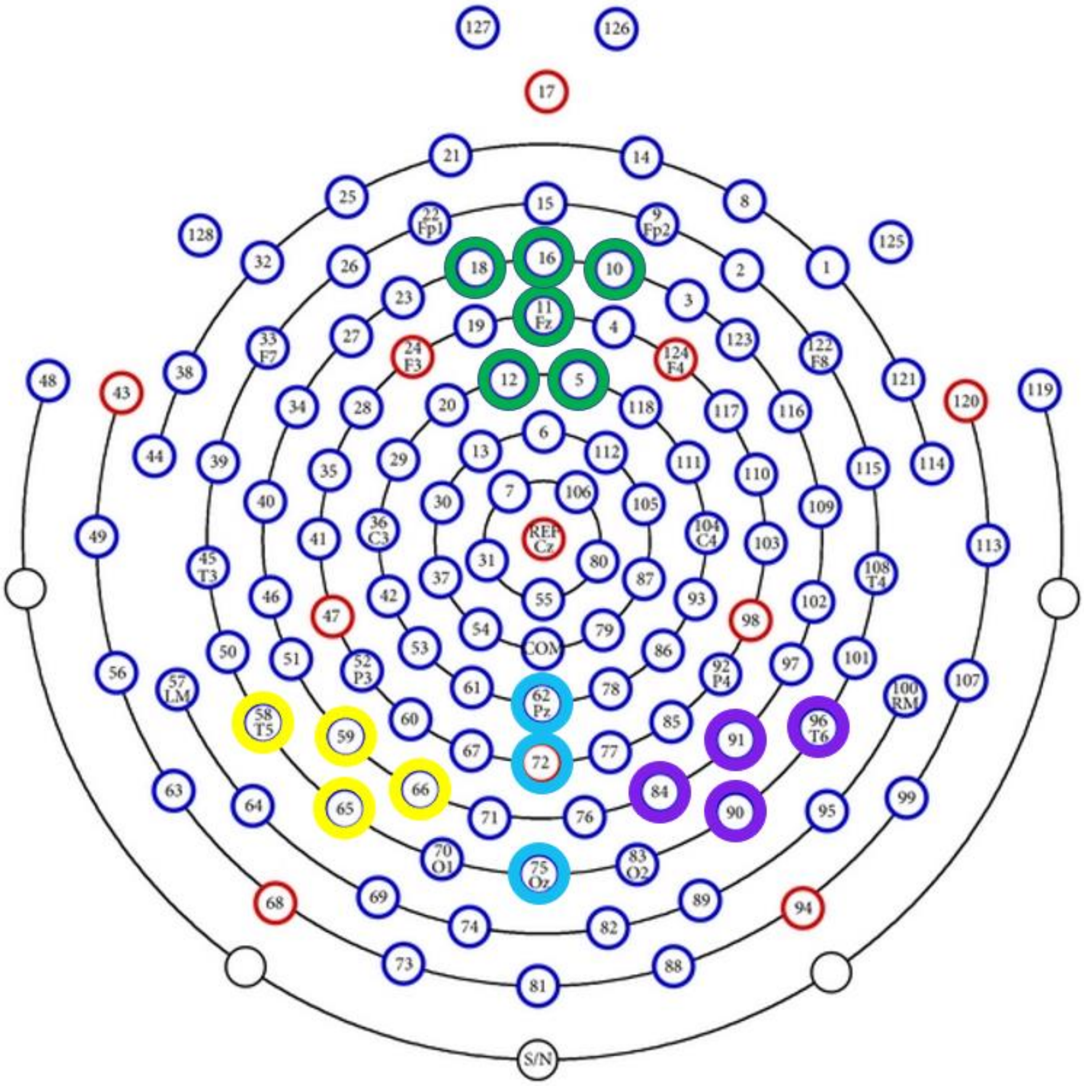
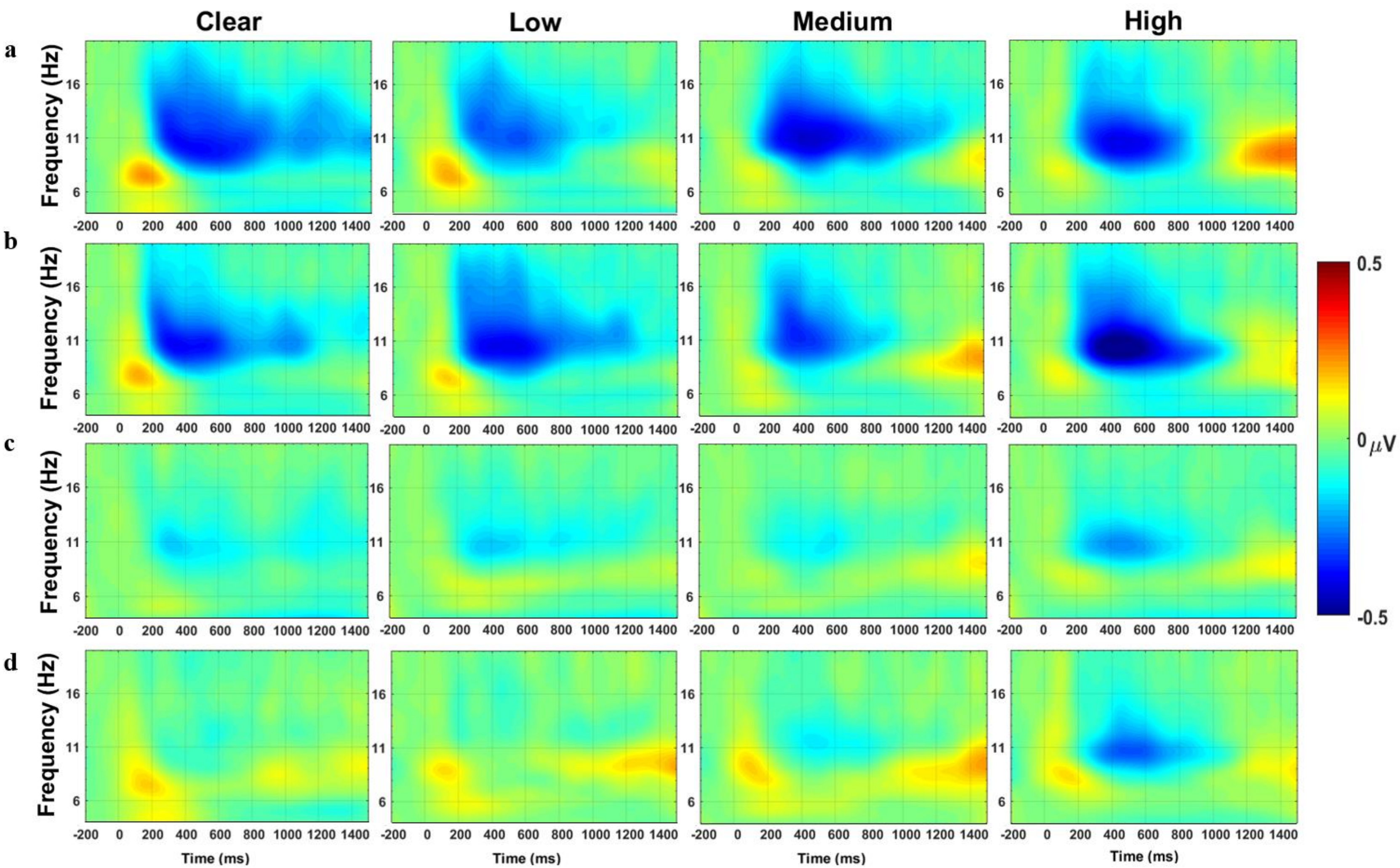


Figure 9 *Averaged time-frequency plots of* ***Prime (alpha response)*** *across conditions: a. The left temporal occipital area; b. The right temporal occipital area; c. The frontal area; d. posterior midline areas*



Frontal Alpha

To examine whether alpha desynchronisation differs between conditions, we conducted multiple *t*-tests to compare alpha response against the baseline across conditions. For frontal alpha, significant alpha desynchronisation was found across all conditions (Table 1). To examine the effect of the condition on frontal alpha, a one-way repeated measures ANOVA was computed. Results showed that there were no significant differences in frontal alpha between conditions ($F(3, 60) = 1.155$, $p = .335$).

Table 1 *Multiple t-tests results for examining alpha ERD over brain regions and conditions*

Brain region	Condition	*t*-value	*p*-value
Frontal	Clear	-3.42	.003***
	Low Blur	-3.51	.002***
	Med Blur	-3.73	.001***
	High Blur	-3.73	.001***
Posterior Midline	Clear	-1.55	.14
	Low Blur	-0.40	.70
	Med Blur	-2.62	.02*
	High Blur	-3.33	.003***
Left Temporal Occipital	Clear	-4.20	<.001***
	Low Blur	-3.69	.002***
	Med Blur	-4.95	<.001***
	High Blur	-3.26	.004***
Right Temporal Occipital	Clear	-4.27	<.001***
	Low Blur	-4.37	<.001***
	Med Blur	-3.66	.001***
	High Blur	-4.16	<.001***

Note. $*p < .05$, $***p < .001$

Posterior Midline Alpha

Multiple *t*-tests were computed to compare posterior midline alpha responses against the baseline to examine alpha desynchronisation (Table 1). Results suggested significantly increased alpha desynchronisation for the Med and High Blur conditions, but not for the Clear and Low Blur conditions (see Figure 10). A one-way repeated measures ANOVA was computed to examine the effect of conditions on posterior midline alpha. Results showed there was a significant main effect of condition on posterior midline alpha ($F(3, 60) = 6.22$, $p < .001$; Figure 11a). Post hoc tests using the Bonferroni correction revealed alpha amplitudes are significantly lower for the High Blur condition, in comparison to the Clear condition ($p_{adjust} = .003$) and the Low Blur condition ($p_{adjust} = .024$).

Figure 10 *Alpha ERD over posterior midline area across conditions. x-axis: time in ms. y-axis: frequency band. The vertical dash line represents the onset of stimulus presentation. The white box represents the time window of interest.*

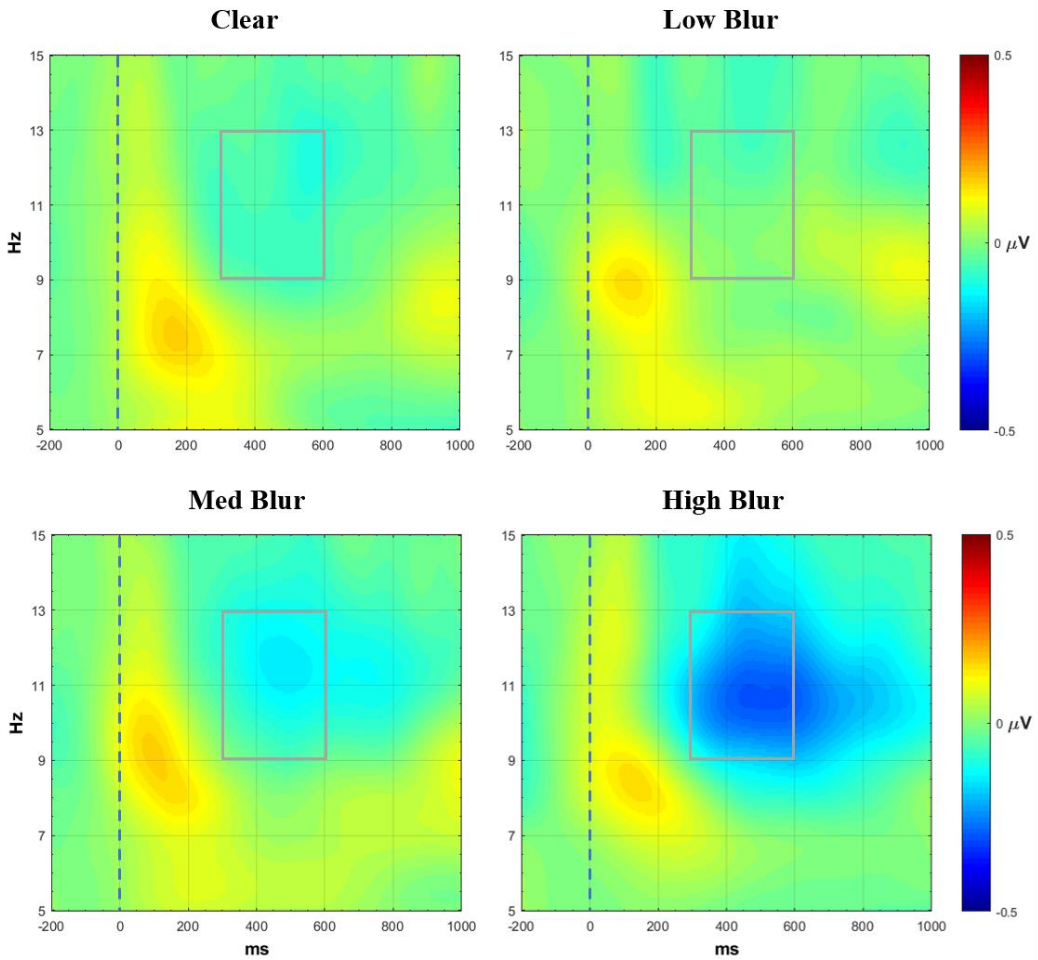
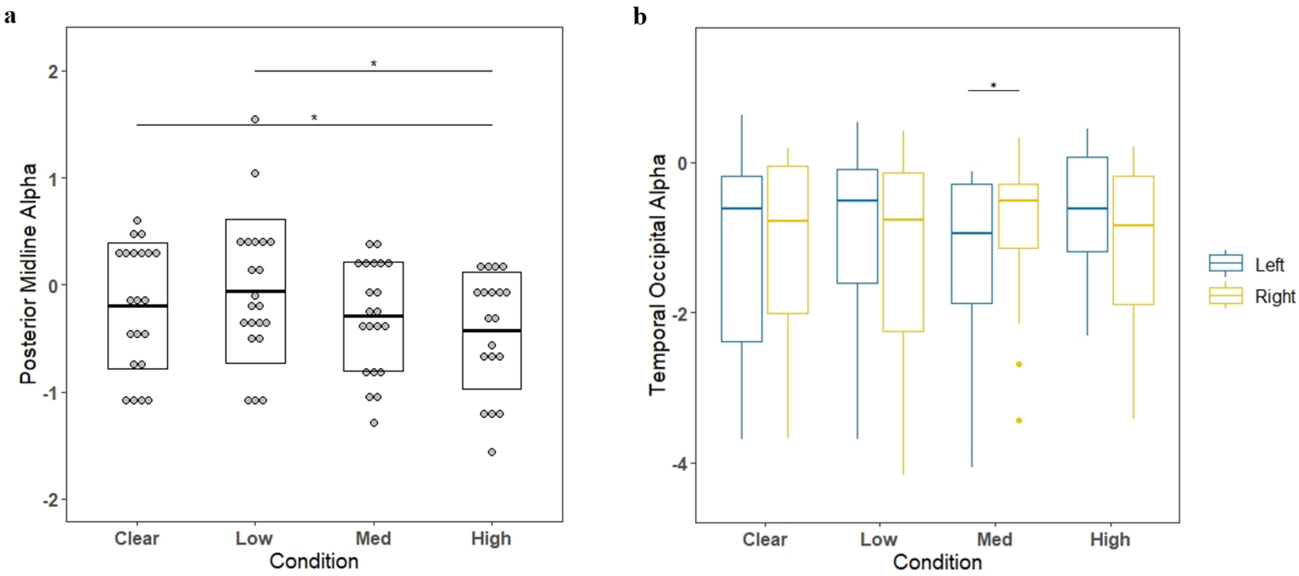


Figure 11 ***a.*** *A boxplot of the posterior midline alpha amplitudes across conditions;* ***b.*** *A boxplot of the temporal occipital alpha amplitudes across conditions and hemispheres.*

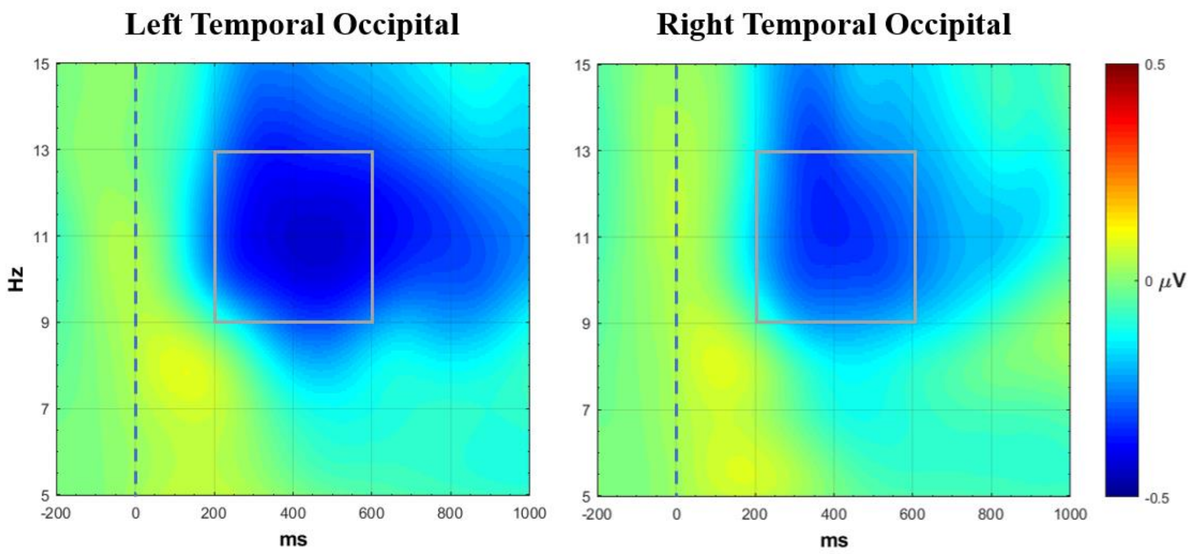


*Note. *p <.05*

Temporal Occipital Alpha

Multiple *t*-tests were computed to compare left and right temporal occipital alpha responses against the baseline. Results of *t*-tests showed significant alpha desynchronisation across all conditions over left and right temporal occipital areas (Table 1). A two-way repeated measures ANOVA was performed to investigate the effects of condition and hemisphere on temporal occipital alpha. The results suggested no significant main effects of condition ($F(3,57) = 1.03$, $p = .385$) or hemisphere ($F(1,19) = 0.01$, $p = .908$) on temporal occipital alpha, but a significant interaction between condition and hemisphere ($F(3, 57) = 6.57$, $p < .001$). To decompose the significant two-way interaction, we ran a one-way ANOVA of the condition at each level of the hemispheres. There was no significant difference between conditions in each hemisphere. A one-way ANOVA of the hemisphere at each level of conditions was conducted (Figure 11b), suggesting that there was an effect of the hemisphere at the Med Blur condition. Simple pairwise comparisons revealed that the alpha amplitudes were significantly lower in the left hemisphere in relation to the right hemisphere (p_{adjust} = .024, see Figure 12).

Figure 12 *Comparisons of left and right temporal occipital alpha ERD for Med Blur condition. x-axis: time in ms. y-axis: frequency band. The vertical dash line represents the onset of stimulus presentation. The grey box represents the window of interest.*



Induced Theta Responses to Target

To decide the scalp areas, time window and frequency band for the theta band analysis, we first located frontal areas based on previous literature where the role of frontal theta responses in cognitive control and context updating is highlighted and Begus and colleagues' work (2015). Next, we plotted time-frequency plots with 4 to 20 Hz from -200 ms before stimulus onset to the end of the stimulus at 1000 ms for each sensor, which revealed theta frequency bands ranging from 4 Hz to 8 Hz in our data. We then plotted scalp maps (Figure 13) with 4-8 Hz frequency bands at every 100 ms interval from the onset of the stimulus to 1000 ms post-stimulus to inspect the time window and sensors. The scalp plots indicated differences in theta responses between conditions over frontal as well as occipital areas. As the frontal areas are the main interest of this study, the analysis for occipital theta was exploratory.

Based on the scale plots, we chose electrodes (see Figure 14 for channel locations) over these two areas. We then plotted the averaged time-frequency plots (Figure 15) of the frontal area (E9, E10, E15, E16, E18, E22, Begus et al., 2015), left occipital area (E65, E66, E70) and right occipital (E83, E84, E90) area from the onset of the stimulus to 1000 ms post-stimulus to refine the frequency bands and time windows. Finally, we measured the induced theta activity from 4-8 Hz over the frontal area from 100 ms to 400 ms, and 4-8 Hz over the occipital areas from onset to 250 ms.

Before conducting statistical analyses, extreme outliers were detected resulting in the exclusion of Subject 06 (Table S3). The assumptions of normality using Shapiro-Wilk's method were tested. Also, see the qqplots in Figure S2 in the supplementary material.

Figure 13 *Scalp maps of* ***Target (theta response)*** *with 4-8 Hz frequency bands at every 100 ms interval from the onset of the stimulus to 1000 ms post-stimulus.*

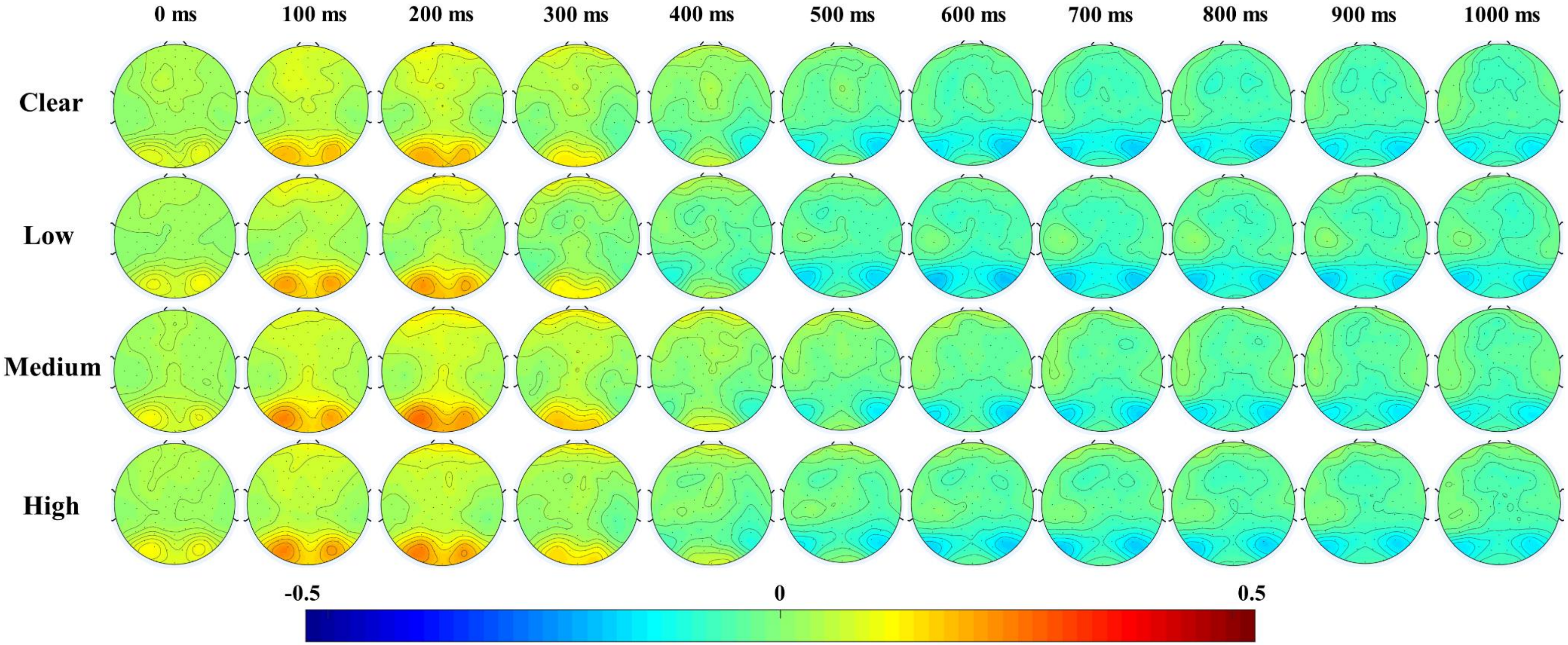


Figure 14 *The averaged channels for **theta** responses over the frontal (green), the left temporal occipital (yellow) and the right temporal occipital (purple) regions.*

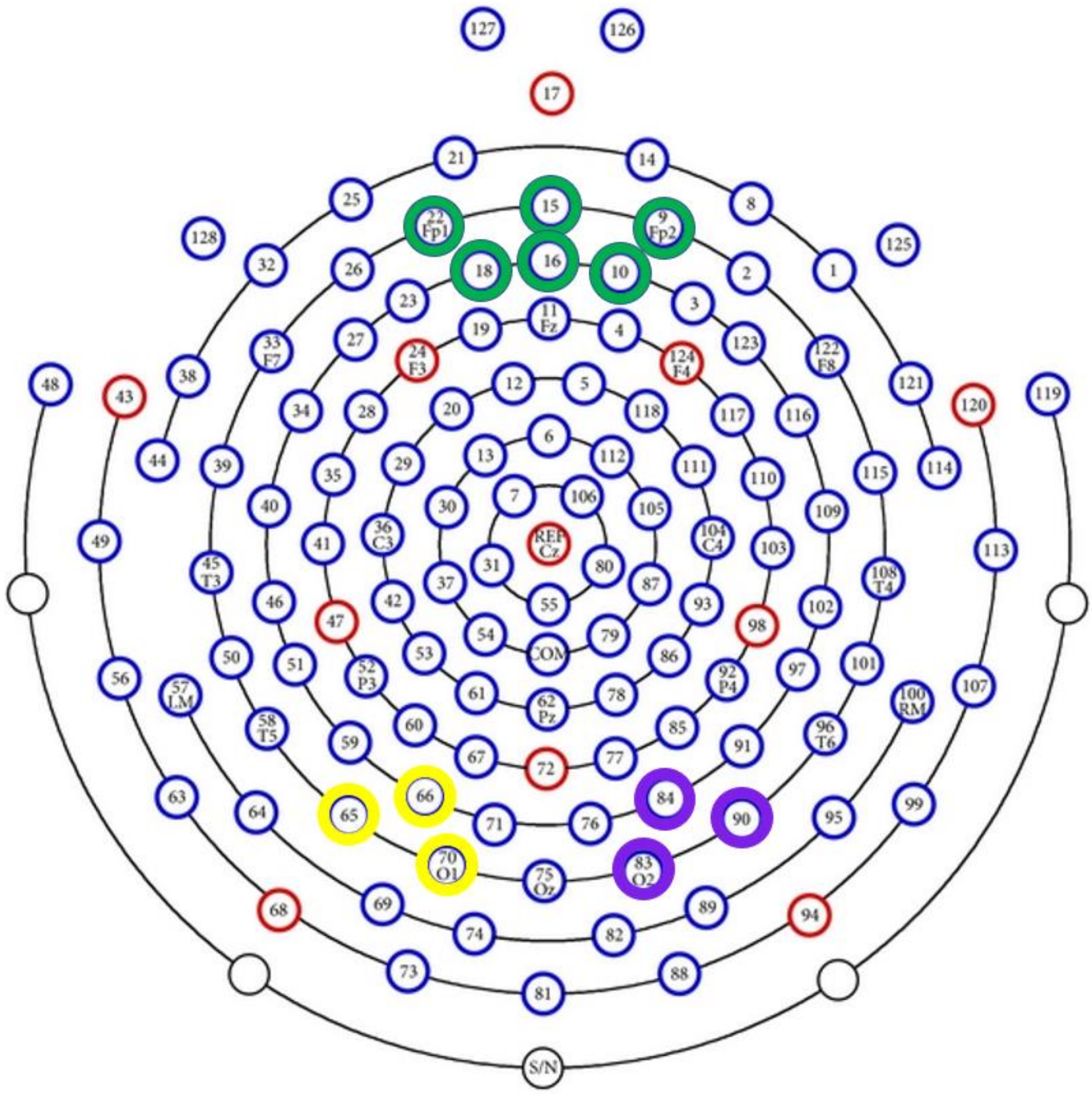
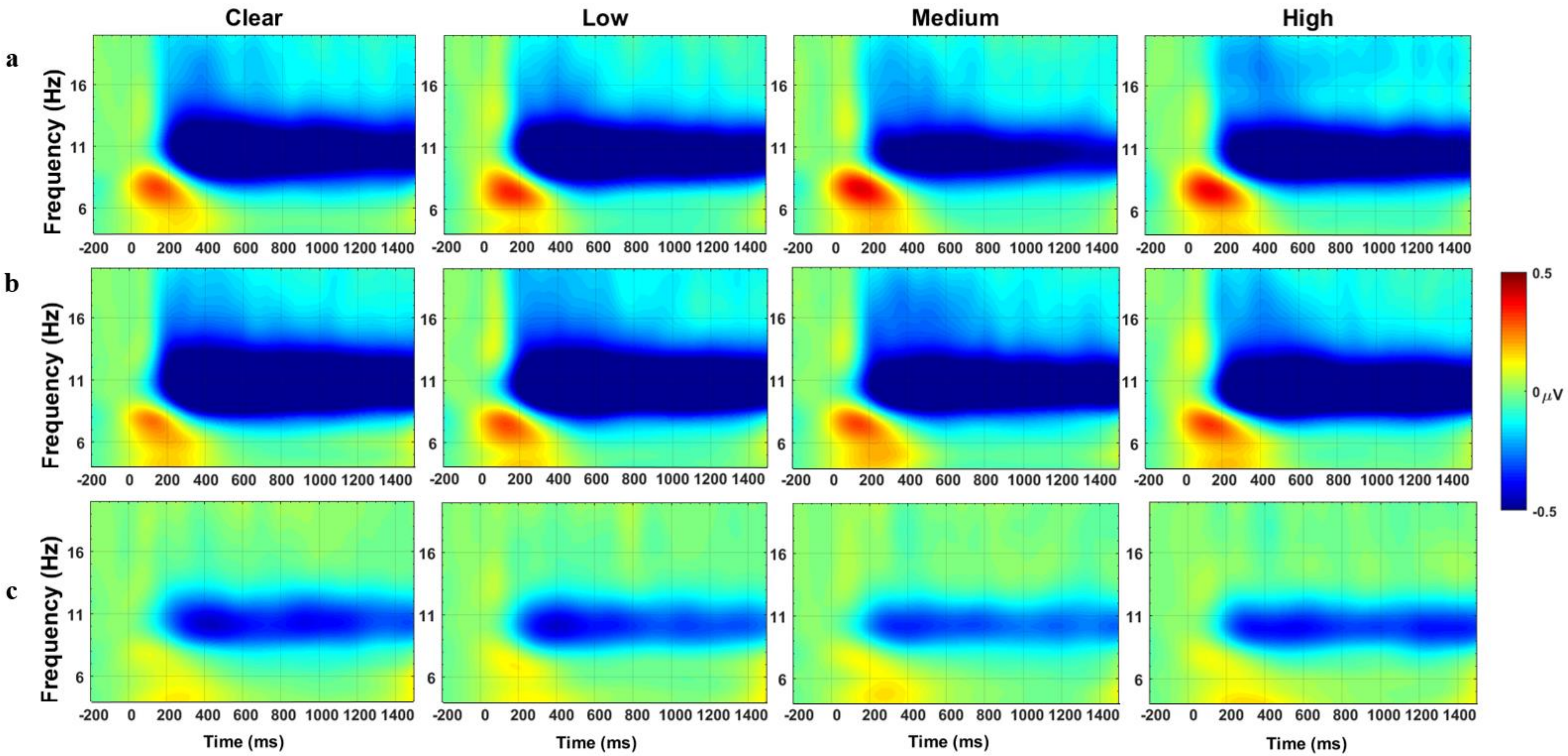


Figure 15 *Averaged time-frequency plots of* ***Target (theta response)*** *across conditions: a. The left occipital area; b. The right occipital area; c. The frontal area*



Frontal Theta

To examine whether theta synchronisation differs between conditions, we conducted multiple *t*-tests to compare theta response against the baseline across conditions. Results revealed significant theta synchronisation across all conditions (Table 2). A one-way repeated measures ANOVA was then computed to examine the effect of the condition on frontal theta responses. The results showed that there were no significant differences in frontal theta between conditions, $F(3, 75) = 0.47$, $p = .71$.

Table 2 *Multiple t-tests results for examining theta ERS over brain regions and conditions*

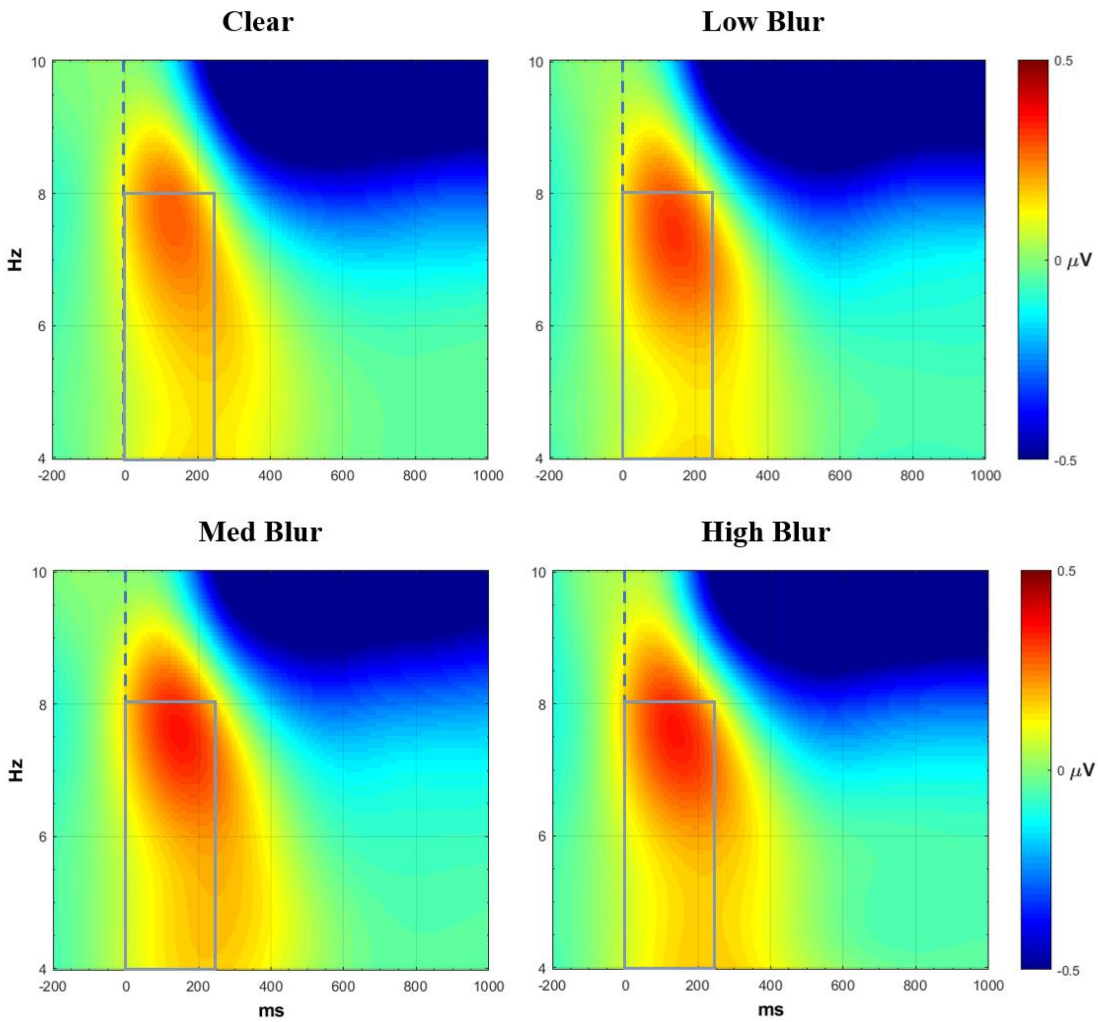
Brain region	Condition	*t*-value	*p*-value
Frontal	Clear	4.15	<.001***
	Low Blur	4.14	<.001***
	Med Blur	4.48	<.001***
	High Blur	4.73	<.001***
Left Occipital	Clear	5.25	<.001***
	Low Blur	5.89	<.001***
	Med Blur	7.75	<.001***
	High Blur	6.93	<.001***
Right Occipital	Clear	5.78	<.001***
	Low Blur	7.43	<.001***
	Med Blur	9.04	<.001***
	High Blur	9.47	<.001***

Note. ***$p<.001$

Occipital Theta

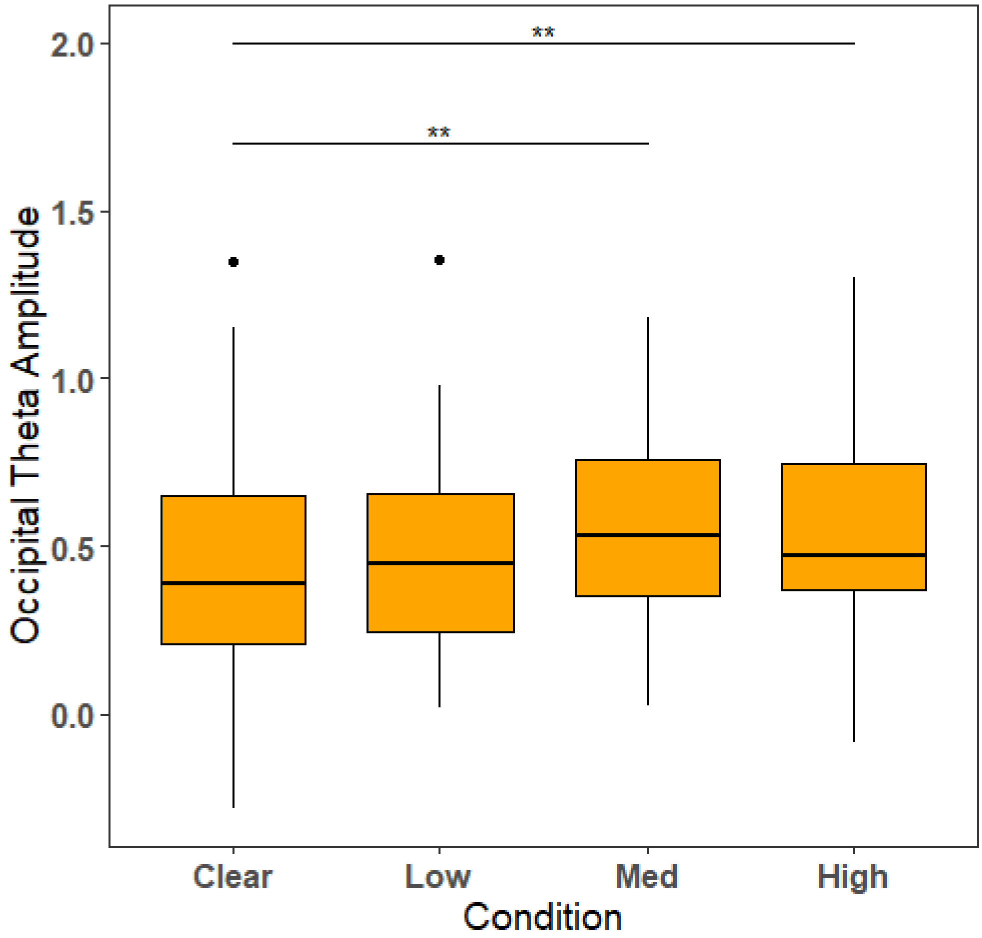
Multiple *t*-tests were computed to compare left and right occipital theta responses against the baseline. Results of *t*-tests showed significant theta synchronisation across all conditions over left and right occipital areas (Table 2 and Figure 16).

Figure 16 *Comparisons of occipital theta ERS across conditions. x-axis: time in ms. y-axis: frequency band. The vertical dash line represents the onset of stimulus presentation. The grey box represents the window of interest.*



A two-way repeated measures ANOVA was performed to investigate the effects of condition and hemisphere on occipital theta. The results suggested a significant main effect of condition ($F(3, 72) = 4.69$, $p = .005$; Figure 17). Post hoc tests using the Bonferroni correction revealed that theta amplitudes for the High Blur condition ($p_{adjust} = .003$) and the Med Blur condition ($p_{adjust} = .002$) were significantly higher than the Clear condition. There were no differences between the Clear and Low Blur conditions, nor between the Med Blur and High Blur conditions.

Figure 17 *A boxplot of the occipital theta amplitudes across conditions*



Note. ***p <.01*

3.4 Discussion

The current study investigated the neural correlations of visual uncertainty and how it relates to curiosity. We used visual stimuli with different degrees of blur (*Prime*) to modulate curiosity. Then, the corresponding clear stimuli (*Target*) were presented to examine the brain reactions to the reduction of uncertainty-modulated curiosity. We evaluated how curious people were about the stimuli using a separate rating study online. We recorded participants' scalp EEG responses to the stimuli and tested their incidental memory of the stimuli. Overall, this study investigated three research questions. Firstly, the extent to which curiosity was modulated by images with various degrees of blur was examined. Secondly, whether alpha desynchronisation would be associated with increased visual uncertainty and how it relates to curiosity were investigated, and finally, we tested whether increased theta activities would be related to high curiosity resolution images.

The curiosity rating data suggested that varying visual uncertainty does modulate curiosity. Clear or Low Blur stimuli were associated with low curiosity ratings, whereas Med Blur and High Blur stimuli were associated with high curiosity ratings. Further confirmation with regards to the relationship between curiosity and blurredness by fitting the rating data to a linear model and comparing it against a quadratic model, revealed a quadratic relationship between curiosity and the degree of uncertainty (i.e., Curiosity = Blur^2 + Blur) in our data. In other words, curiosity peaks when visual uncertainty is high. Interestingly, this quadratic relationship is different from findings of previous curiosity research where curiosity is found to be an inverted U-shaped function of uncertainty, meaning that curiosity peaks when uncertainty is at an intermediate level. For example, in a rather similar study by Nicki (1970), participants were presented with images with different degrees of blurredness (i.e., clear, low blur, medium blur and high blur). For each image, participants were asked to provide their guesses and their confidence in the guesses they made (i.e., How certain you are as to whether your guess is correct?). This subjective uncertainty increased as the blurredness increased and peaked for images at a medium degree of blurredness, then decreased for highly blurred images. Most importantly, the subjective uncertainty was viewed as an index of curiosity as it indeed motivated participants' desires for the resolution images, especially at the intermediate level of subjective uncertainty relative to low or high uncertainty.

One possible reason that we did not replicate Nicki's findings lies in the differences in the measurement of curiosity. We measured curiosity about quantified visual uncertainty by directly asking the degree to which participants would like to know the answer, whereas Nicki measured a theoretical form of curiosity via subjective uncertainty - the interaction effect of the blurredness of the stimuli and confidence (i.e., How certain you are that you know the identity?). The differences in measurement might lead to divergent results. Another possibility could be that the degrees of blurredness of the stimuli vary between the two studies. It is unclear how the degrees of blurredness were quantified in Nicki's study in comparison to ours. It is possible that the degrees of blurredness used for the current study did not well capture individuals' thresholds and full spectrums, meaning that the current data only revealed part of the distribution (the left part of the inverted U-shape curve). It is worth noting that previous research using a trivia question paradigm to evaluate the relationship between uncertainty and curiosity also suggested curiosity is an inverted U-shaped function of uncertainty (Baranes et al., 2015; Dubey & Griffiths, 2020; Kang et al., 2009). In these studies, uncertainty was measured via a confidence rating similar to Nicki's (1970), highlighting that the differences in quantifying uncertainty contributed to the variations in our findings.

Another possibility might be due to the use of different paradigms across studies. In particular, due to the imbalance in prior knowledge and the outcome uncertainty associated with different paradigms respectively (i.e. trivia question paradigm, uncertain picture paradigm and lottery tasks), it might lead to inconsistent results. For example, having a stronger prior, meaning more familiarity, might bias decision-making towards confirmation of predictions and increase curiosity about the resolution. As the current study used blurred, everyday life objects, participants might be more familiar with the stimuli, leading to confirmation bias and increasing curiosity as the degree of blur increases. In terms of the differences in outcome uncertainty between paradigms, the answers to trivia questions are usually very limited and specific, whereas there could be myriad identities associated with one blurred or distorted object (especially for those at medium or high degrees of uncertainty). Large uncertainty was also found to be a linear predictor of curiosity in a lottery task (van Lieshout et al., 2018). In other words, in the current study, the larger outcome uncertainty in the medium or highly blurred images leads to higher curiosity. It is worth noticing that we assessed the clear images using interest measures instead of curiosity measures. In other words, participants were asked how interested they felt in the clear image instead of how curious they felt about it. This difference might have an impact on the overall rating outcomes. Future studies could investigate whether interest rating with all the blurred conditions (instead of curiosity rating) would yield a different result.

Consistent with our hypothesis, the induced alpha oscillations decrease to varied extent as the curiosity rating and the blurredness of the *Prime* stimuli increase over the frontal, posterior midline and temoral-occipital areas (Figure 9 and Table 1). Moreover, additional analyses showed that the alpha amplitudes over the posterior midline areas were significantly lower for the Med Blur and the High Blur conditions, compared to the Clear and Low Blur conditions for the *Prime* stimuli (Figure 10). More importantly, the stimuli in the Med Blur and High Blur conditions were rated as high curiosity stimuli, whereas the ones in the Clear and Low Blur conditions were rated as low curiosity stimuli. Overall, this suggests that the alpha oscillations over the posterior areas to the *Prime* are regulated by the degree of curiosity modulated by visual uncertainty. More specifically, curiosity about the blurred pictures increased attention, therefore increasing alpha desynchronisation. It is also possible that both attention and curiosity about the blurred images produced a combined effect, resulting in increased alpha desynchronisation.

Supportive evidence for this explanation could be found in Freunberger and colleagues' study (2008). In this study, images of everyday objects and meaningless objects were distorted at four levels from highly distorted (Level 4) to slightly distorted (Level 1). All distorted images within the Level 2 were recognisable. Participants were presented with each distorted image consequtively from Level 4 to Level 1 with EEG recorded. It was found that for everyday object images, alpha decreases as the distortion decreases from Level 4 to Level 2 with a sharp decrease at Level 2 (from on the verge of knowing to knowing), but alpha recovers at Level 1 where an object could be clearly identified (no uncertainty). However, for the meaningless images, alpha decreases as the distortion decreases, despite the fact that they are recognisable at Level 2 but they are not identifiable (high uncertainty). In relation to the current study, images in the Med Blur condition might be similar to the distorted object images at Level 2 where a sense of 'feeling of knowing' would be experienced, eliciting curiosity for the desired uncertainty resolution (Brooks et al., 2021; Hanczakowski et al., 2014; Litman et al., 2005; Metcalfe et al., 2017) and leading to alpha desynchronisation. As for the images in the High Blur condition, they might be similar to the distorted meaningless object images that are not possible to identify.

Taken together, these findings indicate that alpha decreases when curiosity modulated by visual uncertainty is at a medium level (i.e. identifiable objects) or at a high level (i.e. not identifiable objects), indicating the extent of uncertainty-modulated alpha desynchronisation is related to a high level of cognitive processes such as active encoding and information retrieval. Alpha oscillation is known to have unique roles in cognitive information processing. Especially when alpha exhibits a decrease in power in relation to events, it is considered an index of focused attention, global arousal, cortical excitation and active information encoding (Hanslmayr & Staudigl, 2014; Klimesch, 1997, 1999, 2012; Pfurtscheller & Aranibar, 1977). In other words, these results offer a possibility that high curiosity-rated stimuli are associated with larger visual and outcome uncertainty, which elicits larger global cortical arousal and excitation. As these stimuli also require more focused attention and more cognitive demands to recognise them, as a result, it leads to larger alpha desynchronisation. It is worth noticing that alpha oscillation is sensitive to the physical properties of the stimulus. Different from Freunberger and colleagues' study (2008), the spatial frequency of the distorted stimuli was not controlled in our experiment. However, given that we obtained similar results, this might not have an influential impact on our results. Further research could be conducted with the control of the physical properties of the stimuli.

Different from our hypothesis and previous literature (Berlyne & Normore, 1972; Jepma et al., 2012), we did not find a significant effect of blurredness on recognition accuracy, suggesting that the beneficial effect of curiosity on learning might vary under different conditions. For example, this null behavioural finding might be due to the design. In both Berlyne's and Jepma's studies, the exposure time of the clear images was longer (5 s) and the numbers of trials was significantly lower (i.e., 24 items in Berlyne's design, 140 items in Jepma's paper), compared to the current study. In other words, shorter processing time, as well as a larger memory load, reduced performance. On the other hand, compared to studies that found a pronounced effect of curiosity on learning (Kang et al., 2009; Gruber et al., 2014), the current study measured curiosity differently with an average curiosity rating for each blur condition. In these studies, participants were asked explicitly about their state of curiosity, meaning that the evaluation, as well as the processing of the content, might be deeper than in the current study, resulting in enhanced learning.

We did not find differences in theta power across conditions over the frontal areas. A possible explanation for the null frontal theta result is that in the current study, the clear corresponding images were always presented to the participants, meaning that there was not much cognitive process needed to keeping tracking of the outcome uncertainty which may play an important role in reinforcing potential learning. Outcome uncertainty is found to be the key to driving learning as it generates prediction errors in the midbrain and excites neurons in dopaminergic pathways, leading to improvement of learning (Bach & Dolan, 2012; Clark, 2013; Colombo, 2017; Friston et al., 2015; Monosov, 2020). Moreover, the objects chosen in the current study were everyday objects. Recognition of these objects happens within milliseconds (Harari et al., 2020), and does not require much of a cognitive effort to update the representations.

However, we found that theta differed between conditions over occipital areas such that theta amplitudes for the Med Blur and High Blur conditions were significantly larger than the Clear condition. Given the important role of the occipital cortex in object recognition (Grill-Spector & Malach, 2004), it may not be of surprise about this finding. Although the precise functional meaning of occipital theta in object recognition is unclear, increasing theta amplitudes have been found at many cortical sites such as posterior and occipital areas in non-spatial working memory tasks (Raghavachari et al., 2001, 2006; Sarnthein et al., 1998), suggesting a 'gating' function for information processing. In these studies, depending on the cognitive efforts needed, theta increased at the start of each trial and continued to increase through the trial but decreased sharply at the end of the trial. Similar to our study (Figure 12), we found that theta increased at the beginning of the trial across many sensors over the posterior and occipital areas. As object recognition could happen as early as 80 ms post-stimulus onset (Harari et al., 2020), our data showed theta increased at the first 100 ms and decreased rapidly after 200 ms post-stimulus. It is possible that as a result of information imbalance, compared to the Clear condition, as images with a high degree of blur may require more cognitive effort to process and update, the Med Blur and High Blur condition, thus, elicited larger theta amplitudes.

It is also possible that the selected time windows did not reflect theta responses to the conditions in the analysis. Previous literature highlighted the role of anticipation for curiosity resolution in learning enhancement, indicating that theta activity might vary during the pre-stimulus duration (i.e., before the clear corresponding image was shown) as a response to anticipation of rewards (i.e., curiosity resolution). This proposal is supported by evidence in

Kang et al's (2009) study showing that participants' pupillary responses ramped up before the trivia answer was displayed. Moreover, in their study participants' activation of reward circuits was found during the presentation of trivia questions, but not when the answers were shown. Most importantly, better memory recall performance was also found positively associated with increased activation during the anticipation of trivia answers in the reward regions of the brain (Gruber et al., 2014). Therefore, future work should examine theta activities during the pre-stimulus time window before the clear corresponding images are shown.

In conclusion, this study investigated the extent to which curiosity is modulated by visual uncertainty using a blurred image paradigm. We found that visual stimuli with medium and high uncertainty (blurredness) induce higher curiosity relative to stimuli with no and low uncertainty. We also investigated the associations between alpha desynchronisation and curiosity about the blurred stimuli (*Prime*) as well as the relationships between theta synchronisation and curiosity resolution images (*Target*). We found alpha desynchronisation over the posterior midline areas was associated with curiosity about the *Prime* stimuli. These support the idea that curiosity driven by visual uncertainty is associated with the extent of alpha desynchronisation and its associated cognitive functions such as exciting global arousal, increasing focused attention and active information processing. However, we did not find differences in frontal theta activities across conditions, providing no evidence for the beneficial effect of uncertainty reduction on learning. Overall, the findings in this investigation shed new light on the cortical responses in relation to curiosity and uncertainty, providing new evidence to the existing literature on how curiosity-modulated uncertainty is related to attention. Apart from the uncontrolled physical properties of stimuli, this study was limited by the indirect measure of curiosity in relation to uncertainty. Further investigation is needed to establish the extent alpha desynchronisation is related to the state of curiosity-driven by visual uncertainty.

References

Adrian, E. D., & Matthews, B. H. C. (1934). The berger rhythm: Potential changes from the occipital lobes in man. *Brain*, *57*(4), 355–385. https://doi.org/10.1093/brain/57.4.355

Bach, D. R., & Dolan, R. J. (2012). Knowing how much you don't know: A neural organization of uncertainty estimates. *Nature Reviews Neuroscience*, *13*(8), 572–586. https://doi.org/10.1038/nrn3289

Baranes, A., Oudeyer, P.-Y., & Gottlieb, J. (2015). Eye movements reveal epistemic curiosity in human observers. *Vision Research*, *117*, 81–90. https://doi.org/10.1016/j.visres.2015.10.009

Bates, D., Maechler, M., Bolker, B., cre, Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., Grothendieck, G., Green, P., Fox, J., Bauer, A., & simulate.formula), P. N. K. (shared copyright on. (2022). *lme4: Linear Mixed-Effects Models using 'Eigen' and S4* (1.1-30). https://CRAN.R-project.org/package=lme4

Begus, K., & Bonawitz, E. (2020). The rhythm of learning: Theta oscillations as an index of active learning in infancy. *Developmental Cognitive Neuroscience*, *45*, 100810. https://doi.org/10.1016/j.dcn.2020.100810

Begus, K., Southgate, V., & Gliga, T. (2015). Neural mechanisms of infant learning: Differences in frontal theta activity during object exploration modulate subsequent object recognition. *Biology Letters*, *11*(5), 20150041. https://doi.org/10.1098/rsbl.2015.0041

Berger, H. (1931). Über das Elektrenkephalogramm des Menschen. *Archiv für Psychiatrie und Nervenkrankheiten*, *94*(1), 16–60. https://doi.org/10.1007/BF01835097

Berlyne, D. E. (1960). *Conflict, arousal, and curiosity* (pp. xii, 350). McGraw-Hill Book Company. https://doi.org/10.1037/11164-000

Berlyne, D. E., & Normore, L. F. (1972). Effects of prior uncertainty on incidental free recall. *Journal of Experimental Psychology*, *96*, 43–48. https://doi.org/10.1037/h0033480

Brod, G., & Breitwieser, J. (2019). Lighting the wick in the candle of learning: Generating a prediction stimulates curiosity. *Npj Science of Learning*, *4*(1), 1–7. https://doi.org/10.1038/s41539-019-0056-y

Brodeur, M. B., Guérard, K., & Bouras, M. (2014). Bank of Standardized Stimuli (BOSS) Phase II: 930 New Normative Photos. *PLOS ONE*, *9*(9), e106953. https://doi.org/10.1371/journal.pone.0106953

Bromberg-Martin, E. S., & Hikosaka, O. (2009). Midbrain dopamine neurons signal preference for advance information about upcoming rewards. *Neuron*, *63*(1), 119–126. https://doi.org/10.1016/j.neuron.2009.06.009

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in Cognitive Sciences*, *18*(8), 414–421. https://doi.org/10.1016/j.tics.2014.04.012

Chen, X., Twomey, K. E., & Westermann, G. (2022). Curiosity enhances incidental object encoding in 8-month-old infants. *Journal of Experimental Child Psychology*, *223*, 105508. https://doi.org/10.1016/j.jecp.2022.105508

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*(3), 181–204. https://doi.org/10.1017/S0140525X12000477

Colombo, M. (2017). Andy Clark, Surfing Uncertainty: Prediction, Action, and the Embodied Mind. *Minds and Machines*, *27*(2), 381–385. https://doi.org/10.1007/s11023-017-9420-y

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Feige, B., Scheffler, K., Esposito, F., Di Salle, F., Hennig, J., & Seifritz, E. (2005). Cortical and subcortical correlates of electroencephalographic alpha rhythm modulation. *Journal of Neurophysiology*, *93*(5), 2864–2872. https://doi.org/10.1152/jn.00721.2004

FitzGibbon, L., Lau, J. K. L., & Murayama, K. (2020). The seductive lure of curiosity: Information as a motivationally salient reward. *Current Opinion in Behavioral Sciences*, *35*, 21–27. https://doi.org/10.1016/j.cobeha.2020.05.014

Foxe, J. J., Simpson, G. V., & Ahlfors, S. P. (1998). Parieto-occipital ∼1 0Hz activity reflects anticipatory state of visual attention mechanisms. *NeuroReport*, *9*(17), 3929–3933.

Freunberger, R., Klimesch, W., Griesmayr, B., Sauseng, P., & Gruber, W. (2008). Alpha phase coupling reflects object recognition. *NeuroImage*, *42*(2), 928–935. https://doi.org/10.1016/j.neuroimage.2008.05.020

Friston, K., Rigoli, F., Ognibene, D., Mathys, C., Fitzgerald, T., & Pezzulo, G. (2015). Active inference and epistemic value. *Cognitive Neuroscience*, *6*(4), 187–214. https://doi.org/10.1080/17588928.2015.1020053

Gottlieb, J., & Oudeyer, P.-Y. (2018). Towards a neuroscience of active sampling and curiosity. *Nature Reviews Neuroscience*, *19*(12), 758–770. https://doi.org/10.1038/s41583-018-0078-0

Gottlieb, J., Oudeyer, P.-Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. *Trends in Cognitive Sciences*, *17*(11), 585–593. https://doi.org/10.1016/j.tics.2013.09.001

Hanslmayr, S., & Staudigl, T. (2014). How brain oscillations form memories—A processing based perspective on oscillatory subsequent memory effects. *NeuroImage*, *85*, 648–655. https://doi.org/10.1016/j.neuroimage.2013.05.121

Harari, D., Benoni, H., & Ullman, S. (2020). Object recognition at the level of minimal images develops for up to seconds of presentation time. *Journal of Vision*, *20*(11), 266. https://doi.org/10.1167/jov.20.11.266

Hu, L., & Zhang, Z. (2019). *EEG signal processing and feature extraction*. Springer.

Jepma, M., Verdonschot, R., van Steenbergen, H., Rombouts, S., & Nieuwenhuis, S. (2012). Neural mechanisms underlying the induction and relief of perceptual curiosity. *Frontiers in Behavioral Neuroscience, 6*. https://www.frontiersin.org/articles/10.3389/fnbeh.2012.00005

Kalnins, I. V., & Bruner, J. S. (1973). The coordination of visual observation and instrumental behavior in early infancy. *Perception*, *2*, 307–314. https://doi.org/10.1068/p020307

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T., & Camerer, C. F. (2009). The wick in the candle of learning: Epistemic curiosity activates reward circuitry and enhances memory. *Psychological Science*, *20*(8), 963–973. https://doi.org/10.1111/j.1467-9280.2009.02402.x

Kidd, C., & Hayden, B. Y. (2015). The psychology and neuroscience of curiosity. *Neuron*, *88*(3), 449–460. https://doi.org/10.1016/j.neuron.2015.09.010

Klimesch, W. (1996). Memory processes, brain oscillations and EEG synchronization. *International Journal of Psychophysiology*, *24*(1), 61–100. https://doi.org/10.1016/S0167-8760(96)00057-8

Klimesch, W. (1997). EEG-alpha rhythms and memory processes. *International Journal of Psychophysiology*, *26*(1), 319–340. https://doi.org/10.1016/S0167-8760(97)00773-3

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews*, *29*(2), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W. (2012). α-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Klimesch, W., Fellinger, R., & Freunberger, R. (2011). Alpha oscillations and early stages of visual encoding. *Frontiers in Psychology*, *2*. https://www.frontiersin.org/articles/10.3389/fpsyg.2011.00118

Klimesch, W., Freunberger, R., Sauseng, P., & Gruber, W. (2008). A short review of slow phase synchronization and memory: Evidence for control processes in different memory systems? *Brain Research*, *1235*, 31–44. https://doi.org/10.1016/j.brainres.2008.06.049

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition–timing hypothesis. *Brain Research Reviews*, *53*(1), 63–88. https://doi.org/10.1016/j.brainresrev.2006.06.003

Lega, B. C., Jacobs, J., & Kahana, M. (2012). Human hippocampal theta oscillations and the formation of episodic memories. *Hippocampus*, *22*(4), 748–761. https://doi.org/10.1002/hipo.20937

Ligneul, R., Mermillod, M., & Morisseau, T. (2018). From relief to surprise: Dual control of epistemic curiosity in the human brain. *NeuroImage*, *181*, 490–500. https://doi.org/10.1016/j.neuroimage.2018.07.038

Lilly, J. M. (2017). Element analysis: A wavelet-based method for analysing time-localized events in noisy time series. *Proceedings of the Royal Society A: Mathematical,* *Physical and Engineering Sciences*, *473*(2200), 20160776. https://doi.org/10.1098/rspa.2016.0776

Litman, J., Hutchins, T., & Russon, R. (2005). Epistemic curiosity, feeling-of-knowing, and exploratory behaviour. *Cognition and Emotion*, *19*, 559–582. https://doi.org/10.1080/02699930441000427

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*, 75–98. https://doi.org/10.1037/0033-2909.116.1.75

Makeig, S., Delorme, A., Westerfield, M., Jung, T.-P., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2004). Electroencephalographic brain dynamics following manually responded visual targets. *PLOS Biology*, *2*(6), e176. https://doi.org/10.1371/journal.pbio.0020176

Metcalfe, J., Schwartz, B. L., & Bloom, P. A. (2017). The tip-of-the-tongue state and curiosity. *Cognitive Research: Principles and Implications*, *2*(1), 31. https://doi.org/10.1186/s41235-017-0065-4

Metcalfe, J., Schwartz, B. L., & Eich, T. S. (2020). Epistemic curiosity and the region of proximal learning. *Current Opinion in Behavioral Sciences*, *35*, 40–47. https://doi.org/10.1016/j.cobeha.2020.06.007

Monosov, I. E. (2020). How outcome uncertainty mediates attention, learning, and decision-making. *Trends in Neurosciences*, *43*(10), 795–809. https://doi.org/10.1016/j.tins.2020.06.009

Moreno-Martínez, F. J., & Montoro, P. R. (2012). An ecological alternative to Snodgrass & Vanderwart: 360 high quality colour images with Norms for seven psycholinguistic variables. *PLoS ONE*, *7*. https://doi.org/10.1371/journal.pone.0037527

Nicki, R. M. (1970). The reinforcing effect of uncertainty reduction on a human operant. *Canadian Journal of Psychology/Revue Canadienne de Psychologie*, *24*, 389–400. https://doi.org/10.1037/h0082875

Nobach, H., Tropea, C., Cordier, L., Bonnet, J.-P., Delville, J., Lewalle, J., Farge, M., Schneider, K., & Adrian, R. (2007). Review of some fundamentals of data processing. In C. Tropea, A. L. Yarin, & J. F. Foss (Eds.), *Springer Handbook of Experimental Fluid Mechanics* (pp. 1337–1398). Springer. https://doi.org/10.1007/978-3-540-30299-5_22

Parise, E., & Csibra, G. (2013). Neural responses to multimodal ostensive signals in 5-month-old infants. *PLOS ONE*, *8*(8), e72360. https://doi.org/10.1371/journal.pone.0072360

Pfurtscheller, G., & Aranibar, A. (1977). Event-related cortical desynchronization detected by power measurements of scalp EEG. *Electroencephalography and Clinical Neurophysiology*, *42*(6), 817–826. https://doi.org/10.1016/0013-4694(77)90235-8

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *110*(11), 1842–1857. https://doi.org/10.1016/s1388-2457(99)00141-8

Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., Johnson, R., Miller, G. A., Ritter, W., Ruchkin, D. S., Rugg, M. D., & Taylor, M. J. (2000). Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology*, *37*(2), 127–152.

Raghavachari, S., Kahana, M. J., Rizzuto, D. S., Caplan, J. B., Kirschen, M. P., Bourgeois, B., Madsen, J. R., & Lisman, J. E. (2001). Gating of human theta oscillations by a working memory task. *Journal of Neuroscience*, *21*(9), 3175–3183. https://doi.org/10.1523/JNEUROSCI.21-09-03175.2001

Raghavachari, S., Lisman, J. E., Tully, M., Madsen, J. R., Bromfield, E. B., & Kahana, M. J. (2006). Theta oscillations in human cortex during a working-memory task: Evidence for local generators. *Journal of Neurophysiology*, *95*(3), 1630–1638. https://doi.org/10.1152/jn.00409.2005

Sarnthein, J., Petsche, H., Rappelsberger, P., Shaw, G. L., & von Stein, A. (1998). Synchronization between prefrontal and posterior association cortex during human working memory. *Proceedings of the National Academy of Sciences*, *95*(12), 7092–7096. https://doi.org/10.1073/pnas.95.12.7092

Schmider, E., Ziegler, M., Danay, E., Beyer, L., & Bühner, M. (2010). Is it really robust? Reinvestigating the robustness of ANOVA against violations of the normal distribution assumption. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, *6*, 147–151. https://doi.org/10.1027/1614-2241/a000016

Solomon, E. A., Kragel, J. E., Sperling, M. R., Sharan, A., Worrell, G., Kucewicz, M., Inman, C. S., Lega, B., Davis, K. A., Stein, J. M., Jobst, B. C., Zaghloul, K. A., Sheth, S. A., Rizzuto, D. S., & Kahana, M. J. (2017). Widespread theta synchrony and high-frequency desynchronization underlies enhanced cognition. *Nature Communications*, *8*(1), 1704. https://doi.org/10.1038/s41467-017-01763-2

Suffczynski, P., Kalitzin, S., Pfurtscheller, G., & Lopes da Silva, F. H. (2001). Computational model of thalamo-cortical networks: Dynamical control of alpha rhythms in relation to focal attention. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *43*(1), 25–40. https://doi.org/10.1016/s0167-8760(01)00177-5

van Lieshout, L. L. F., Vandenbroucke, A. R. E., Müller, N. C. J., Cools, R., & de Lange, F. P. (2018). Induction and relief of curiosity elicit parietal and frontal activity. *The*

Journal of Neuroscience: The Official Journal of the Society for Neuroscience, *38*(10), 2579–2588. https://doi.org/10.1523/JNEUROSCI.2816-17.2018

Wade, S., & Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psychonomic Bulletin & Review*, *26*, 1377–1387. https://doi.org/10.3758/s13423-019-01598-6

Weiss, S., Müller, H. M., & Rappelsberger, P. (2000). Theta synchronization predicts efficient memory encoding of concrete and abstract nouns. *NeuroReport*, *11*(11), 2357–2361.

Supplementary Materials

Table S1 *The descriptive statistics of curiosity ratings of stimuli across conditions*

Condition	Mean	SD	Median
Clear	29.60	27.10	20
Low Blur	36.64	28.47	30
Med Blur	54.74	29.27	60
High Blur	58.23	32.53	60

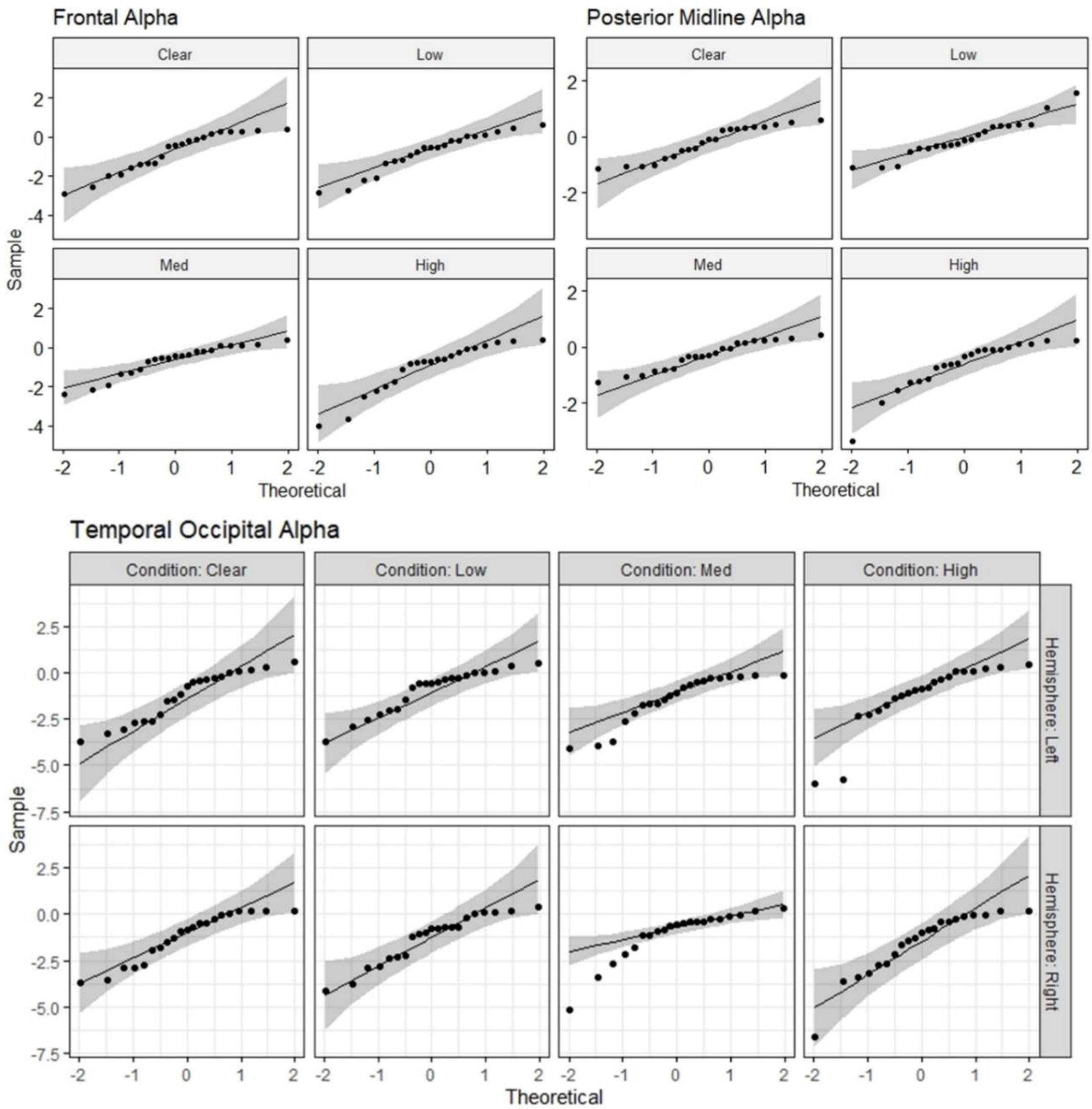
Table S2 *Extreme outliers of* ***alpha*** *responses of Prime across brain regions, conditions and subjects*

Brain region	Condition	Subject
Frontal	NA	NA
Posterior midline	NA	NA
Left temporal occipital	NA	NA
Right temporal occipital	Med Blur	22

Table S3 *Extreme outliers of* ***theta*** *responses of Target across brain regions, conditions and subjects*

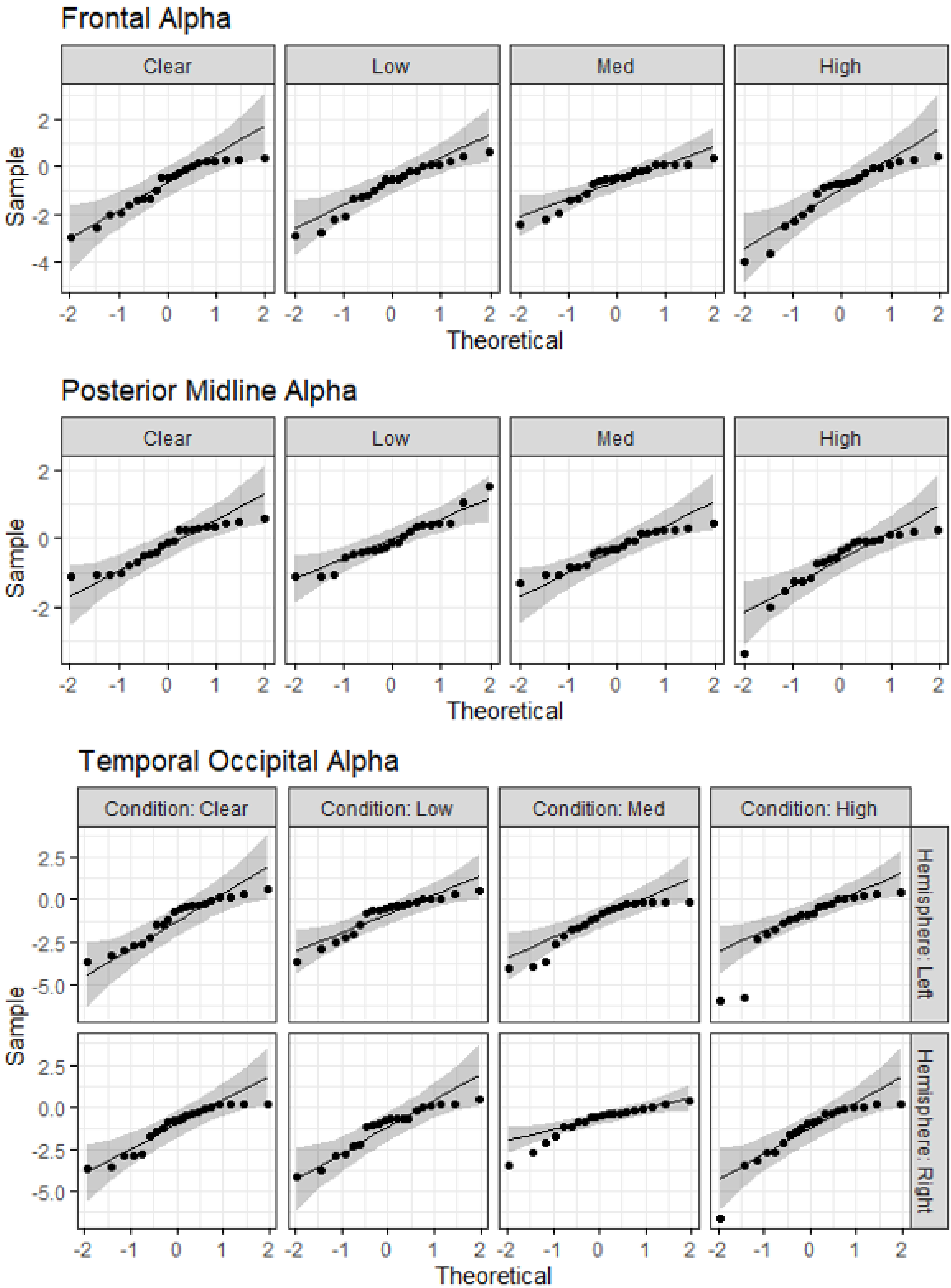
Brain region	Condition	Subject
Frontal	NA	NA
Left occipital	Clear	6
Left occipital	Low Blur	6
Left occipital	Med Blur	6
Left occipital	High Blur	6
Right occipital	NA	NA

Figure S1 *Tests of the assumption of normality using Shapiro-Wilk's method for* ***Prime*** *across brain regions and conditions.*



The Shapiro-Wilk's test results suggest that the amplitude of the Clear (p = .04), Med Blur (p = .03) and High Blur (p = .02) condition of the frontal regions, the High Blur condition of the Posterior Midline regions (p = .003) and almost all of the conditions over the temporal occipital regions violated the assumption of normality. However, given that ANOVA is considered robust against violations of the normality and the qqplots above seem acceptable to carry on the analysis (Schmider et al., 2010).

Figure S2 *Tests of the assumption of normality using Shapiro-Wilk's method for* ***Target*** *across brain regions and conditions.*



The results of Shapiro-Wilk's tests suggest that the amplitude of the Low Blur condition of the left occipital theta (p = .03) violated the assumption of normality. As ANOVA is considered robust against violations of the normality and the qqplots above seem good enough to carry on the analysis (Schmider et al., 2010).

Chapter 4

The Roles of Metacognitive Abilities and Curiosity in Learning

Despite the evidence in the literature suggesting metacognitive abilities such as confidence and prior knowledge estimate would influence curiosity and learning. It is unclear the degree to which these metacognitive abilities modulate curiosity and the effects of these metacognitive abilities and curiosity on learning. Moreover, the current literature concerning these questions was derived predominantly from trivia question paradigms, limiting the generalisation of the results. Thus, this chapter presents a study using a blurred picture paradigm to investigate (1) the relationship between metacognitive abilities and curiosity, and (2) the effects of metacognitive abilities and curiosity on learning.

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Table of Contents

Abstract

The current study investigates how metacognitive abilities such as confidence and prior knowledge estimates relate to curiosity. We also investigate the roles of these metacognitive abilities and curiosity in predicting learning. Instead of using linguistically-mediated information such as trivia questions as in the majority of research on curiosity, this study used blurred images of day-to-day objects and living creatures across a wide range of categories, aiming to improve ecological validity and extend the generalisability of research findings in the curiosity field. In this online study, participants were presented with a set of blurred pictures. For each blurred picture, participants were asked to provide a best guess for the identity of the blurred picture, and whether they knew the answer, then rated their confidence in their guess as well as their level of curiosity about the image. Our findings suggest that metacognitive abilities such as subjective prior knowledge estimates and confidence predict curiosity, such that negative subjective prior knowledge estimates and high confidence are associated with higher curiosity. We also find that learning is best predicted by a learner's metacognitive appraisal of their knowledge gap, especially when they are at the verge of knowing. Further, this learning enhancement is independent of curiosity. These findings have important educational implications in the context of promoting learners' curiosity, highlighting the role of metacognitive abilities in learning.

4.1 Introduction

Curiosity is the intrinsic desire to acquire new information for understanding (Kidd & Hayden, 2015; Loewenstein, 1994; Oudeyer & Smith, 2016). As a key driver of knowledge acquisition, empirical research has shown that curiosity boosts learning and enhances memory (Berlyne & Normore, 1972; Gruber et al., 2014; Kang et al., 2009; Wade & Kidd, 2019). Evidence at the behavioural level shows that high curiosity enhances learning and memory of both task materials (Fandakova & Gruber, 2021; Jepma et al., 2012) and unrelated items (Gruber et al., 2014). This beneficial effect of curiosity on learning also persists over time (Fastrich et al., 2018; Stare et al., 2018). Much research has highlighted the role of anticipation of the resolution of curiosity (Baranes et al., 2015; Kang et al., 2009; van Lieshout et al., 2018), curiosity resolution itself (Jirout & Klahr, 2012; Kang et al., 2009; Kidd & Hayden, 2015) and the discrepancy between curiosity anticipation and resolution (Gruber & Ranganath, 2019; Marvin & Shohamy, 2016) in this enhancement effect. To encapsulate the potential mechanisms underlying these findings, it is thought that high curiosity creates a state of anticipation, setting up a 'ready-to-learn' mode for a learner (Baranes et al., 2015; Brod & Breitwieser, 2019; Gottlieb et al., 2013; van Lieshout et al., 2018). The discrepancy between curiosity anticipation (excepted information/reward) and curiosity resolution (received information/reward) motivates exploratory behaviours (Dubey & Griffiths, 2020; Gottlieb et al., 2013). On the other hand, the information received in curiosity resolution is intrinsically rewarding, which activates the reward circuitry and hippocampal areas that facilitate memory retention and consolidation (Fandakova & Gruber, 2019; Jepma et al., 2012; Kang et al., 2009; Ligneul et al., 2018; van Lieshout et al., 2018).

Given the crucial role of curiosity in boosting learning outcomes, identifying facilitators of curiosity may have great educational implications and consequently the field of curiosity research is growing. Variables such as metacognition in estimating prior knowledge and confidence in prediction are found to be associated with curiosity (Dubey & Griffiths, 2020; Kang et al., 2009; Wade & Kidd, 2019), while better learning outcomes are predicted by curiosity, actual knowledge levels and prediction errors (den Ouden et al., 2012; Metcalfe, 2017). Hence, in this chapter, we examine how metacognitive abilities such as confidence and prior knowledge estimates are associated with curiosity. We also investigate the roles of these metacognitive abilities and curiosity in learning.

Metacognition, especially metacognitive appraisal in evaluating one's subjective prior knowledge state, is one of the factors that trigger curiosity, and it substantially influences subsequent information-seeking behaviours (Litman, 2009; Loewenstein, 1994; Metcalfe et al., 2020). This idea was first explicitly introduced in the *information gap* theory (Loewenstein, 1994) in which curiosity is defined as a cognitive desire that arises from the perception of a gap in knowledge and understanding. Curiosity stems from an individual's awareness of a gap between what one knows and what one wants to know. In other words, at least two prerequisites are emphasised in triggering curiosity: the learner's estimation of their current level of knowledge and the identification of a piece of specific information for understanding. On this information gap account, when a learner believes they possess the knowledge to solve the task at hand (i.e., the '*I Know*' state, Litman, 2009), little curiosity associated with information seeking behaviours is induced as there is no new knowledge needed. When a learner thinks they do not have the knowledge at all, this corresponds to the '*I Don't Know*' state in which less curiosity and fewer information-seeking behaviours are provoked, as the knowledge gap is too large and the desired knowledge will not be accessible (Brooks et al., 2021; Loewenstein, 1994; Metcalfe et al., 2020). However, when a learner appraises that they have some knowledge but are uncertain whether their current knowledge is sufficient, it creates a state of '*Feeling-of-Knowing*', which elicits more curiosity and exploratory behaviours in order to obtain the desired information (Brooks et al., 2021; Hanczakowski et al., 2014; Litman et al., 2005; Metcalfe et al., 2017).

Indeed, the relationship between these patterns of metacognitive appraisal of prior knowledge and curiosity has been demonstrated in many studies. This work consistently shows that the '*I Know*' and the '*I Don't Know*' state are associated with less curiosity, whereas the '*Not Sure*' or '*Feeling-of-Knowing*' state is related not just to greater curiosity but also to longer search duration for the desired information as well as to subsequent information sampling (Brooks et al., 2021; Hanczakowski et al., 2014; Litman et al., 2005). In a study by Brooks et al. (2021), participants learned a set of face-name pairs (i.e., cue-target) before the test phase of an experiment in which they were asked to recall the target name when the cue face was presented. Participants then provided their '*Feeling-of-Knowing*' judgement. Afterwards, participants were given the opportunity to choose a limited set of face-name pairs to restudy. Restudy choices here served as a direct marker of state curiosity. It was found that items rated as higher '*Feeling-of-Knowing*' were more likely to be selected to restudy, motivating subsequent information seeking behaviours. Similar outcomes were obtained by Litman and colleagues (2005) using a related approach. In their study, participants were asked to answer 12 general knowledge questions and to evaluate their '*Feeling-of-Knowing*' states and curiosity about the answers. Afterwards, participants were offered the opportunity to restudy the questions. The authors found that higher '*Feeling-of-Knowing*' states induced greater curiosity and prompted more exploratory behaviours (i.e., restudying more questions) relative to the '*I Know*' and the '*I Don't Know*' state, indicating a mediating effect of metacognitive appraisal between curiosity and exploratory behaviours.

Of relevance, many studies have investigated the effects of confidence in curiosity-based learning (Crandall, 1971; Fastrich et al., 2018; Kang et al., 2009; Theobald et al., 2022), suggesting that confidence (as an index of epistemic states) reflects uncertainty and is theoretically considered to have an inverted U-shaped relationship with curiosity. Specifically, very low and very high confidence e.g., in the answer to a trivia question, indicating low uncertainty, are associated with low curiosity, whereas an intermediate level of confidence is related to maximal uncertainty and curiosity (Loewenstein, 1994; Kang et al., 2009). Among these studies, the best-known study is by Kang and colleagues (2009). In this study, a set of trivia questions was used to induce curiosity. Participants were asked to guess the answer to the questions and to rate their confidence in their guesses. In line with the theoretical assumption (Loewenstein, 1994), the authors found an inverted U-shaped relationship between curiosity and confidence, indicating that when at an intermediate level of confidence (equivalent to participants' maximal uncertainty as to whether they knew the answer), curiosity peaks. Similar findings were reported also in Baranes et al. (2015), Dubey and Griffiths (2020) and Metcalfe et al. (2020). For example, using a similar paradigm, Baranes and colleagues (2015) replicated the finding regarding the relationship between confidence and curiosity. Interestingly, it was also found that when participants had the opportunity to choose one from two trivia questions to learn in each trial, participants were more likely to choose the question for which they had lower confidence relative to higher confidence in knowing the answer, suggesting that confidence might also influence information seeking behaviour.

On the other hand, inconsistent findings also suggest that high confidence rather than medium confidence predicts curiosity due to the desire to confirm predictions. For example, Wade and Kidd (2019), using a similar trivia question paradigm, found that participants were more curious about the questions when they believed their predictions were correct (high confidence in guess). Theobald et al. (2022), using pupil dilation as an index of curiosity, found that participants' pupil size increased when seeing trivia questions to which they were more confident in knowing the correct answer relative to questions with lower confident.

Overall, these studies suggest that confidence may serve various functions in relation to mediating curiosity. One is that confidence reflects subjective uncertainty in evaluating the knowledge gap (Loewenstein, 1994) and is an index of learners' strength of knowledge on the topic (Metcalfe et al., 2020). Learners should prefer to choose the information that is slightly above their current strength of knowledge to optimise their learning (Metcalfe et al., 2020; Oudeyer et al., 2016). The other function of confidence in curiosity might be associated with wanting to confirm or verify predictions as a way of updating one's prior schema of the world (Singh & Manjaly, 2021). The more confidence in a prediction, the more curiosity would be provoked (Theobald et al., 2022; Wade & Kidd, 2019). Therefore, more research is needed to examine the associations between confidence and curiosity in diverse contexts and with different paradigms.

Few studies so far have addressed the effect of confidence (as compared to curiosity) on learning. Several studies using typical general knowledge questions to study the relationships between confidence and learning (without considering curiosity) found that participants were more likely to remember the correct answer associated with wrong answers given in the context of high confidence than when confidence about the answer was low (Metcalfe & Miele, 2014). Incorrect predictions made with high confidence are linked to surprise reactions, which increase attention to the correcting information, resulting in enhanced memory for that information (Metcalfe, 2017). High confidence ratings might also reflect a high degree of familiarity with the information. In other words, updating high-confidence error responses when the correct information is already stored (but was not retrieved correctly) is relatively easier compared to low-confidence error responses (Butterfield & Metcalfe, 2006). Overall, it is evident that both curiosity and confidence can influence learning. So far, however, there has been a lack of investigations comparing and differentiating the effects of curiosity and confidence on learning.

In the existing curiosity literature, linguistically-mediated information such as trivia questions has been frequently used (Brod & Breitwieser, 2019; Gruber et al., 2014; Kang et al., 2009; McGillivray et al., 2015; Metcalfe et al., 2020; Wade & Kidd, 2019). However, we also encounter an enormity of visual, non-linguistic information such as the objects and the living things we see in our everyday life. Thus, in this study, we used images of day-to-day objects and living creatures across a wide range of categories. As previous curiosity literature highlights the role of an intermediate level of uncertainty in inducing curiosity (Berlyne & Normore, 1972; Jepma et al., 2012; Nicki, 1970), following this literature we blurred these stimuli with a medium blur filter and used (instead of trivia questions) to induce curiosity. Using different types of stimuli to investigate similar research questions may improve ecological validity and extend the generalisability of research findings in the curiosity field. Thus, we were interested in, when seeing a blurred image, 1) whether there would be an inverted U-shaped relationship between curiosity and confidence, 2) whether participants' subjective prior knowledge estimates and confidence predicted curiosity, 3) whether subjective prior knowledge estimates, confidence and curiosity predicted better learning outcomes.

To answer the first two research questions, we showed participants a series of blurred images. For each blurred picture, participants were asked to provide a best guess for the identity of the blurred picture, and whether they knew the answer, then rated their confidence in their guess as well as their level of curiosity about the image. Based on the currently available literature, we hypothesised that confidence would be an inverted U-shaped function of curiosity (Kang et al., 2009; Baranes et al. 2015; Dubey and Griffiths, 2020). Further, we expected subjective prior knowledge estimates of "*Yes*" and "*No*" to correspond with lower curiosity compared to the choice of "*Not Sure*". To investigate the third question, participants completed a surprise memory recall test. After answering questions about each blurred image, they were shown all blurred images again and were asked to recall as many correct answers as they could. Recall accuracy was viewed as a learning outcome. As both curiosity and confidence in prediction have substantial impacts on learning, we hypothesised that high curiosity and high confidence would be associated with better memory recall performance.

4.2 Methods

Participants

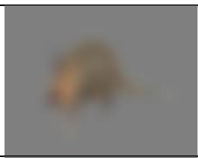
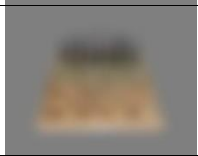
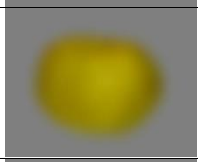
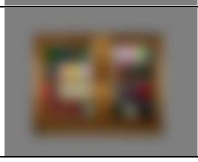
A total of 108 participants, recruited online from Sona Systems (https://www.sona-systems.com) and Prolific (https://prolific.ac), took part in the online experiment on the Gorilla online experimental platform (www.gorilla.sc). The sample size was pre-determined based on similar research (Wade & Kidd, 2019) with the expected effect size. Eight participants were excluded for providing the same curiosity rating on at least 90% of trials in the learning phase, resulting in 100 participants (M_{age} = 22.64, SD_{age} = 7.60, N_{female} = 74) in the final analysis. Participants received either university course credits or monetary rewards (£10 per hour). Participants were given information about the study and they provided informed consent before participation. The browser for the online task was limited to Google Chrome only as it has been shown that Google Chrome is more compatible with running an experiment in Gorilla (Anwyl-Irvine et al., 2021) compared to other types of browsers. The device was limited to laptops only for the same reason. The study was ethically approved by Lancaster University in the UK.

Materials

All stimuli were adapted from Moreno-Martínez and Montoro's (2012) database of 360 high-quality colour images. Stimuli consisted of 60 clear, 450 by 350-pixel object images of animals, food, instruments, furniture, utensils and vehicles, placed in the middle of a grey background. The 60 object images were then blurred with a 30-degree Gaussian filter in

Matlab (Version R2016b), resulting in 60 blurred and 60 corresponding clear images (see Table 1 for examples).

Table 1 *Exemplars of the object images with their blurred versions and corresponding labels.*

Clear object	Blurred object	Object label
		Armadillo
		Chess
		Quince
		Bookcase

Note: Stimuli are available at https://osf.io/wh9g7/ .

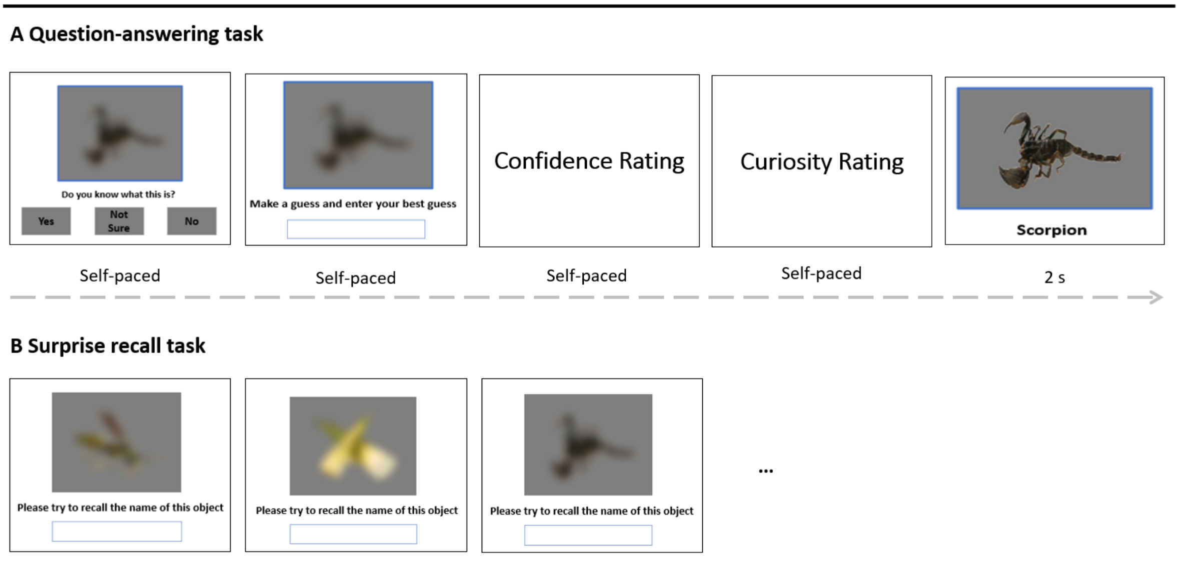
Task Design

This experiment consisted of two tasks (see Figure 1): a question-answering task and an incidental recall task. In the question-answering task, participants were presented with the 60 blurred images, one image at a time. For each image, participants were asked the following questions in sequence: (1) subjective prior knowledge estimate. Participants saw the question "*Do you know what this is?*", and were asked to give their response by clicking one of three response buttons ("*Yes*", "*Not Sure*" and "*No*"); (2) providing a guess: participants were asked to make a best guess and type their guess into a box; (3) confidence: participants were asked the question "*How close was your guess to the actual answer*?" and to rate their confidence in their guess on a scale from 1 (Not at all) to 6 (Very close); (4)

curiosity: participants rated their curiosity by answering the question "*How much do you want to know the actual answer?*" on a scale from 1 (Not at all) to 6 (Very much). All the questions were self-paced. As soon as participants responded, the task automatically proceeded. In each trial, after participants responded to the curiosity question, a clear image corresponding to the blurred image with its label was presented for 2 s.

After the question-answering task, participants were then asked to complete a surprise recall task in which all the blurred images from the question-answering task were presented again one image at a time. Participants were asked to recall the name of each image by typing their answer into a box. The order of the stimuli was randomised across participants and phases.

Figure 1 *Top (A): Trial structure of the question-answering task. Bottom (B): A surprise memory recall task after the question-answering task.*



Response Accuracy Rating

The accuracy of the guesses from the question-answering task as well as the responses from the incidental recall task were judged by three raters independently. The three raters were asked to judge if a participant's response was the same as the correct label. If a response was too generic ('animal' for rabbit), too vague ('a fruit that I did not know existed' for lemon) or lacked content ('??' or "no idea"), it was scored as incorrect. If a response included an obvious typing mistake ('rebbit' for rabbit) or had different labels with the same meaning ('bookshelf' for bookcase), it was marked as a correct response. For each response, only if it was rated as correct by at least two raters, was it accepted as a correct response. The reliability of agreement for multiple raters was assessed using Fleiss' kappa analysis (Falotico & Quatto, 2015; Fleiss et al., 2013) using the 'irr' package (Gamer et al., 2019) in R. A Fleiss' kappa value greater than 0.75 is taken to represent high agreement. There was excellent agreement (*kappa* = .83 , p <.0001), suggesting a high inter-rater reliability between three raters.

Data Analysis

Raw data were exported from Gorilla and imported to RStudio (Version 1.3.1093) for cleaning and analysis. Each participant provided guesses and ratings for 60 trials, resulting in a total of 6000 trials. All 6000 trials were included to examine the relationships between subjective prior knowledge estimate, confidence and curiosity. For predicting recall accuracy, trials were excluded if the guesses in the question-answering task were correct (N = 1980 trials), or not appropriate (e.g., "?", "no idea"; N = 8 trials), resulting in 4010 trials for statistical analysis (66.83% of all 6000 trials). The reason for excluding the correct trials was due to our interest in how much participants learned from the provided labels. Trials with correct guesses would mean that participants have already known the labels, potentially causing a ceiling effect.

Statistical models were fitted accordingly to answer each of the three questions. For ease of interpretation, the respective analysis and the associated results will be presented together below. The associated R code can be found on OSF: https://osf.io/wh9g7/

4.3 Results

Sample Characteristics

On average, participants rated confidence at 3.25 out of 6 (*SD* = 1.46, *Median* = 3) and curiosity at 4.44 out of 6 (*SD* =1.29, *Median* = 5). Two bubble plots (Figure S1 and Figure S2 in Supplementary Materials) in the supplementary materials show the frequency distributions of the ratings between confidence and curiosity as well as subjective prior estimates and curiosity respectively. Raw accuracy in the question answering task before excluding all correct trials was 33.17%, suggesting the difficulty of the task was at a reasonable level.

Question 1: Is Curiosity a U-shaped Function of Confidence?

As theoretical work suggests curiosity is an inverted U-shaped function of confidence, we first set out to evaluate whether in our data, curiosity and confidence would show a similar relationship. Based on the information-gap theory (Loewenstein, 1994; Kang et al., 2009), curiosity would peak when confidence P, is at a moderate level (P = 0.5) as confidence reflects a maximal level of uncertainty U, ($U = P(1-P)$, $P \in [0,1]$, Kang et al., 2009). In other words, either low or high confidence would suggest low uncertainty, thus would be associated with low curiosity. Hence, confidence should be a polynomial term in predicting curiosity (Lowenstein, 1994; Kang et al., 2009).

Therefore, we included confidence and confidence^2 in a cumulative link mixed effect model (CLM) predicting curiosity, using the clmm function from the ordinal package (Christensen, 2019) in R to estimate the relationship between curiosity and confidence. There are two reasons for applying this model. First, curiosity ratings in the current study are ordinal data. A cumulative link model can be viewed as an extension of the binary-logistic model. The benefit of using a cumulative link model here is that it allows the modelling of several responses (e.g., rating responses from 1 to 6) and how they vary with several predictors. Second, CLM allows us to take into account random effects for each participant as well as each stimulus. As indicated in a similar study by Fastrich et al. (2018), item effect and participant effect need considering whenever possible, given that both of these effects contribute substantial variances in predicting curiosity ratings.

Confidence was z-transformed for better fitting. The model included maximised random intercepts for *Participant* and *Stimulus* and by-participant and by-item random slopes for confidence. To avoid multiple testing (Schielzeth & Forstmeier, 2009), the full model was compared with a null model consisting of only the random effect terms from the full model. The significance of predictors was determined by dropping each predictor from the full model one at a time. The result of each reduced model was compared with the full model using a likelihood ratio test. In addition, collinearity between the two predictors was examined using Variance Inflation Factors (VIF) from the car package (Fox et al., 2022). The results suggested that there were no collinearity issues (Table S1 in Supplementary Materials).

Full Model 1 structure:

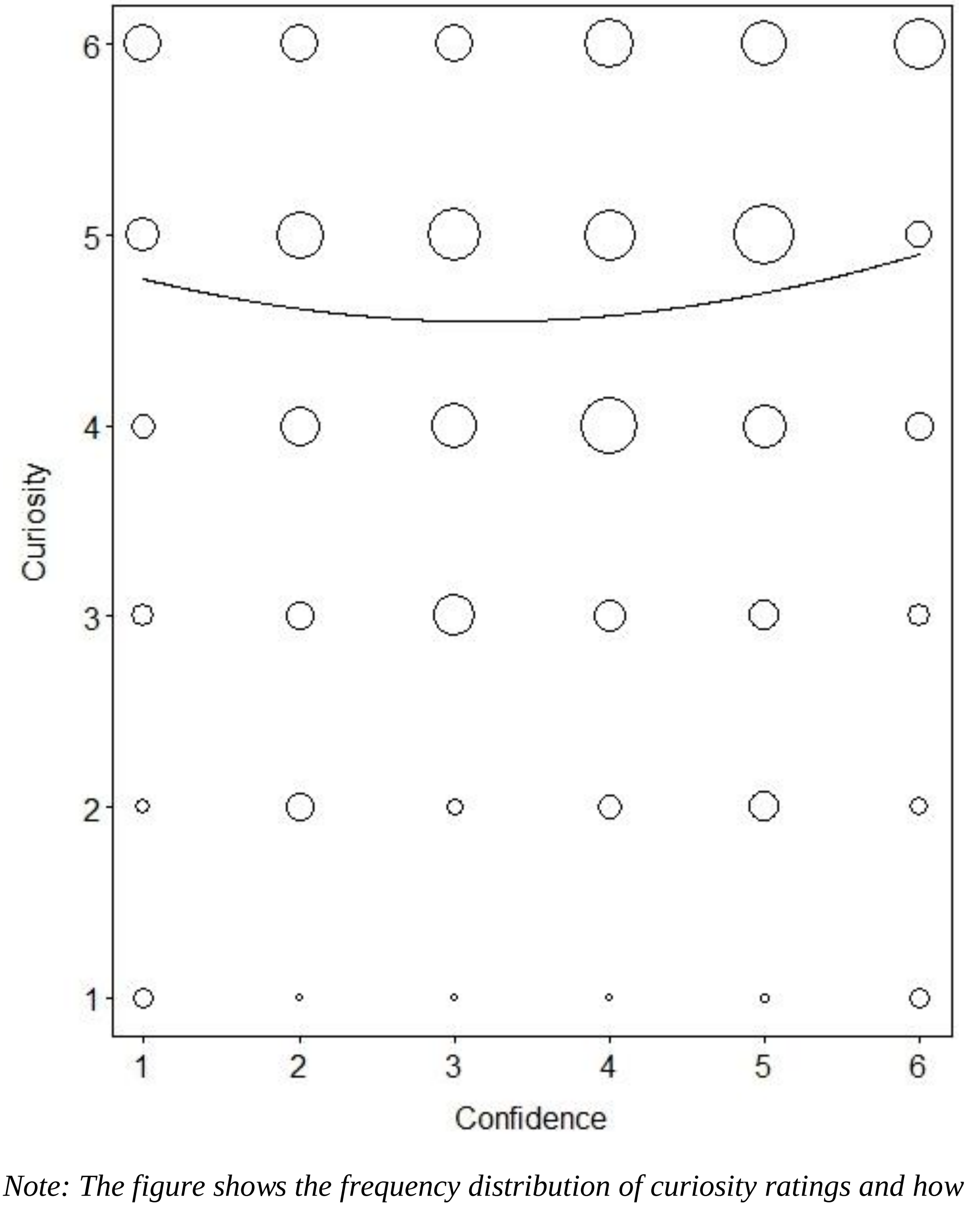
Curiosity ~ Confidence + Confidence^2 + (1+ Confidence | Participant) + (1 + Confidence | Stimulus)

Null Model 1 structure:

Curiosity ~ (1 + Confidence | Participant) + (1 + Confidence | Stimulus)

Results of the full-null model comparison revealed significant fixed effects of curiosity rating (χ^2 = 52.41, *df* = 11, *p* < .001, see Table 2). More specifically, confidence^2 was significantly associated with a high curiosity rating, $\beta = 0.23,\ SE = 0.03, p < .001$. We then plotted the fitted model with bootstrapped (n=1000) confidence interval, as shown in Figure 2. Overall, our data suggest a non-monotonic relationship between confidence and curiosity, but in contrast with previous work, our data revealed that higher confidence is associated with higher curiosity ratings.

Figure 2 *A bubble plot of Confidence and Curiosity ratings with a fitted line.*



Note: The figure shows the frequency distribution of curiosity ratings and how they varied with Confidence. Bubbles indicate the relative frequency of ratings. The fitted line shows the relationship between confidence and curiosity.

Table 2. *Cumulative link mixed effect model estimates of Model 1. The threshold coefficient and spacing are the intercepts for each rating category.*

Terms	Estimate	*SE*	Lower 95% CI	Upper 95% CI	*z*-score	*p*-value
Threshold						
1|2	-5.49	0.24	-5.96	-5.02	-22.80	-
2|3	-3.61	0.22	-4.05	-3.17	-16.10	-
3|4	-2.09	0.22	-2.52	-1.66	-9.53	-
4|5	-0.32	0.22	-0.75	0.11	-1.48	-
5|6	2.02	0.22	1.59	2.45	9.18	-
Coefficients						
Confidence	0.14	0.12	-0.10	0.38	1.15	.25
Confidence^2	0.23	0.03	0.17	0.29	7.08	<.001***

Note: $^{**}p < .01$, $^{***}p < .001$

Result interpretation: In the context of an ordinal model, the "intercepts" in Table 2 are usually termed as "threshold coefficients", representing the ordinal character of the responses. These threshold coefficients inform about the probability (the inverse logit transformation) of observing a given outcome (assuming the rest to be zero). For example, the first estimate (1|2) of -5.49 informs about how likely it is to observe curiosity rating as "1" (i.e., not curious at all) which would be 0.4% (inverse logic transformation of -5.49). The second estimate (2|3) of -3.61 informs about the probability of observing a curiosity rating of 2, which would be 2.63%, and so on

Question 2: What Predicts Curiosity?

To estimate the extent to which participants' curiosity ratings varied with their subjective prior knowledge estimate, confidence and confidence^2, we fitted a second CLM. We initially fitted the interactions of these three variables as fixed effects (i.e., confidence*confidence^2*subjective prior knowledge estimate), however, the model fell to converge. Thus, in the final fitted CLM, confidence, confidence^2, and subjective prior knowledge estimate were included as fixed effects. The model included maximised random intercepts for *Participant* and *Stimulus* as well as random slopes for confidence and subjective prior knowledge. Model fitting procedures were identical to the analysis of Question 1. There were no collinearity issues (Table S2 in Supplementary Materials).

Full Model 2 structure:

Curiosity ~ Confidence + (Confidence^2) + Subjective Prior Knowledge + (1 + Confidence + Subjective Prior Knowledge | Participant) + (1+Confidence + Subjective Prior Knowledge | Stimulus)

Null Model 2 structure:

Curiosity ~ 1 + (1 + Confidence + Subjective Prior Knowledge | Participant) + (1+ Confidence + Subjective Prior Knowledge | Stimulus)

Results of the full-null model comparison revealed significant fixed effects on curiosity rating (χ^2 = 59.98, df = 17, p < .001; Table 3). Specifically, subjective prior knowledge estimate of *No* (the '*I Don't Know*' state, $\beta(logit) = 0.37,\ SE = 0.15, p = .01$) and Not Sure (the '*Feeling of Knowing*' state, $\beta(logit) = 0.34,\ SE = 0.10,\ p < .001$) were significantly associated with higher curiosity ratings. When participants thought they did not know or were not sure about the answers, they were likely to be more curious about the actual answers. Similar to the results in Question 1, we also found that both higher confidence ($\beta(logit) = 0.26,\ SE = 0.12, p = .03$) and confidence^2 ($\beta(logit) = 0.24$, $SE = 0.04,\ p < .001$) were associated with higher curiosity ratings, suggesting that participants were most curious about the actual answers when they were confident with their guess being correct.

Table 3. *Cumulative link mixed effect model estimates of Model 2. Threshold coefficient and spacing are the intercepts for each rating category.*

Terms	Estimate	*SE*	Lower 95% CI	Upper 95% CI	*z*-score	*p*-value
Threshold						
1|2	-5.37	0.25	-6.22	-5.20	-21.43	-
2|3	-3.47	0.23	-4.29	-3.33	-14.70	-
3|4	-1.92	0.23	-2.74	-1.80	-8.36	-
4|5	-0.12	0.23	-0.94	-0.01	-0.53	-
5|6	2.27	0.23	1.44	2.39	9.81	-
Coefficients						
Confidence	0.26	0.12	0.02	0.49	2.12	.03*
Confidence^2	0.24	0.03	0.17	0.31	6.93	<.001***
Subjective Prior Knowledge: No	0.37	0.10	-0.21	0.19	-0.12	.01**
Subjective Prior Knowledge: NotSure	0.34	0.14	-0.62	-0.07	-2.44	<.001***

Note: *<.05, ***p* < .01, ***p < .001

Question 3: What Predicts Learning?

To investigate whether curiosity, confidence and subjective prior estimate influenced participants' recall accuracy, only the trials with incorrect guess trials were included in this analysis. A binomial generalised logistic mixed-effects model (GLMM) was fitted (Baayen, 2008) using the lme4 package (Bates et al., 2015). The full model included curiosity, confidence, subjective prior estimate and their interactions as fixed effects and the individual participant and stimulus as random effects. As the rating scales for curiosity and confidence had six levels, and their distributions were approximately normally distributed (Robitzsch, 2020; Snijders & Bosker, 2011), curiosity and confidence were fitted to the model as continuous variables after being *z*-transformed to ease model convergence and make model interpretation easier. One theoretically identifiable random slope component (the *z*-transformed confidence term within-participant) was included to avoid an overconfident model and inflation of the type I error rate (Barr et al., 2013; Schielzeth & Forstmeier, 2009). To avoid multiple testing (Schielzeth & Forstmeier, 2009), the full model was compared with a null model consisting of only the same random effect terms as the full model.

Full Model 3 structure:

Recall Accuracy ~ Curiosity * Confidence * Subjective Prior Knowledge + (1 + Confidence | Participant) + (1 | Stimulus), family = binomial

Null Model 3 structure:

Recall Accuracy ~ 1 + (1+ Confidence | Participant) + (1 | Stimulus), family = binomial

Additionally, the collinearity of the fixed effects was checked using VIF. The results suggested that there were no serious collinearity issues (Table S3 in Supplementary Materials). We assessed model stability by comparing the estimates obtained from the model based on all data with those obtained from models with the levels of the random effect factors excluded one at a time. This revealed the model to be of good stability. Confidence intervals (95%) were derived using the function bootMer from the lme4 package with 1000 parametric bootstraps.

The results revealed a significant fixed effect of subjective prior knowledge estimate on recall accuracy (see Table 4). More specifically, the *Not Sure* response (the '*feeling-of-*

knowing' state) of subjective prior knowledge estimate was positively associated with recall accuracy ($\beta(logit) = 0.36,\ SE = 0.13,\ z = 2.75,\ p < .01$). In contrast to previous literature, curiosity did not have a significant effect on predicting recall accuracy ($\beta(logit) = -0.04,\ SE = 0.12,\ z = -0.31,\ p = .76$). Different from our hypotheses, confidence did not have a significant impact on test recall accuracy ($\beta(logit) = -0.04,\ SE = 0.10,\ z = -0.43,\ p = .72$). There was no significant interaction between curiosity, confidence and subjective prior in predicting recall accuracy.

Table 4 *Estimates from the binomial generalised linear mixed model (Model 3) predicting test recall accuracy*

Terms	Est.	*SE*	Lower 95% CI	Upper 95% CI	*z*-score	*p*-value
Intercept	0.50	0.21	0.09	0.85	2.32	.02*
Confidence	-0.04	0.10	-0.23	0.12	-0.43	.72
Curiosity	-0.04	0.12	-0.25	0.17	-0.31	.76
Prior:NotSure	0.36	0.13	0.13	0.63	2.75	<.01**
Prior:Yes	0.20	0.17	-0.11	0.49	1.15	.25
Confidence*Curiosity	-0.07	0.10	-0.25	0.09	-0.65	.49
Confidence* Prior:NotSure	0.10	0.13	-0.12	0.36	0.76	.43
Confidence* Prior:Yes	0.11	0.14	-0.18	0.41	0.74	.46
Curiosity* Prior:NotSure	0.14	0.13	-0.08	0.40	1.02	.31
Curiosity* Prior:Yes	0.22	0.16	0.01	0.59	1.39	.16
Confidence*Curiosity*Prior:NotSure	0.08	0.12	-0.12	0.25	0.62	.52
Confidence*Curiosity*Prior:Yes	-0.05	0.13	-0.32	0.14	-0.41	.69

Note: *p < .05; **p < .01; Prior = Subjective Prior Knowledge

4.4 Discussion

The results of the current study help disentangle the roles of metacognitive abilities such as subjective prior knowledge estimates and confidence in curiosity. These results also help clarify the effects of curiosity, confidence and subjective prior knowledge estimates on learning. Metacognition, specifically monitoring and identifying one's own knowledge, has been demonstrated to provoke curiosity (Litman, 2009; Loewenstein, 1994; Metcalfe et al., 2020). For example, in Litman and colleagues' study (2005), participants were asked to answer 12 general questions and to evaluate their '*Feeling-of-Knowing*' states and curiosity about the answers. Afterwards, participants were offered the opportunities to restudy the questions. They found that higher '*Feeling-of-Knowing*' states predicted greater curiosity and prompted more exploratory behaviours (i.e., restudy more questions) relative to the '*I Know*' and the '*I Don't Know*' state, indicating a mediating effect of metacognitive appraisal on curiosity and exploratory behaviours. By assessing one's prior knowledge states, individuals can direct their subsequent information sampling accordingly. Indeed, our results showed that metacognitive estimation of subjective prior knowledge is closely related to curiosity and learning, such that higher curiosity ratings were significantly related to the '*I Don't Know*' state and the '*Feeling of Knowing*' state of subjective prior knowledge estimation. The '*Feeling of Knowing*' state involves partial retrieval of information from memory. The evaluation and selection between the retrieved alternatives may have resulted in greater uncertainty, which requires additional cognitive process and greater motivation to resolve the cognitive conflicts, leading to higher curiosity (Litman et al., 2005; Litman, 2009).

Unlike the '*Feeling of Knowing*' state, the '*I Don't Know*' state is thought to be associated with less curiosity due to the unsuccessful information retrieval yielding a knowledge gap that is too large to eliminate (Loewenstein, 1994). However, our finding suggests that the '*I Don't Know*' state is also linked to higher curiosity ratings. This might be due to the nature of stimuli used in the current study, specifically images of objects. As humans are exposed to an enormous amount of visual input, participants' default prior with regards to an object might be '*I must have seen this object'* (as a relatively strong prior), but the possibility of the identities of the object could be numerous, leading to larger outcome uncertainty and increased curiosity (van Lieshout et al., 2018). It is also possible that the '*I Don't Know*' state is associated with higher perceived novelty of the blurred stimuli, which also drives curiosity (Berlyne et al., 1963; Dubey & Griffiths, 2020)

Our results also suggest that curiosity is associated with confidence. More specifically, our data suggested that curiosity has a quadratic relationship with confidence: curiosity peaked when confidence was the highest. Our results are in line with the study of Wade and Kidd (2019), which found that a desire to verify or confirm one's predictions triggers higher curiosity. Evidence from Brod and Breitwieser (2019) also showed that when participants were in a high state of curiosity, having a prediction in mind produced larger pupil dilation during the anticipation of the answers to trivia questions, compared to not having a prediction. This work suggests that making a prediction generates or increases a relevant knowledge gap, which in turn increases curiosity, motivating verification and confirmation of the prediction (Loewenstein, 1994).

Interestingly, previous research using trivia question paradigms highlights that curiosity is an inverted U-shaped function of confidence instead (as an index of outcome uncertainty) such that curiosity peaks with medium confidence and is lowest with low and high confidence (Kang et al., 2009). One possible reason for our different findings is the differences between paradigms used across studies, and the effect of these differences on prior knowledge and outcome uncertainty. In trivia question paradigms, participants are asked to answer questions such as '*What instrument was invented to sound like a human singing?*' or '*What is the name of the galaxy that earth is a part of?*', then to rate their curiosity to know the actual answers, before the answers are revealed (in this case, *'violin'* and '*milky way*'). With the help of the keywords such as '*instrument'* or '*galaxy'* in the questions, the search spaces for the answers are limited and the associated semantic memory would be activated relatively quickly. However, using blurred images paradigms, when being asked about the identity of a blurred object, it could be associated with many unspecific objects that look alike. The search spaces for the identity would be enlarged, making it difficult to associate with related semantic memory. In other words, with regard to the differences in the outcome uncertainty between the two paradigms, answers to trivia questions are usually very specific (less uncertain), whereas there could be myriad identities for a given blurred object (more uncertain). Moreover, compared to trivia questions, when using blurred object images to induce curiosity, participants would have a stronger default prior ('*I must have seen this object'*) to the blurred objects due to the everyday visual experiences with objects. Having a stronger prior might bias decision making towards confirmation of predictions; whereas larger outcome uncertainty motivates curiosity to reduce the uncertainty.

We also examined whether curiosity, confidence, and subjective prior knowledge estimates affected accuracy of recalling the task materials. Surprisingly, in contrast to previous literature (Baranes et al., 2015; Brod & Breitwieser, 2019; Gruber et al., 2014; Jepma et al., 2012; Kang et al., 2009; Wade & Kidd, 2019), curiosity did not obviously affect recall accuracy in our study. Instead, recall accuracy was best predicted by subjective prior knowledge estimate, such that the '*Not Sure*' or '*Feeling-of-Knowing*' state of subjective prior knowledge estimate was related to higher recall accuracy. Although it is consistent with previous studies (Brooks et al., 2021; Hanczakowski et al., 2014; Litman et al., 2005) that in our data, the '*Not Sure*' or '*Feeling-of-Knowing*' state is associated with greater curiosity, these previous studies also highlight the role of knowledge states in modulating curiosity, and most importantly, their combined effects on promoting learning. However, our data suggest that there is no interaction effect on learning between the '*Not Sure*' state and curiosity. Instead, our finding suggests the '*Not Sure*' state alone predicted better learning. This result could be explained by the region of proximal learning framework (Kornell & Metcalfe, 2006; Metcalfe, 2009). According to this framework, the judgement of metacognitive states could lead to effective learning such that learners would focus on learning the easiest information they do not know over the already known or the most difficult information. In our case, the metacognitive state of '*Not Sure*' or '*Feeling-of-Knowing*' indicates that a learner is in the 'optimal learning zone' where they can focus on and prioritise learning information that is on the verge of being known, resulting in effective learning (Metcalfe et al., 2020).

Overall, our results with regards to what drives curiosity suggest that metacognitive abilities such as subjective prior knowledge estimates and confidence drive curiosity. Our data also reveal the diversity of the objectives of learners' curiosity, including missing information for resolving the knowledge gap as well as confirmation of their guesses. Surprisingly, we find that learning is best predicted by a learner's metacognitive appraisal of their knowledge gap. Especially when at the verge of knowing, metacognition is associated with better learning outcomes. Further, this learning enhancement is independent of curiosity, which raises the possibility that the cognitive effects of curiosity on learning might differ from those of metacognitive abilities. Taken together, these findings provide educational implications in the context of promoting curiosity, given that curiosity is closely linked to motivation for learning and interest (Ainley et al., 2002; Peterson & Hidi, 2019). By increasing the learners' awareness of their metacognitive abilities in identifying a suitable knowledge gap in the region of proximal learning, learners' curiosity should be boosted. Moreover, the current study provides empirical evidence by using a different paradigm relative to a trivia question paradigm, increasing the generalisability of this line of research.

References

Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology*, *94*, 545–561. https://doi.org/10.1037/0022-0663.94.3.545

Anwyl-Irvine, A., Dalmaijer, E. S., Hodges, N., & Evershed, J. K. (2021). Realistic precision and accuracy of online experiment platforms, web browsers, and devices. *Behavior Research Methods*, *53*(4), 1407–1425. https://doi.org/10.3758/s13428-020-01501-5

Baayen, R. H. (2008). *Analyzing Linguistic Data: A Practical Introduction to Statistics using R*. Higher Education from Cambridge University Press; Cambridge University Press. https://doi.org/10.1017/CBO9780511801686

Baranes, A., Oudeyer, P.Y., & Gottlieb, J. (2015). Eye movements reveal epistemic curiosity in human observers. *Vision Research*, *117*, 81–90. https://doi.org/10.1016/j.visres.2015.10.009

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, *68*(3), 10.1016/j.jml.2012.11.001. https://doi.org/10.1016/j.jml.2012.11.001

Berlyne, D. E., Craw, M. A., Salapatek, P. H., & Lewis, J. L. (1963). Novelty, complexity, incongruity, extrinsic motivation, and the GSR. *Journal of Experimental Psychology*, *66*, 560–567. https://doi.org/10.1037/h0045767

Berlyne, D. E., & Normore, L. F. (1972). Effects of prior uncertainty on incidental free recall. *Journal of Experimental Psychology*, *96*, 43–48. https://doi.org/10.1037/h0033480

Brod, G., & Breitwieser, J. (2019). Lighting the wick in the candle of learning: Generating a prediction stimulates curiosity. *Npj Science of Learning*, *4*(1), 1–7. https://doi.org/10.1038/s41539-019-0056-y

Brooks, G., Yang, H., & Köhler, S. (2021). Feeling-of-knowing experiences breed curiosity. *Memory (Hove, England)*, *29*(2), 153–167. https://doi.org/10.1080/09658211.2020.1867746

Butterfield, B., & Metcalfe, J. (2006). The correction of errors committed with high confidence. *Metacognition and Learning*, *1*(1), 69–84. https://doi.org/10.1007/s11409-006-6894-z

Christensen, R (2019). A Tutorial on fitting Cumulative Link Mixed Models with clmm2 from the ordinal Package. *Tutorial for the R Package Ordinal Https://Cran. r-Project. Org/Web/Packages/Ordinal/Accessed*, *1*.

Clatworthy, J., Buick, D., Hankins, M., Weinman, J., & Horne, R. (2005). The use and reporting of cluster analysis in health psychology: A review. *British Journal of Health Psychology*, *10*(Pt 3), 329–358. https://doi.org/10.1348/135910705X25697

Crandall, J. E. (1971). Relation of epistemic curiosity to subjective uncertainty. *Journal of Experimental Psychology*, *88*, 273–276. https://doi.org/10.1037/h0030886

Den Ouden, H., Kok, P., & De Lange, F. (2012). How Prediction Errors Shape Perception, Attention, and Motivation. *Frontiers in Psychology*, *3*. https://www.frontiersin.org/articles/10.3389/fpsyg.2012.00548

Dubey, R., & Griffiths, T. L. (2020). Reconciling novelty and complexity through a rational analysis of curiosity. *Psychological Review*, *127*, 455–476. https://doi.org/10.1037/rev0000175

Falotico, R., & Quatto, P. (2015). Fleiss' kappa statistic without paradoxes. *Quality & Quantity*, *49*(2), 463–470. https://doi.org/10.1007/s11135-014-0003-1

Fandakova, Y., & Gruber, M. J. (2021). States of curiosity and interest enhance memory differently in adolescents and in children. *Developmental Science*, *24*(1), e13005. https://doi.org/10.1111/desc.13005

Fastrich, G. M., Kerr, T., Castel, A. D., & Murayama, K. (2018). The role of interest in memory for trivia questions: An investigation with a large-scale database. *Motivation Science, 4*, 227–250. https://doi.org/10.1037/mot0000087

Fleiss, J. L., Levin, B., & Paik, M. C. (2013). *Statistical Methods for Rates and Proportions*. John Wiley & Sons.

Fox, J., Weisberg, S., Price, B., Adler, D., Bates, D., Baud-Bovy, G., Bolker, B., Ellison, S., Firth, D., Friendly, M., Gorjanc, G., Graves, S., Heiberger, R., Krivitsky, P., Laboissiere, R., Maechler, M., Monette, G., Murdoch, D., Nilsson, H., … R-Core. (2022). *car: Companion to Applied Regression* (3.1-0). https://CRAN.R-project.org/package=car

Gamer, M., Lemon, J., & Singh, I. F. P. (2019). *irr: Various Coefficients of Interrater Reliability and Agreement* (0.84.1). https://CRAN.R-project.org/package=irr

Gottlieb, J., Oudeyer, P.Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. *Trends in Cognitive Sciences, 17*(11), 585–593. https://doi.org/10.1016/j.tics.2013.09.001

Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of Curiosity Modulate Hippocampus-Dependent Learning via the Dopaminergic Circuit. *Neuron*, *84*(2), 486–496. https://doi.org/10.1016/j.neuron.2014.08.060

Gruber, M. J., & Ranganath, C. (2019). How Curiosity Enhances Hippocampus-Dependent Memory: The Prediction, Appraisal, Curiosity, and Exploration (PACE) Framework. *Trends in Cognitive Sciences*, *23*(12), 1014–1025. https://doi.org/10.1016/j.tics.2019.10.003

Hanczakowski, M., Zawadzka, K., & Cockcroft-McKay, C. (2014). Feeling of knowing and restudy choices. *Psychonomic Bulletin & Review*, *21*(6), 1617–1622. https://doi.org/10.3758/s13423-014-0619-0

Jepma, M., Verdonschot, R., van Steenbergen, H., Rombouts, S., & Nieuwenhuis, S. (2012). Neural mechanisms underlying the induction and relief of perceptual curiosity. *Frontiers in Behavioral Neuroscience*, *6*. https://www.frontiersin.org/articles/10.3389/fnbeh.2012.00005

Jirout, J., & Klahr, D. (2012). Children's scientific curiosity: In search of an operational definition of an elusive concept. *Developmental Review*, *32*(2), 125–160. https://doi.org/10.1016/j.dr.2012.04.002

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T., & Camerer, C. F. (2009). The wick in the candle of learning: Epistemic curiosity activates reward circuitry and enhances memory. *Psychological Science*, *20*(8), 963–973. https://doi.org/10.1111/j.1467-9280.2009.02402.x

Kassambara, A., & Mundt, F. (2017). Package 'factoextra'. *Extract and Visualize the Results of Multivariate Data Analyses*, *76*(2).

Kidd, C., & Hayden, B. Y. (2015). The psychology and neuroscience of curiosity. *Neuron*, *88*(3), 449–460. https://doi.org/10.1016/j.neuron.2015.09.010

Kornell, N., & Metcalfe, J. (2006). Study efficacy and the region of proximal learning framework. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*, 609–622. https://doi.org/10.1037/0278-7393.32.3.609

Ligneul, R., Mermillod, M., & Morisseau, T. (2018). From relief to surprise: Dual control of epistemic curiosity in the human brain. *NeuroImage*, *181*, 490–500. https://doi.org/10.1016/j.neuroimage.2018.07.038

Litman, J. (2009). Curiosity and metacognition. *Metacognition: New Research Developments*, *105*, 116.

Litman, J., Hutchins, T., & Russon, R. (2005). Epistemic curiosity, feeling-of-knowing, and exploratory behaviour. *Cognition and Emotion*, *19*, 559–582. https://doi.org/10.1080/02699930441000427

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*, 75–98. https://doi.org/10.1037/0033-2909.116.1.75

Marvin, C. B., & Shohamy, D. (2016). Curiosity and reward: Valence predicts choice and information prediction errors enhance learning. *Journal of Experimental Psychology: General*, *145*, 266–272. https://doi.org/10.1037/xge0000140

McGillivray, S., Murayama, K., & Castel, A. D. (2015). Thirst for knowledge: The effects of curiosity and interest on memory in younger and older adults. *Psychology and Aging*, *30*, 835–841. https://doi.org/10.1037/a0039801

Metcalfe, J. (2009). Metacognitive Judgments and Control of Study. *Current Directions in Psychological Science*, *18*(3), 159–163. https://doi.org/10.1111/j.1467-8721.2009.01628.x

Metcalfe, J. (2017). Learning from Errors. *Annual Review of Psychology*, *68*, 465–489. https://doi.org/10.1146/annurev-psych-010416-044022

Metcalfe, J., & Miele, D. B. (2014). Hypercorrection of high confidence errors: Prior testing both enhances delayed performance and blocks the return of the errors. *Journal of Applied Research in Memory and Cognition*, *3*, 189–197. https://doi.org/10.1016/j.jarmac.2014.04.001

Metcalfe, J., Schwartz, B. L., & Bloom, P. A. (2017). The tip-of-the-tongue state and curiosity. *Cognitive Research: Principles and Implications*, *2*(1), 31. https://doi.org/10.1186/s41235-017-0065-4

Metcalfe, J., Schwartz, B. L., & Eich, T. S. (2020). Epistemic curiosity and the region of proximal learning. *Current Opinion in Behavioral Sciences*, *35*, 40–47. https://doi.org/10.1016/j.cobeha.2020.06.007

Moreno-Martínez, F. J., & Montoro, P. R. (2012). An ecological alternative to Snodgrass & Vanderwart: 360 high quality colour images with Norms for seven psycholinguistic variables. *PLoS ONE*, *7*. https://doi.org/10.1371/journal.pone.0037527

Nicki, R. M. (1970). The reinforcing effect of uncertainty reduction on a human operant. *Canadian Journal of Psychology/Revue Canadienne de Psychologie*, *24*, 389–400. https://doi.org/10.1037/h0082875

Oudeyer, P.-Y., Gottlieb, J., & Lopes, M. (2016). Intrinsic motivation, curiosity, and learning: Theory and applications in educational technologies. *Progress in Brain Research*, *229*, 257–284. https://doi.org/10.1016/bs.pbr.2016.05.005

Oudeyer, P.-Y., & Smith, L. B. (2016). How Evolution May Work Through Curiosity-Driven Developmental Process. *Topics in Cognitive Science*, *8*(2), 492–502. https://doi.org/10.1111/tops.12196

Peterson, E. G., & Hidi, S. (2019). Curiosity and interest: Current perspectives. *Educational Psychology Review*, *31*(4), 781–788. https://doi.org/10.1007/s10648-019-09513-0

Robitzsch, A. (2020). Why Ordinal Variables Can (Almost) Always Be Treated as Continuous Variables: Clarifying Assumptions of Robust Continuous and Ordinal Factor Analysis Estimation Methods. *Frontiers in Education*, *5*. https://www.frontiersin.org/articles/10.3389/feduc.2020.589965

Royston, P. (2007). Profile Likelihood for Estimation and Confidence Intervals. *The Stata Journal*, *7*(3), 376–387. https://doi.org/10.1177/1536867X0700700305

Schielzeth, H., & Forstmeier, W. (2009). Conclusions beyond support: Overconfident estimates in mixed models. *Behavioral Ecology*, *20*, 416–420. https://doi.org/10.1093/beheco/arn145

Singh, A., & Manjaly, J. A. (2021). The effect of information gap and uncertainty on curiosity and its resolution. *Journal of Cognitive Psychology*, *33*, 403–423. https://doi.org/10.1080/20445911.2021.1908311

Snijders, T. A. B., & Bosker, R. J. (2011). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. SAGE.

Stare, C. J., Gruber, M. J., Nadel, L., Ranganath, C., & Gómez, R. L. (2018). Curiosity-driven memory enhancement persists over time but does not benefit from post-learning sleep. *Cognitive Neuroscience*, *9*(3–4), 100–115. https://doi.org/10.1080/17588928.2018.1513399

Theobald, M., Galeano-Keiner, E., & Brod, G. (2022). Predicting vs. guessing: The role of confidence for pupillometric markers of curiosity and surprise. *Cognition & Emotion*, *36*(4), 731–740. https://doi.org/10.1080/02699931.2022.2029733

van Lieshout, L. L. F., Vandenbroucke, A. R. E., Müller, N. C. J., Cools, R., & de Lange, F. P. (2018). Induction and Relief of Curiosity Elicit Parietal and Frontal Activity. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *38*(10), 2579–2588. https://doi.org/10.1523/JNEUROSCI.2816-17.2018

Wade, S., & Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psychonomic Bulletin & Review*, *26*, 1377–1387. https://doi.org/10.3758/s13423-019-01598-6

Supplementary Materials

Table S1. *Variance Inflation Factors (VIF) for collinearity between variables in Model 1*

Variable	VIF
Confidence	1.58
Confidence^2	1.67

Note: VIF < 5 indicates no reason for concern about collinearity

Table S2. *Variance Inflation Factors (VIF) for collinearity between variables in Model 2*

Variable	VIF
Subjective Prior Knowledge	1.03
Confidence	1.02
Confidence^2	1.04

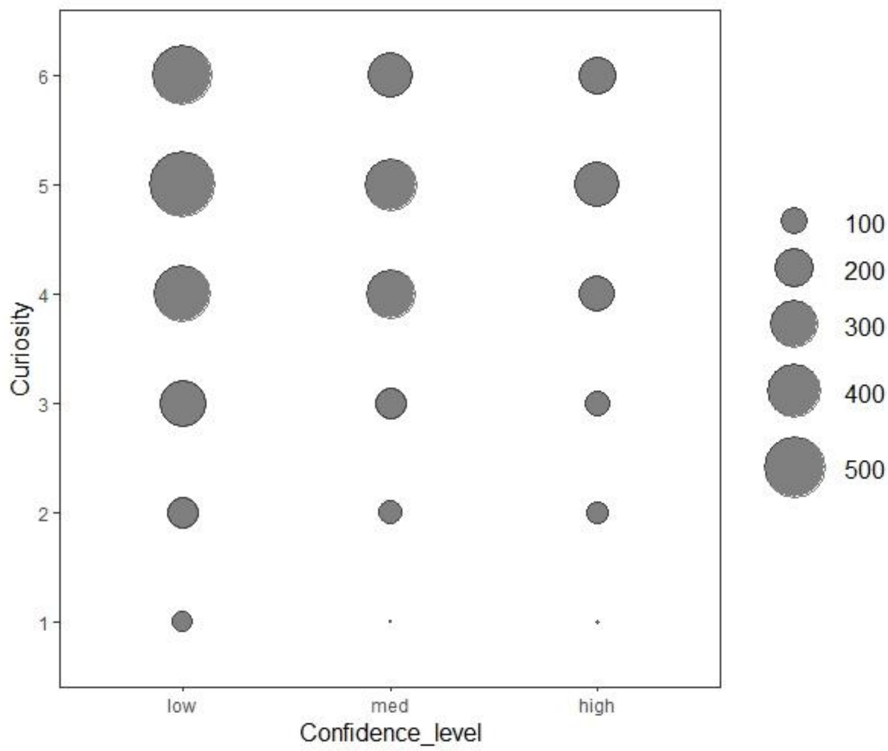
Note: VIF < 5 indicates no reason for concern about collinearity

Table S3. *VIF for collinearity between variables in the binomial generalised logistic mixed-effects model (Model 3)*

Variable	VIF
Curiosity	2.52
Confidence	2.13
Subjective Prior Knowledge	1.31
Curiosity * Confidence	2.63
Curiosity * Subjective Prior Knowledge	1.74
Confidence* Subjective Prior Knowledge	1.56
Curiosity* Confidence* Subjective Prior Knowledge	1.68

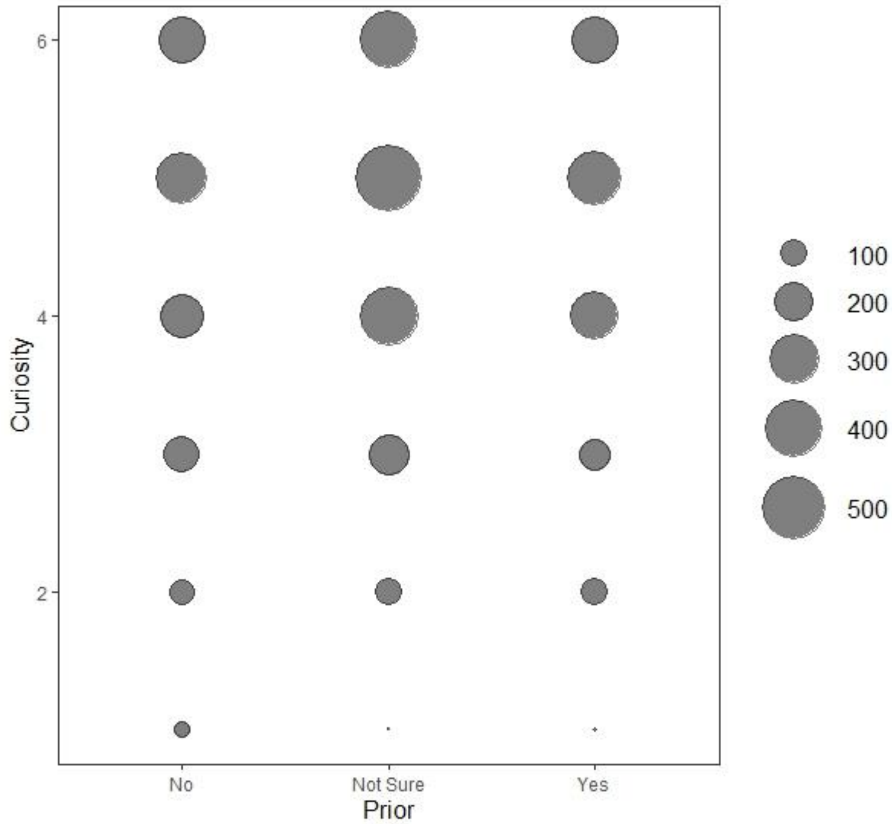
Note: VIF < 5 should not be a concern of collinearity

Figure S1 *A bubble plot of Confidence and Curiosity ratings*



This figure shows the frequency distribution of curiosity ratings and how they varied between Confidence levels. Bubbles indicate the relative frequency of ratings.

Figure S2 *A bubble plot of Subjective prior estimate and Curiosity ratings*



This figure shows the frequency distribution of curiosity ratings and how they varied between different levels of subjective prior estimates. Bubbles indicate the relative frequency of ratings.

Chapter 5

General Discussion

This thesis aimed to understand the cognitive and neural mechanisms of curiosity driven by visual uncertainty and the associated effect on learning in both young infants and adults. This was achieved by using a combination of approaches, integrating data from behaviour, eye tracking, EEG measures, and self-report. This thesis presents new results that complement the existing literature and address research gaps in the field. The current thesis also raises needs for future investigations on the extent to which curiosity boosts learning. In this chapter, first, a summary of the studies conducted and their key findings are presented. Then, critical reflections on the existing theories of curiosity in light of this work are provided. Finally, the limitations of this thesis and future direction for curiosity research are discussed.

5.1 Summary of Research

The approach to investigating the relationship between curiosity and visual uncertainty in learning in this thesis was to present participants with pictures with various degrees of visual uncertainty, implemented as blurredness, to modulate states of curiosity. Then, surprise memory tests were conducted to examine the extent to which curiosity might play a role in improving learning outcomes. Depending on the age group tested and the research question, a range of designs, paradigms and measures were applied across three studies.

In Chapter 2, two eye-tracking experiments were carried out to explore, firstly, whether by being exposed to blurred pictures, infants' curiosity would enhance the learning of incidental information and, secondly, whether infants would seek to resolve the induced curiosity by preferring resolution over novelty. In the first experiment, infants saw a learning phase consisting of two sequences of pictures. One sequence (Curiosity sequence) started with a blurred picture to induce curiosity, followed by an unrelated incidental object, and then a clear corresponding picture of the blurred picture to resolve the uncertainty. The other sequence (Non-Curiosity sequence) as a baseline control, began with a clear picture, followed by another unrelated incidental object, and then the same clear picture. After the presentation of these two sequences, the degree of learning for the incidental objects was assessed using a preferential-looking test. The two different, unrelated incidental objects were presented side-by-side on a screen. Infants' eye movements were measured to establish whether they would show a systematic preference for one image over the other, indicating differences in the degree of processing. It was found that despite spending equal time looking at the incidental objects during the learning phase, infants showed a significant preference for the objects presented in the Non-Curiosity sequence over the objects in the Curiosity sequence. This result indicates that curiosity induced by blurred pictures enhanced the processing of the incidental objects, resulting in a novelty preference for the objects shown in the Non-Curiosity sequence.

In the second experiment, infants were presented with a blurred picture to induce their curiosity, followed by its corresponding clear picture together with a clear picture of a novel toy side-by-side on a screen, providing infants with an opportunity to resolve the uncertainty induced by the originally blurred image. Infants' looking behaviours were measured using an eye tracker. Infants did not show a preference for either image, giving no evidence of a preference for uncertainty resolution. In the context of existing literature on older children and adults (Fandakova & Gruber, 2021; Gruber et al., 2014), this work indicates potential developmental changes across the lifespan in the role and function of curiosity. Specifically, curiosity might manifest as general attentional arousal in young infants. Then, with the development of memory and metacognition, curiosity becomes more focused and goal-directed in seeking a specific resolution to resolve uncertainty.

Chapter 3 explored the role of metacognitive abilities in identifying a knowledge gap and triggering curiosity. The knowledge gap account of curiosity has been emphasised notably in theoretical (Loewenstein, 1994) and empirical work (Kang et al., 2009), the latter typically using trivia question paradigms. Different from the trivia question approach, blurred visual stimuli of day-to-day objects and living creatures across a wide range of categories were used, hoping to improve ecological validity and extend the generalizability of research findings. This chapter, therefore, examined the extent to which these metacognitive abilities influence curiosity and learning using a blurred picture paradigm. To this end, we conducted an online experiment in combination with self-reported measures to investigate the role of metacognitive abilities (i.e., participants' prior knowledge estimates, confidence) and curiosity on learning. Participants were presented with a set of blurred pictures presented sequentially. For each blurred picture, participants were asked to give a best guess about the identity of the blurred picture, to estimate whether they knew the answer, to rate their confidence in their guess, and to rate their curiosity about the answer. After answering all the questions, participants completed a surprise recall test of the identities of the blurred pictures.

In contrast to the theoretical inverted U-shaped relationship discussed in existing work, in which intermediate confidence evokes the greatest curiosity, higher confidence evoked higher curiosity, revealing the diverse drivers of curiosity under different contexts. For example, based on this study, curiosity might not be entirely driven by an intermediate knowledge gap but rather motivated by a desire to confirm a prediction. Interestingly, it was also found that learning was best predicted by participants' prior knowledge estimates, independently of curiosity, specifically, when participants were at the verge of knowing the identity of an image. Combining these findings with literature that demonstrates the beneficial effect of curiosity on learning, together these results may have educational implications in the context of promoting curiosity by increasing learners' awareness of metacognitive abilities (Ainley et al., 2002; Peterson & Hidi, 2019). For example, deliberately promoting learners to evaluate their current knowledge levels and help them identify a manageable knowledge gap, could potentially generate feelings of knowing and curiosity, creating a combined boosting effect on learning. On the other hand, these findings may also raise a possibility that the cognitive mechanisms of curiosity in learning might differ from those of metacognitive abilities.

Chapter 4 comprises two separate experiments with an online rating study and an EEG study. In the online rating study, a set of pictures with no, low, medium and high degrees of blur were assessed to establish the extent to which curiosity would be associated with different degrees of visual uncertainty. Participants were presented with one picture at a time and were asked to rate their curiosity about the identity of the picture. It was found that clear and low blurred pictures were associated with low curiosity, whereas medium and highly blurred pictures were related to high curiosity. Then, these pictures were used in an EEG study to investigate the neural correlates of visual uncertainty and how it relates to curiosity and learning. Pictures were presented to participants (curiosity induction) once at a time, followed by the corresponding clear pictures (curiosity reduction). After the presentation of all pictures, a surprise recall test of a subset of the presented pictures was conducted to examine learning outcomes. EEG was recorded throughout the picture presentation and the surprise recall test. As the induction of curiosity about blurred images is associated with certain attention or arousal enhancement mechanisms, whereas the reduction of curiosity about blurred images promotes better learning outcomes (Jepma et al., 2012). Thus, alpha desynchronisation was measured during the induction of curiosity as an index of focused attention, global arousal and active information encoding (Hanslmayr & Staudigl, 2014; Klimesch, 1997, 1999). Theta synchronisation was recorded during the reduction of curiosity as an index of active cognitive engagement and learning (Begus & Bonawitz, 2020).

Results showed that stronger alpha desynchronisation was found for pictures with a medium and high degree of blur relative to clear and low blurred pictures over the posterior midline areas during curiosity induction. Most importantly, these medium and highly blurred pictures were associated with high curiosity in the online rating study. With regards to learning, no strong evidence of a learning enhancement effect was found in the surprise memory test, nor the theta activities over the frontal areas during curiosity reduction across pictures with various degrees of visual uncertainty. Taken together, these results indicate that visual uncertainty may indeed induce curiosity via a mechanism of creating a state of global arousal that enhances focused attention, as indicated by increased alpha desynchronisation over occipital regions. On the other hand, the absence of evidence for increased theta activities of high uncertainty resolution pictures might be due to participants' competence in rapid object recognition (Harari et al, 2020), such that it was too fast to be reflected by neural oscillations.

5.2 Critical Reflection

Having introduced the key theories in Chapter 1 and summarised the main findings of this thesis above, this section aims to provide a critical reflection on curiosity theories in light of the findings of this thesis and recent findings in the curiosity literature.

5.2.1 Redefinition: Discard the Dichotomies and Recognise the Cores of Curiosity

As mentioned in Chapter 1 (sections 1.2 and 1.3.1), existing literature tends to divide curiosity into various dimensionalities where these dimensionalities are usually in dichotomous pairs (e.g. Berlyne, 1954). This section discusses the impracticalities of the current consensus that curiosity can be subset into separate, distinct constructs, which imposes challenges in forming a unifying definition of curiosity. Discarding these dichotomous ways of thinking would help researchers identify the fundamental core of curiosity and formalise an integrated definition for future research. In this section, one of the most frequently considered pairs concerning the sources that generate curiosity (i.e., perceptual curiosity versus epistemic curiosity) is discussed, together with supporting evidence that they are inseparable. Of relevance, curiosity is often viewed as a drive for seeking non-instrumental (i.e., for the sake of knowledge) rather than instrumental information (e.g., with potential utility or value). This section also suggests discarding this dichotomy and proposes a new focus on the essence of the objective of curiosity: information gain rather than the potential instrumental value of the sought informaiton might be a more important curiosity objective.

It is widely assumed that curiosity arises from two distinct sources: perceptual curiosity versus epistemic curiosity; and curiosity ends and aims for non-instrumental information rather than instrumental information. To begin with, the origin of curiosity, as mentioned in Chapter 1 (section 1.2.1), Berlyne's views on perceptual curiosity and epistemic curiosity as distinct phenomena seem intuitive, yet it has been noted that these categories are not clearly separable. According to Berlyne (1954), the difference between perceptual and epistemic curiosity lies in the sources that elicit it. Perceptual curiosity is triggered by sensory stimulation (i.e., collative variables such as surprise, ambiguity, novelty and so on), resulting in seeking the sensory situation through visual investigation or inspections. For example, upon hearing a rumbling sound (sensory stimulation) coming from a corner on the street, one orientates their attention towards the corner and searches for the source (visual investigation). A young infant obtained a new, noisy and flashy toy (sensory stimulation), and started to manipulate the toy (inspection). On the other hand, epistemic curiosity is evoked by the awareness of a missing piece of information in one's current mental representations, resulting in seeking that specific information. However, whether an information seeking behaviour is perceptual-driven or epistemic-driven is hard to differentiate (Collins et al., 2004; Kidd & Hayden, 2015; Litman & Spielberger, 2003; Oudeyer & Kaplan, 2007).

In fact, the two mechanisms are convergent and highly inter-connected (Litman & Spielberger, 2003). For example, a preverbal child could be attracted to explore a novel toy (no prior exposure; perceptual-driven). Equally, however, such exploratory behaviours could also be elicited because the child internally tries to figure out what this toy can do and what sounds it can make (epistemic-driven). It could also be that novelty triggers perceptual curiosity at first, but by continuously exploring the toy, the child then wants more functional information about the toy. Take the example of Chapter 4: curiosity induced by blurred pictures would be regarded as perceptual curiosity that aims for sensory clarification via visual investigation. However, by taking into account the relationship with metacognitive abilities, Chapter 4 also showed that curiosity about visual uncertainty was closely related to participants' estimate of prior knowledge in terms of identifying a knowledge gap in their current representation. Participants were most curious about the blurred pictures that they believed they knew, suggesting that this 'perceptual curiosity' to some extent involves evaluations of one's knowledge base. Interestingly, this awareness of a knowledge gap is regarded as an essential element for epistemic curiosity. In other words, Chapter 4 demonstrates that regardless of the sources of curiosity, experiences of sensations could lead to intellectual inquiry, whereas epistemic curiosity could lead to a desire for new sensory experiences (Reio et al., 2006).

These findings also indicate a shared core between perceptual and epistemic curiosity objectives: information seeking, regardless of the sources that trigger it, or the instrumental value embedded in the sought information. Many definitions in the literature have emphasised curiosity as a heuristic drive that seeks information "for the sake of knowledge" and involves no tangible reward (Gottlieb et al., 2013; Gottlieb & Oudeyer, 2018; Harlow & McClearn, 1954), indicating the sought information is non-instrumental. However, internal states and motivations are miscellaneous, and the true, underlying goals that a curious learner may have are not always clear. For example, one could indeed be intrinsically driven to seek information (e.g., a puzzle) for fun, whereas information seeking could also be driven by other implicit intentions (e.g., to solve the puzzle to prove competence). For example, results from Chapter 4 suggest that participants were mostly curious about the blurred pictures that they believed they knew but not the ones that they did not know, indicating their objective of curiosity to be confirmation of prediction, or to verify whether they were correct or not (i.e., competence). Similar results were also obtained by Wade and Kidd (2019) using a trivia question paradigm. Overall, more and more empirical advances are starting to show that curiosity-type behaviours can be driven by motives other than pure curiosity for the sake of knowledge (Szumowska & Kruglanski, 2020). For example, popularity and the potential usefulness of information could serve as motives for information seeking. Dubey et al., (2021) found participants were more curious about everyday questions that were considered high popularity relative to questions with low popularity. High popularity might suggest high usefulness, indicating that curiosity could be driven by utility and by the instrumental need to learn.

Taken together, this section raises doubts about the existing definition of curiosity, questioning the practicality of viewing perceptual and epistemic sources as a dichotomy in triggering curiosity and, equally, viewing the source of curiosity as non-instrumental, ‘pure interest’. Rather, exploration and active information seeking could be in service of other motives (e.g., competence, easing boredom or uncertainty resolution). Thus, a new way to understand these curious behaviours is to concentrate on their shared cores - regardless of the various triggers of curiosity, curiosity is *intrinsic* motivation that drives an individual to *actively* seek information and to *autonomously* organise exploratory behaviours, emphasizing a sense of agency and control in information sampling (Markant et al., 2016; Saylor & Ganea, 2018). More importantly, the sought information need not be non-instrumental.

5.2.2 Do We Need Meta-Cognitive Ability to Be Curious?

Another critical reflection concerns the prominence of the information gap theory in the current literature. Berlyne (1954) and Loewenstein's (1994) accounts on epistemic curiosity highlight the role of meta-cognitive abilities in identifying an information gap or a missing piece of information in eliciting epistemic curiosity. This would require one to access one's prior knowledge store, which Berlyne and Loewenstein referred to as the "symbolic system". It would also need a clear goal about what information to seek out to fill such a knowledge gap. Indeed, this approach neatly captures curiosity-driven behaviour manifested in older children and adults and has inspired a wealth of empirical work. Evidence from studies that used blurred pictures or trivia questions to generate an information gap, does show that curiosity is closely related to attributes of the perceived gap (Gruber et al., 2014; Jepma et al., 2012; Marvin & Shohamy, 2016). For example, the specificity of the knowledge gap influences the breadth of information-seeking behaviour such that having a precise goal leads to specific information sampling, with broader goals leading to more a general search for information (Gottlieb et al., 2013). The magnitude of a perceived gap also has an impact on curiosity such that a small gap intensifies the perception of the gap, motivating the need to seek specific information to close the gap (Jepma et al., 2012; Litman et al., 2005; Nicki, 1970). On the other hand, a large gap might spark a sense of discovery and inspiration to expand the knowledge repertoire (Noordewier & van Dijk, 2020). This work has identified the important role of meta-cognition in relation to a perceived knowledge gap in curiosity.

However, it is unclear whether these prerequisite meta-cognitive abilities can underlie curiosity in young children. On one hand, young infants as naïve learners often encounter a new environment of which they have no prior knowledge. Based on the information gap account, in a new environment, young infants would be unlikely to be curious as, without prior knowledge, it is impossible to identify a gap. Yet, robust evidence of novelty preference in infancy indicates the opposite (section 1.3.2): for example, infants are sensitive to novel subtle changes and novel information (Aslin & Smith, 1988; Fantz, 1964; Haith, 1986). Once familiarity with the detected difference is gained, they quickly shift their visual preferences for new, novel information (Hunter et al., 1983; Spelke, 1985). Infants also actively explore the environment. They show great competencies in extracting regularities in the environment and flexibly seek an environment that could offer learning opportunities and information gains (Poli et al., 2020). They babble, point and inquiry for information they would like to know about (Begus & Southgate, 2012; Goldstein et al., 2010; Ronfard et al., 2018).

On the other hand, young children may have very limited meta-cognitive ability to monitor what information would be needed, and they may also have limited executive functions in organising information-seeking behaviour (Beate et al., 2012). In light of Chapter 2, the second experiment provided no evidence that 8-month-old infants resolved the induced curiosity by seeking a specific resolution. It is still unclear at what age children's meta-cognition would develop fully enough to keep track of the nuances of the knowledge gap mentioned above. de Eccher and Mani (2022, in prep) examined whether five-year-old children could use their own meta-cognitive judgements in an active word-object learning task. Children showed high engagement in learning object-word pairs on a tablet by tapping and listening. Afterwards, they were then asked to judge whether they knew the learned objects. It was found that children were able to correctly judge their prior knowledge in relation to whether they knew the objects, but were unable to use this information to learn new objects in later trials. Thus, even at this later stage, when language has developed, children do not appear to be able to use meta-cognition in a way that would allow them to identify an information gap.

Overall, the information gap theory might not be able to fully explain curiosity in young children and it fails to capture developmental changes in curiosity across the lifespan. Most importantly, although meta-cognition is crucial in curiosity, especially for adults, it might not be necessary for curiosity in young children. On the other hand, as the current literature is largely built upon epistemic curiosity, it is important to develop new methods to measure epistemic curiosity and to investigate the critical age range when epistemic curiosity is strongly present in young children.

5.3 Limitations and Future directions

Besides the limitations mentioned in the previous sections and chapters, this section discusses the general limitations of this thesis and provides ideas and directions for future research. In a nutshell, this section first reflects on the designs of the current thesis, then emphasises the need for developing suitable paradigms and designs for curiosity research across the lifespan in an ecological environment in order to capture the developmental changes of curiosity.

5.3.1 Measure Young Children's Curiosity Ecologically

This thesis intended to investigate states of curiosity about visual uncertainty and the associated effect of object processing in young infants. As reflected in section 1.3.2, curiosity arises from an individual's intrinsic state that motivates one to actively and autonomously seek information, highlighting a sense of agency and control in information sampling. Yet, the two experiments presented in Chapter 2 of the current thesis were typical, lab-based studies where infants passively perceived the given information and were unable to interact with or control the flow of the presented information. As a result, such passive viewing designs might not be able to fully capture young children's curiosity. Moreover, the ongoing debates with regard to the interpretations of familiarity-novelty preference impose uncertainty on our interpretations of the data in Chapter 2. Indeed, although novelty preference was the most reasonable explanation, it is still possible that infants showed a familiar preference due to reasons other than curiosity. Although the thesis did not provide further data to follow up on the infant study, it sheds lights on the direction for future investigation. For example, adding physiological measures such as pupil response should provide data to justify whether being exposed to visual uncertain information would lead to changes in attention, and the consequences of these changes on object learning.

Recently, in light of these limitations of passive viewing designs in capturing curiosity in young infants and children, there has been an increasing amount of studies that used alternative designs such as gaze-contingency paradigms in young infants (Bazhydai et al., 2022; Eiteljoerge et al., 2020) and active learning paradigms utilizing touch-screen based devices in older children (Ackermann et al., 2020; Ruggeri et al., 2019; Sim et al., 2015). Both gaze-contingent paradigms and touch-screen-based learning designs allow children to actively engage and interact with the provided information. Most importantly, these techniques provide opportunities for young children to actively choose the information they prefer to interact with, making them suitable tools for studying curiosity-based learning in young children. These advances are in line with an emerging framework of ecologically-valid research into active learning in the developmental field (Cervera et al., 2020; Ruggeri, 2022), suggesting that performance in laboratory tasks does not reflect how we really are in a rich and natural world. In Ruggeri's framework, the significance of developing age-appropriate paradigms is highlighted, and in particular, designs that allow researchers to capture young children's competence in constructing their own learning. In addition, such designs should encompass options for young children to actively and adaptively explore the ecology (e.g., structure and characteristics) of a learning environment.

More broadly, future curiosity research in young children could take the ecology of a learning environment into account when designing a study and offer young children chances to actively control their learning. However, this is not a one-sided statement in favour of ecological paradigms. Notwithstanding limitations of the ecological issues, most of the lab-based studies such as the two infant experiments in Chapter 2, allowed experimenters to precisely control what stimulus could be exposed to infants, making them well-fitted designs to answer the research questions in Chapter 2. In sum, continued efforts are needed to integrate both lab-based studies and ecological paradigms for developmental research.

5.3.2 Curiosity in Adults: Design

Reviews on neural studies of curiosity also advocate the need for suitable paradigms to capture curiosity behaviours (Cervera et al., 2020), given that laboratory tasks highly constrain human behaviour and performance relative to real-life situations. Moreover, due to methodological limitations, lab-based neural studies can be lengthy and indirect, adding artefacts to participants' performance. Take Chapter 3 in this thesis as an example. Chapter 3 aimed to investigate the neural correlates of curiosity triggered by visual uncertainty. However, the measurements were indirect, as curiosity was measured separately in an online study, and EEG signals were obtained from a laboratory task with a different group of participants. This was due to a practical concern in using EEG: being able to obtain a sufficient number of trials is crucial for gaining good-quality EEG data. Thus, by separating the entire study into two, it reduced the total amount of time for testing each individual, allowing us to increase the total number of trials gathered from each participant. Further reserach may explore how direct measure of curiosity (i.e., measure each individual's curiosity) influence frequencies of interest in relation to visual uncertainty.

Another limitation of Chapter 3 concerns the design of the EEG study and the instruction given to the participants in relation to controls of eye blinks during testing. As EEG signals are susceptible to artefacts such as head and eye movements, a fixation cross at the beginning of each trial was implemented to offer a time interval during which participants could blink. Participants were instructed to blink whenever they needed to during the presentation of the fixation cross. As a result, most of the eye blink artefacts appeared to be at the start and the end of each trial. Large artefacts at the beginning and/or the end of an EEG epoch would cause boundary effects in wavelet transformation, masking the lower frequencies (Hu & Zhang, 2019; Lilly, 2017; Nobach et al., 2007). Luckily, the boundary effect found in the initial analysis was corrected (Chapter 3 Data Analysis) in the final analysis and did not affect the frequency bands and the time window of interest. Thus, technical advice for future research would be to implement a specific time window outside of the test trial for participants to relax (i.e., eye blink or head movement).

5.3.3 Curiosity in Adults: Stimuli

For the majority of research on curiosity in adults, trivia questions have been the most frequently used stimuli to modulate states of curiosity (Kang et al., 2009; Gruber et al., 2014). In an effort to improve ecological validity and to extend the generalizability of these research findings, this thesis used visual stimuli consisting of images of day-to-day objects and living creatures across a wide range of categories. These visual stimuli were modified with different degrees of blur (i.e., no, low, medium and high) and were tested in two different ways. Overall, findings regarding the relationship between curiosity and uncertainty were inconsistent with previous literature. Previous work using trivia question paradigms (Gruber et al., 2014; Kang et al., 2009) as well as uncertain picture paradigms (Cohanpour et al., 2022) found that curiosity is an inverted U-shaped function of uncertainty. In Chapter 4, visual stimuli with a medium degree of blur were used to assess the relationship between curiosity and subjective uncertainty (i.e., an indirect index of confidence). Results revealed that as confidence rises, curiosity increases. Most importantly, in contrast to previous findings, curiosity peaked when participants were most confident that they knew the answers. Inconsistent findings were also obtained in Chapter 3 with a different measure. In Chapter 3, visual stimuli with no, low, medium and high degrees of blur were rated online. Visual uncertainty thus was objectively defined by degrees of blur. In this study, curiosity increased as objective visual uncertainty increased. Moreover, curiosity peaked for pictures with a medium and high degree of blur or maximal uncertainty.

One possible explanation for the inconsistency between previous work and the findings in this thesis is that the degree of blur does not entirely map onto the degree of uncertainty in previous studies. In other words, the highest degree of blur was not 'blurred' enough, resulting in a partially inverted U-shaped (the left part) curve. Supporting evidence comes from a recent study by Cohanpour and colleagues (2022) where uncertain pictures that were barely recognizable were applied to induce curiosity, whereas medium to highly blurred pictures used in this thesis were recognizable to some extent (see Chapter 3). These inconsistent findings raise questions about the generalizability of the existing literature on curiosity, revealing an important need for future research in relation to curiosity and uncertainty. In light of this thesis, future work could firstly focus on finding objective measures (e.g., eye movements and pupillometry) rather than subjective measures of curiosity, and secondly, verify the relationship between objective curiosity and a full range of visual uncertainty. For example, this could be achieved by presenting continuous blurring pictures from clear to unrecognizably blurry. Third, in future investigations, variations in measurements across different studies need to be considered.

5.4 Concluding Remarks

In conclusion, this thesis explored cognitive and neural mechanisms of curiosity triggered by visual uncertainty and examined its influence on learning in young infants and adults. To date, this thesis includes the first empirical study to explore how states of curiosity affect object encoding in infants and the role of curiosity resolution in this process. This thesis also includes the first empirical EEG study to investigate the neural correlates of curiosity to visual uncertainty and its effect on learning. The findings reported in this study shed new light on the fundamental mechanism of curiosity, suggesting that visual uncertainty may indeed induce curiosity via a mechanism of creating a state of global arousal that enhances focused attention. Moreover, the empirical studies in this thesis also contributed to the growing literature on the role of metacognition in curiosity, highlighting the significance of a learner's awareness of metacognitive abilities in boosting curiosity. Although the data in the current thesis did not provide strong evidence for the beneficial effect of curiosity on learning, given the extensive literature that found a pronounced effect and the significant role of meta cognition in increasing curiosity in our findings. The insights gained from this thesis may provide educational implications in the context of promoting curiosity by explicitly prompting metacognitive appraisal, creating a combined boosting effect of curiosity and metacognition on learning. Moreover, the current thesis also raises a possibility that the cognitive mechanisms by which curiosity affects learning might differ from the mechanisms by which metacognitive abilities affect learning. Furthermore, this thesis provides a deeper insight into the developmental changes in curiosity, such that curiosity might manifest as general, attentional arousal in young infants, but as memory and metacognition develop, curiosity becomes more focused and goal-directed in seeking a specific resolution to resolve uncertainty.

Consolidated Bibliography

Ackermann, L., Lo, C. H., Mani, N., & Mayor, J. (2020). Word learning from a tablet app: Toddlers perform better in a passive context. *PLOS ONE*, *15*(12), e0240519. https://doi.org/10.1371/journal.pone.0240519

Adrian, E. D., & Matthews, B. H. C. (1934). The berger rhythm: Potential changes from the occipital lobes in man. *Brain*, *57*(4), 355–385. https://doi.org/10.1093/brain/57.4.355

Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology*, *94*, 545–561. https://doi.org/10.1037/0022-0663.94.3.545

Anwyl-Irvine, A., Dalmaijer, E. S., Hodges, N., & Evershed, J. K. (2021). Realistic precision and accuracy of online experiment platforms, web browsers, and devices. *Behavior Research Methods*, *53*(4), 1407–1425. https://doi.org/10.3758/s13428-020-01501-5

Aslin, R. N., & Smith, L. B. (1988). Perceptual development. *Annual Review of Psychology*, *39*(1), 435–473. https://doi.org/10.1146/annurev.ps.39.020188.002251

Baayen, R. H. (2008, March 6). *Analyzing Linguistic Data: A Practical Introduction to Statistics using R*. Higher Education from Cambridge University Press; Cambridge University Press. https://doi.org/10.1017/CBO9780511801686

Bach, D. R., & Dolan, R. J. (2012). Knowing how much you don't know: A neural organization of uncertainty estimates. *Nature Reviews Neuroscience*, *13*(8), Article 8. https://doi.org/10.1038/nrn3289

Baranes, A., Oudeyer, P.-Y., & Gottlieb, J. (2015). Eye movements reveal epistemic curiosity in human observers. *Vision Research*, *117*, 81–90. https://doi.org/10.1016/j.visres.2015.10.009

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, *68*(3), 10.1016/j.jml.2012.11.001. https://doi.org/10.1016/j.jml.2012.11.001

Bates, D., Maechler, M., Bolker [aut, B., cre, Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., Grothendieck, G., Green, P., Fox, J., Bauer, A., & simulate.formula), P. N. K. (shared copyright on. (2022). *lme4: Linear Mixed-Effects Models using 'Eigen' and S4* (1.1-30). https://CRAN.R-project.org/package=lme4

Bazhydai, M., Jones, S. D., & Westermann, G. (2022). *Does curiosity enhance word learning in 18-month-old infants? A Registered Report.* OSF Preprints. https://doi.org/10.31219/osf.io/bm5a9

Bazhydai, M., Westermann, G., & Parise, E. (2020). "I don't know but I know who to ask": 12-month-olds actively seek information from knowledgeable adults. *Developmental Science*, *23*(5), e12938. https://doi.org/10.1111/desc.12938

Begus, K., & Bonawitz, E. (2020). The rhythm of learning: Theta oscillations as an index of active learning in infancy. *Developmental Cognitive Neuroscience*, *45*, 100810. https://doi.org/10.1016/j.dcn.2020.100810

Begus, K., Gliga, T., & Southgate, V. (2014). Infants Learn What They Want to Learn: Responding to Infant Pointing Leads to Superior Learning. *PLOS ONE*, *9*(10), e108817. https://doi.org/10.1371/journal.pone.0108817

Begus, K., & Southgate, V. (2012). Infant pointing serves an interrogative function. *Developmental Science*, *15*, 611–617. https://doi.org/10.1111/j.1467-7687.2012.01160.x

Begus, K., Southgate, V., & Gliga, T. (2015). Neural mechanisms of infant learning: Differences in frontal theta activity during object exploration modulate subsequent object recognition. *Biology Letters*, *11*(5), 20150041. https://doi.org/10.1098/rsbl.2015.0041

Berger, H. (1931). Über das Elektrenkephalogramm des Menschen. *Archiv für Psychiatrie und Nervenkrankheiten*, *94*(1), 16–60. https://doi.org/10.1007/BF01835097

Berlyne, D. E. (1954). A theory of human curiosity. *British Journal of Psychology. General Section*, *45*(3), 180–191. https://doi.org/10.1111/j.2044-8295.1954.tb01243.x

Berlyne, D. E. (1960). *Conflict, arousal, and curiosity* (pp. xii, 350). McGraw-Hill Book Company. https://doi.org/10.1037/11164-000

Berlyne, D. E. (1966). Curiosity and exploration. *Science (New York, N.Y.)*, *153*(3731), 25–33. https://doi.org/10.1126/science.153.3731.25

Berlyne, D. E., & Normore, L. F. (1972). Effects of prior uncertainty on incidental free recall. *Journal of Experimental Psychology*, *96*, 43–48. https://doi.org/10.1037/h0033480

Brod, G., & Breitwieser, J. (2019). Lighting the wick in the candle of learning: Generating a prediction stimulates curiosity. *Npj Science of Learning*, *4*(1), Article 1. https://doi.org/10.1038/s41539-019-0056-y

Brodeur, M. B., Guérard, K., & Bouras, M. (2014). Bank of Standardized Stimuli (BOSS) Phase II: 930 New Normative Photos. *PLOS ONE*, *9*(9), e106953. https://doi.org/10.1371/journal.pone.0106953

Bromberg-Martin, E. S., & Hikosaka, O. (2009). Midbrain dopamine neurons signal preference for advance information about upcoming rewards. *Neuron*, *63*(1), 119–126. https://doi.org/10.1016/j.neuron.2009.06.009

Brooks, G., Yang, H., & Köhler, S. (2021). Feeling-of-knowing experiences breed curiosity. *Memory (Hove, England)*, *29*(2), 153–167. https://doi.org/10.1080/09658211.2020.1867746

Brydevall, M., Bennett, D., Murawski, C., & Bode, S. (2018). The neural encoding of information prediction errors during non-instrumental information seeking. *Scientific Reports*, *8*(1), Article 1. https://doi.org/10.1038/s41598-018-24566-x

Butterfield, B., & Metcalfe, J. (2006). The correction of errors committed with high confidence. *Metacognition and Learning*, *1*(1), 69–84. https://doi.org/10.1007/s11409-006-6894-z

Cabrero, J. M. R., Zhu, J.-Q., & Ludvig, E. A. (2019). Costly curiosity: People pay a price to resolve an uncertain gamble early. *Behavioural Processes*, *160*, 20–25. https://doi.org/10.1016/j.beproc.2018.12.015

Cao, A., Raz, G., Saxe, R., & Frank, M. C. (2022). *Habituation reflects optimal exploration over noisy perceptual samples*. PsyArXiv. https://doi.org/10.31234/osf.io/jb7qy

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in Cognitive Sciences*, *18*(8), 414–421. https://doi.org/10.1016/j.tics.2014.04.012

Cervera, R. L., Wang, M. Z., & Hayden, B. Y. (2020). Systems neuroscience of curiosity. *Current Opinion in Behavioral Sciences*, *35*, 48–55. https://doi.org/10.1016/j.cobeha.2020.06.011

Chen, X., Twomey, K. E., & Westermann, G. (2022). Curiosity enhances incidental object encoding in 8-month-old infants. *Journal of Experimental Child Psychology*, *223*, 105508. https://doi.org/10.1016/j.jecp.2022.105508

Chow, V., Poulin-Dubois, D., & Lewis, J. (2008). To see or not to see: Infants prefer to follow the gaze of a reliable looker. *Developmental Science*, *11*(5), 761–770. https://doi.org/10.1111/j.1467-7687.2008.00726.x

Christensen, R. H. B. (2019). A Tutorial on fitting Cumulative Link Mixed Models with clmm2 from the ordinal Package. *Tutorial for the R Package Ordinal Https://Cran. r-Project. Org/Web/Packages/Ordinal/Accessed*, *1*.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*(3), 181–204. https://doi.org/10.1017/S0140525X12000477

Clatworthy, J., Buick, D., Hankins, M., Weinman, J., & Horne, R. (2005). The use and reporting of cluster analysis in health psychology: A review. *British Journal of Health Psychology*, *10*(Pt 3), 329–358. https://doi.org/10.1348/135910705X25697

Cohanpour, M., Aly, M., & Gottlieb, J. (2022). *Leveraging vision to understand curiosity* (p. 2022.09.23.509220). bioRxiv. https://doi.org/10.1101/2022.09.23.509220

Cohen, L. B., DeLoache, J. S., & Rissman, M. W. (1975). The Effect of Stimulus Complexity on Infant Visual Attention and Habituation. *Child Development*, *46*(3), 611–617. https://doi.org/10.2307/1128557

Collins, R. P., Litman, J. A., & Spielberger, C. D. (2004). The measurement of perceptual curiosity. *Personality and Individual Differences*, *36*, 1127–1141. https://doi.org/10.1016/S0191-8869(03)00205-8

Colombo, M. (2017). Andy Clark, Surfing Uncertainty: Prediction, Action, and the Embodied Mind. *Minds and Machines*, *27*(2), 381–385. https://doi.org/10.1007/s11023-017-9420-y

Cowan, N. (2016). Working Memory Maturation: Can We Get at the Essence of Cognitive Growth? *Perspectives on Psychological Science*, *11*(2), 239–264. https://doi.org/10.1177/1745691615621279

Crandall, J. E. (1971). Relation of epistemic curiosity to subjective uncertainty. *Journal of Experimental Psychology*, *88*, 273–276. https://doi.org/10.1037/h0030886

Daddaoua, N., Lopes, M., & Gottlieb, J. (2016). Intrinsically motivated oculomotor exploration guided by uncertainty reduction and conditioned reinforcement in non-human primates. *Scientific Reports*, *6*(1), Article 1. https://doi.org/10.1038/srep20202

de Eccher, M., & Mani, N. (2022). Active learning, feedback and hypercorrection effect in word learning. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *44*(44). https://escholarship.org/uc/item/30p609jv

Deci, E. L., & Ryan, R. M. (1981). *Curiosity and Self-Directed Learning: The Role of Motivation in Education*. Ablex Publishing Corporation. https://eric.ed.gov/?id=ED206377

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Dember, W. N., & Earl, R. W. (1957). Analysis of exploratory, manipulatory, and curiosity behaviors. *Psychological Review*, *64*, 91–96. https://doi.org/10.1037/h0046861

Den Ouden, H., Kok, P., & De Lange, F. (2012). How Prediction Errors Shape Perception, Attention, and Motivation. *Frontiers in Psychology*, *3*. https://www.frontiersin.org/articles/10.3389/fpsyg.2012.00548

Dubey, R., & Griffiths, T. L. (2020a). Reconciling novelty and complexity through a rational analysis of curiosity. *Psychological Review*, *127*, 455–476. https://doi.org/10.1037/rev0000175

Dubey, R., & Griffiths, T. L. (2020b). Understanding exploration in humans and machines by formalizing the function of curiosity. *Current Opinion in Behavioral Sciences*, *35*, 118–124. https://doi.org/10.1016/j.cobeha.2020.07.008

Dubey, R., Mehta, H., & Lombrozo, T. (2021). Curiosity is contagious: A social influence intervention to induce curiosity. *Cognitive Science*, *45*(2), e12937. https://doi.org/10.1111/cogs.12937

Durik, A. M., Shechter, O. G., Noh, M., Rozek, C. S., & Harackiewicz, J. M. (2015). What if I can’t? Success expectancies moderate the effects of utility value information on situational interest and performance. *Motivation and Emotion*, *39*, 104–118. https://doi.org/10.1007/s11031-014-9419-0

Dzubak, C. M. (2008). Multitasking: The good, the bad, and the unknown. *The Journal of the Association for the Tutoring Profession*, *1*(2), 1–12.

Eiteljoerge, S., Adam, M., Elsner, B., & Mani, N. (2020). *Do preferences for words and actions influence word-object and action-object learning in early childhood?* PsyArXiv. https://doi.org/10.31234/osf.io/jubw5

Falotico, R., & Quatto, P. (2015). Fleiss’ kappa statistic without paradoxes. *Quality & Quantity*, *49*(2), 463–470. https://doi.org/10.1007/s11135-014-0003-1

Fandakova, Y., & Gruber, M. J. (2021). States of curiosity and interest enhance memory differently in adolescents and in children. *Developmental Science*, *24*(1), e13005. https://doi.org/10.1111/desc.13005

Fantz, R. L. (1958). Pattern vision in young infants. *The Psychological Record*, *8*, 43–47.

Fantz, R. L. (1961). The origin of form perception. *Scientific American*, *204*, 66–72. https://doi.org/10.1038/scientificamerican0561-66

Fantz, R. L. (1964). Visual experience in infants: Decreased attention to familiar patterns relative to novel ones. *Science*, *146*(3644), 668–670. https://doi.org/10.1126/science.146.3644.668

Fantz, R. L., & Miranda, S. B. (1975). Newborn Infant Attention to Form of Contour. *Child Development*, *46*(1), 224–228. https://doi.org/10.2307/1128853

Fantz, R. L., & Nevis, S. (1967). Pattern Preferences and Perceptual-Cognitive Development in Early Infancy. *Merrill-Palmer Quarterly of Behavior and Development*, *13*(1), 77–108.

Fastrich, G. M., Kerr, T., Castel, A. D., & Murayama, K. (2018). The role of interest in memory for trivia questions: An investigation with a large-scale database. *Motivation Science*, *4*, 227–250. https://doi.org/10.1037/mot0000087

Feige, B., Scheffler, K., Esposito, F., Di Salle, F., Hennig, J., & Seifritz, E. (2005). Cortical and subcortical correlates of electroencephalographic alpha rhythm modulation. *Journal of Neurophysiology*, *93*(5), 2864–2872. https://doi.org/10.1152/jn.00721.2004

Festinger, L. (1962). *A theory of cognitive dissonance* (Vol. 2). Stanford university press.

Fisher-Thompson, D. (2014). Exploring the Emergence of Side Biases and Familiarity–Novelty Preferences from the Real-Time Dynamics of Infant Looking. *Infancy*, *19*(3), 227–261. https://doi.org/10.1111/infa.12051

Fisher-Thompson, D., & Peterson, J. A. (2004). Infant Side Biases and Familiarity-Novelty Preferences During a Serial Paired-Comparison Task. *Infancy*, *5*(3), 309–340. https://doi.org/10.1207/s15327078in0503_4

FitzGibbon, L., Lau, J. K. L., & Murayama, K. (2020). The seductive lure of curiosity: Information as a motivationally salient reward. *Current Opinion in Behavioral Sciences*, *35*, 21–27. https://doi.org/10.1016/j.cobeha.2020.05.014

Fleiss, J. L., Levin, B., & Paik, M. C. (2013). *Statistical Methods for Rates and Proportions*. John Wiley & Sons.

Forbes, S., Dink, J., & Ferguson, B. (2021). *eyetrackingR: Eye-Tracking Data Analysis* (0.2.0). https://CRAN.R-project.org/package=eyetrackingR

Fox, J., Weisberg, S., Price, B., Adler, D., Bates, D., Baud-Bovy, G., Bolker, B., Ellison, S., Firth, D., Friendly, M., Gorjanc, G., Graves, S., Heiberger, R., Krivitsky, P., Laboissiere, R., Maechler, M., Monette, G., Murdoch, D., Nilsson, H., … R-Core. (2022). *car: Companion to Applied Regression* (3.1-0). https://CRAN.R-project.org/package=car

Foxe, J. J., Simpson, G. V., & Ahlfors, S. P. (1998). Parieto-occipital ∼1 0Hz activity reflects anticipatory state of visual attention mechanisms. *NeuroReport*, *9*(17), 3929–3933.

Freunberger, R., Klimesch, W., Griesmayr, B., Sauseng, P., & Gruber, W. (2008). Alpha phase coupling reflects object recognition. *NeuroImage*, *42*(2), 928–935. https://doi.org/10.1016/j.neuroimage.2008.05.020

Friedman, S. (1972). Habituation and recovery of visual response in the alert human newborn. *Journal of Experimental Child Psychology*, *13*(2), 339–349. https://doi.org/10.1016/0022-0965(72)90095-1

Friston, K., Rigoli, F., Ognibene, D., Mathys, C., Fitzgerald, T., & Pezzulo, G. (2015). Active inference and epistemic value. *Cognitive Neuroscience*, *6*(4), 187–214. https://doi.org/10.1080/17588928.2015.1020053

Gamer, M., Lemon, J., & Singh, I. F. P. (2019). *irr: Various Coefficients of Interrater Reliability and Agreement* (0.84.1). https://CRAN.R-project.org/package=irr

Goldstein, M. H., Schwade, J., Briesch, J., & Syal, S. (2010). Learning While Babbling: Prelinguistic Object-Directed Vocalizations Indicate a Readiness to Learn. *Infancy*, *15*(4), 362–391. https://doi.org/10.1111/j.1532-7078.2009.00020.x

Golman, R., & Loewenstein, G. (2018). Information gaps: A theory of preferences regarding the presence and absence of information. *Decision*, *5*, 143–164. https://doi.org/10.1037/dec0000068

Gottlieb, J., & Oudeyer, P.-Y. (2018). Towards a neuroscience of active sampling and curiosity. *Nature Reviews Neuroscience*, *19*(12), Article 12. https://doi.org/10.1038/s41583-018-0078-0

Gottlieb, J., Oudeyer, P.-Y., Lopes, M., & Baranes, A. (2013). Information seeking, curiosity and attention: Computational and neural mechanisms. *Trends in Cognitive Sciences*, *17*(11), 585–593. https://doi.org/10.1016/j.tics.2013.09.001

Goupil, L., & Proust, J. (2022). Curiosity as a metacognitive feeling. *Cognition*, *231*, 105325. https://doi.org/10.1016/j.cognition.2022.105325

Gruber, M. J., & Fandakova, Y. (2021). Curiosity in childhood and adolescence—What can we learn from the brain. *Current Opinion in Behavioral Sciences*, *39*, 178–184. https://doi.org/10.1016/j.cobeha.2021.03.031

Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of curiosity modulate hippocampus-dependent learning via the dopaminergic vircuit. *Neuron*, *84*(2), 486–496. https://doi.org/10.1016/j.neuron.2014.08.060

Gruber, M. J., & Ranganath, C. (2019). How Curiosity Enhances Hippocampus-Dependent Memory: The Prediction, Appraisal, Curiosity, and Exploration (PACE) Framework. *Trends in Cognitive Sciences*, *23*(12), 1014–1025. https://doi.org/10.1016/j.tics.2019.10.003

Gureckis, T. M., & Markant, D. B. (2012). Self-Directed Learning: A Cognitive and Computational Perspective. *Perspectives on Psychological Science*, *7*(5), 464–481. https://doi.org/10.1177/1745691612454304

Haith, M. M. (1986). Sensory and perceptual processes in early infancy. *The Journal of Pediatrics*, *109*(1), 158–171. https://doi.org/10.1016/S0022-3476(86)80601-1

Hanczakowski, M., Zawadzka, K., & Cockcroft-McKay, C. (2014). Feeling of knowing and restudy choices. *Psychonomic Bulletin & Review*, *21*(6), 1617–1622. https://doi.org/10.3758/s13423-014-0619-0

Hanslmayr, S., & Staudigl, T. (2014). How brain oscillations form memories—A processing based perspective on oscillatory subsequent memory effects. *NeuroImage*, *85*, 648–655. https://doi.org/10.1016/j.neuroimage.2013.05.121

Harari, D., Benoni, H., & Ullman, S. (2020). Object recognition at the level of minimal images develops for up to seconds of presentation time. *Journal of Vision*, *20*(11), 266. https://doi.org/10.1167/jov.20.11.266

Harlow, H. F., & McClearn, G. E. (1954). Object discrimination learned by monkeys on the basis of manipulation motives. *Journal of Comparative and Physiological Psychology*, *47*, 73–76. https://doi.org/10.1037/h0058241

Hebb, D. O. (1955). Drives and the C. N. S. (conceptual nervous system). *Psychological Review*, *62*, 243–254. https://doi.org/10.1037/h0041823

Hertwig, R., & Engel, C. (2016). Homo Ignorans: Deliberately Choosing Not to Know. *Perspectives on Psychological Science*, *11*(3), 359–372. https://doi.org/10.1177/1745691616635594

Horst, J. S., & Hout, M. C. (2016). The Novel Object and Unusual Name (NOUN) Database: A collection of novel images for use in experimental research. *Behavior Research Methods*, *48*(4), 1393–1409. https://doi.org/10.3758/s13428-015-0647-3

Houston-Price, C., & Nakai, S. (2004). Distinguishing novelty and familiarity effects in infant preference procedures. *Infant and Child Development*, *13*(4), 341–348. https://doi.org/10.1002/icd.364

Hu, L., & Zhang, Z. (2019). *EEG signal processing and feature extraction*. Springer.

Hunt, J. (1965). Intrinsic motivation and its role in psychological development. *Nebraska Symposium on Motivation*, *13*, 189–282.

Hunter, M. A., & Ames, E. W. (1988). A multifactor model of infant preferences for novel and familiar stimuli. *Advances in Infancy Research*, *5*, 69–95.

Hunter, M. A., Ames, E. W., & Koopman, R. (1983). Effects of stimulus complexity and familiarization time on infant preferences for novel and familiar stimuli. *Developmental Psychology*, *19*, 338–352. https://doi.org/10.1037/0012-1649.19.3.338

Inamizu, S., Yamada, E., Ogata, K., Uehara, T., Kira, J., & Tobimatsu, S. (2020). Neuromagnetic correlates of hemispheric specialization for face and word recognition. *Neuroscience Research*, *156*, 108–116. https://doi.org/10.1016/j.neures.2019.11.006

Jarosz, A., & Wiley, J. (2014). What Are the Odds? A Practical Guide to Computing and Reporting Bayes Factors. *The Journal of Problem Solving*, *7*(1). https://doi.org/10.7771/1932-6246.1167

Jaswal, V. K., & Neely, L. A. (2006). Adults Don't Always Know Best: Preschoolers Use Past Reliability Over Age When Learning New Words. *Psychological Science*, *17*(9), 757–758. https://doi.org/10.1111/j.1467-9280.2006.01778.x

Jepma, M., Verdonschot, R., van Steenbergen, H., Rombouts, S., & Nieuwenhuis, S. (2012). Neural mechanisms underlying the induction and relief of perceptual curiosity. *Frontiers in Behavioral Neuroscience*, *6*. https://www.frontiersin.org/articles/10.3389/fnbeh.2012.00005

Jirout, J., & Klahr, D. (2012). Children's scientific curiosity: In search of an operational definition of an elusive concept. *Developmental Review*, *32*, 125–160. https://doi.org/10.1016/j.dr.2012.04.002

Johnson, S. P. (2010). How infants learn about the visual world. *Cognitive Science*, *34*, 1158–1184. https://doi.org/10.1111/j.1551-6709.2010.01127.x

Kachel, G., Moore, R., Hepach, R., & Tomasello, M. (2021). Toddlers Prefer Adults as Informants: 2- and 3-Year-Olds' Use of and Attention to Pointing Gestures From Peer and Adult Partners. *Child Development*, *92*(4), e635–e652. https://doi.org/10.1111/cdev.13544

Kalnins, I. V., & Bruner, J. S. (1973). The coordination of visual observation and instrumental behavior in early infancy. *Perception*, *2*, 307–314. https://doi.org/10.1068/p020307

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T., & Camerer, C. F. (2009). The wick in the candle of learning: Epistemic curiosity activates reward circuitry and enhances memory. *Psychological Science*, *20*(8), 963–973. https://doi.org/10.1111/j.1467-9280.2009.02402.x

Kassambara, A., & Mundt, F. (2017). Package 'factoextra'. *Extract and Visualize the Results of Multivariate Data Analyses*, *76*(2).

Kidd, C., & Hayden, B. Y. (2015). The psychology and neuroscience of curiosity. *Neuron*, *88*(3), 449–460. https://doi.org/10.1016/j.neuron.2015.09.010

Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2012). The Goldilocks Effect: Human Infants Allocate Attention to Visual Sequences That Are Neither Too Simple Nor Too Complex. *PLOS ONE*, *7*(5), e36399. https://doi.org/10.1371/journal.pone.0036399

Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2014). The Goldilocks Effect in Infant Auditory Attention. *Child Development*, *85*(5), 1795–1804. https://doi.org/10.1111/cdev.12263

Kinney, D. K., & Kagan, J. (1976). Infant Attention to Auditory Discrepancy. *Child Development*, *47*(1), 155–164. https://doi.org/10.2307/1128294

Klimesch, W. (1996). Memory processes, brain oscillations and EEG synchronization. *International Journal of Psychophysiology*, *24*(1), 61–100. https://doi.org/10.1016/S0167-8760(96)00057-8

Klimesch, W. (1997). EEG-alpha rhythms and memory processes. *International Journal of Psychophysiology*, *26*(1), 319–340. https://doi.org/10.1016/S0167-8760(97)00773-3

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews*, *29*(2), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W. (2012). α-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Klimesch, W., Fellinger, R., & Freunberger, R. (2011). Alpha oscillations and early stages of visual encoding. *Frontiers in Psychology*, *2*. https://www.frontiersin.org/articles/10.3389/fpsyg.2011.00118

Klimesch, W., Freunberger, R., Sauseng, P., & Gruber, W. (2008). A short review of slow phase synchronization and memory: Evidence for control processes in different memory systems? *Brain Research*, *1235*, 31–44. https://doi.org/10.1016/j.brainres.2008.06.049

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition–timing hypothesis. *Brain Research Reviews*, *53*(1), 63–88. https://doi.org/10.1016/j.brainresrev.2006.06.003

Kobayashi, K., & Hsu, M. (2019). Common neural code for reward and information value. *Proceedings of the National Academy of Sciences*, *116*(26), 13061–13066. https://doi.org/10.1073/pnas.1820145116

Kobayashi, K., Ravaioli, S., Baranès, A., Woodford, M., & Gottlieb, J. (2019). Diverse motives for human curiosity. *Nature Human Behaviour*, *3*(6), 587–595. https://doi.org/10.1038/s41562-019-0589-3

Kornell, N., & Metcalfe, J. (2006). Study efficacy and the region of proximal learning framework. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*, 609–622. https://doi.org/10.1037/0278-7393.32.3.609

Lau, J. K. L., Ozono, H., Kuratomi, K., Komiya, A., & Murayama, K. (2020). Shared striatal activity in decisions to satisfy curiosity and hunger at the risk of electric shocks. *Nature Human Behaviour*, *4*, 531–543. https://doi.org/10.1038/s41562-020-0848-3

Lega, B. C., Jacobs, J., & Kahana, M. (2012). Human hippocampal theta oscillations and the formation of episodic memories. *Hippocampus*, *22*(4), 748–761. https://doi.org/10.1002/hipo.20937

Ligneul, R., Mermillod, M., & Morisseau, T. (2018). From relief to surprise: Dual control of epistemic curiosity in the human brain. *NeuroImage*, *181*, 490–500. https://doi.org/10.1016/j.neuroimage.2018.07.038

Lilly, J. M. (2017). Element analysis: A wavelet-based method for analysing time-localized events in noisy time series. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *473*(2200), 20160776. https://doi.org/10.1098/rspa.2016.0776

Liquin, E. G., Callaway, F., & Lombrozo, T. (2021). Developmental Change in What Elicits Curiosity. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *43*(43). https://escholarship.org/uc/item/43g7m167

Litman, J. A., & Spielberger, C. D. (2003). Measuring epistemic curiosity and its diversive and specific components. *Journal of Personality Assessment*, *80*(1), 75–86. https://doi.org/10.1207/S15327752JPA8001_16

Litman, J., Hutchins, T., & Russon, R. (2005). Epistemic curiosity, feeling-of-knowing, and exploratory behaviour. *Cognition and Emotion*, *19*, 559–582. https://doi.org/10.1080/02699930441000427

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*, 75–98. https://doi.org/10.1037/0033-2909.116.1.75

Lucca, K., & Wilbourn, M. P. (2018). Communicating to Learn: Infants' Pointing Gestures Result in Optimal Learning. *Child Development*, *89*(3), 941–960. https://doi.org/10.1111/cdev.12707

Makeig, S., Delorme, A., Westerfield, M., Jung, T.-P., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2004). Electroencephalographic brain dynamics following manually responded visual targets. *PLOS Biology*, *2*(6), e176. https://doi.org/10.1371/journal.pbio.0020176

Markant, D. B., Ruggeri, A., Gureckis, T. M., & Xu, F. (2016). Enhanced memory as a common effect of active learning. *Mind, Brain, and Education*, *10*, 142–152. https://doi.org/10.1111/mbe.12117

Martin, A. (2007). The Representation of Object Concepts in the Brain. *Annual Review of Psychology*, *58*(1), 25–45. https://doi.org/10.1146/annurev.psych.57.102904.190143

Marvin, C. B., & Shohamy, D. (2016). Curiosity and reward: Valence predicts choice and information prediction errors enhance learning. *Journal of Experimental Psychology: General*, *145*, 266–272. https://doi.org/10.1037/xge0000140

McGillivray, S., Murayama, K., & Castel, A. D. (2015). Thirst for knowledge: The effects of curiosity and interest on memory in younger and older adults. *Psychology and Aging*, *30*, 835–841. https://doi.org/10.1037/a0039801

Metcalfe, J. (2009). Metacognitive Judgments and Control of Study. *Current Directions in Psychological Science*, *18*(3), 159–163. https://doi.org/10.1111/j.1467-8721.2009.01628.x

Metcalfe, J. (2017). Learning from Errors. *Annual Review of Psychology*, *68*, 465–489. https://doi.org/10.1146/annurev-psych-010416-044022

Metcalfe, J., & Miele, D. B. (2014). Hypercorrection of high confidence errors: Prior testing both enhances delayed performance and blocks the return of the errors. *Journal of Applied Research in Memory and Cognition*, *3*, 189–197. https://doi.org/10.1016/j.jarmac.2014.04.001

Metcalfe, J., Schwartz, B. L., & Bloom, P. A. (2017). The tip-of-the-tongue state and curiosity. *Cognitive Research: Principles and Implications*, *2*(1), 31. https://doi.org/10.1186/s41235-017-0065-4

Metcalfe, J., Schwartz, B. L., & Eich, T. S. (2020). Epistemic curiosity and the region of proximal learning. *Current Opinion in Behavioral Sciences*, *35*, 40–47. https://doi.org/10.1016/j.cobeha.2020.06.007

Monosov, I. E. (2020). How outcome uncertainty mediates attention, learning, and decision-making. *Trends in Neurosciences*, *43*(10), 795–809. https://doi.org/10.1016/j.tins.2020.06.009

Moreno-Martínez, F. J., & Montoro, P. R. (2012). An ecological alternative to Snodgrass & Vanderwart: 360 high quality colour images with Norms for seven psycholinguistic variables. *PLoS ONE*, *7*. https://doi.org/10.1371/journal.pone.0037527

Mullaney, K. M., Carpenter, S. K., Grotenhuis, C., & Burianek, S. (2014). Waiting for feedback helps if you want to know the answer: The role of curiosity in the delay-of-feedback benefit. *Memory & Cognition*, *42*, 1273–1284. https://doi.org/10.3758/s13421-014-0441-y

Murayama, K. (2022). A reward-learning framework of knowledge acquisition: An integrated account of curiosity, interest, and intrinsic–extrinsic rewards. *Psychological Review*, *129*, 175–198. https://doi.org/10.1037/rev0000349

Murayama, K., Blake, A. B., Kerr, T., & Castel, A. D. (2016). When enough is not enough: Information overload and metacognitive decisions to stop studying information. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *42*(6), 914–924. https://doi.org/10.1037/xlm0000213

Murayama, K., FitzGibbon, L., & Sakaki, M. (2019). Process Account of Curiosity and Interest: A Reward-Learning Perspective. *Educational Psychology Review, 31*(4), 875–895. https://doi.org/10.1007/s10648-019-09499-9

Nicki, R. M. (1970). The reinforcing effect of uncertainty reduction on a human operant. *Canadian Journal of Psychology/Revue Canadienne de Psychologie*, *24*, 389–400. https://doi.org/10.1037/h0082875

Nobach, H., Tropea, C., Cordier, L., Bonnet, J.-P., Delville, J., Lewalle, J., Farge, M., Schneider, K., & Adrian, R. (2007). Review of some fundamentals of data processing. In C. Tropea, A. L. Yarin, & J. F. Foss (Eds.), *Springer Handbook of Experimental Fluid Mechanics* (pp. 1337–1398). Springer. https://doi.org/10.1007/978-3-540-30299-5_22

Noordewier, M. K., & van Dijk, E. (2020). Deprivation and discovery motives determine how it feels to be curious. *Current Opinion in Behavioral Sciences*, *35*, 71–76. https://doi.org/10.1016/j.cobeha.2020.07.017

Norcia, A. M., & Tyler, C. W. (1985). Infant VEP acuity measurements: Analysis of individual differences and measurement error. *Electroencephalography & Clinical Neurophysiology*, *61*, 359–369. https://doi.org/10.1016/0013-4694(85)91026-0

Ofen, N. (2012). The development of neural correlates for memory formation. *Neuroscience & Biobehavioral Reviews*, *36*(7), 1708–1717. https://doi.org/10.1016/j.neubiorev.2012.02.016

Ong, Y. S., & Gupta, A. (2016). Evolutionary Multitasking: A Computer Science View of Cognitive Multitasking. *Cognitive Computation*, *8*(2), 125–142. https://doi.org/10.1007/s12559-016-9395-7

Oudeyer, P. Y., & Kaplan, F. (2007). What is intrinsic motivation? A typology of computational approaches. *Frontiers in Neurorobotics*, *1*, 6. https://doi.org/10.3389/neuro.12.006.2007

Oudeyer, P. Y., & Smith, L. B. (2016). How Evolution May Work Through Curiosity-Driven Developmental Process. *Topics in Cognitive Science*, *8*(2), 492–502. https://doi.org/10.1111/tops.12196

Parise, E., & Csibra, G. (2013). Neural responses to multimodal ostensive signals in 5-month-old infants. *PLOS ONE*, *8*(8), e72360. https://doi.org/10.1371/journal.pone.0072360

Park, J., Shimojo, E., & Shimojo, S. (2010). Roles of familiarity and novelty in visual preference judgments are segregated across object categories. *Proceedings of the National Academy of Sciences*, *107*(33), 14552–14555. https://doi.org/10.1073/pnas.1004374107

Partridge, E., McGovern, M. G., Yung, A., & Kidd, C. (2015). Young children's self-directed information gathering on touchscreens. *Proceedings of the 37th Annual Conference of the Cognitive Science Society, Austin, Tx. Cognitive Science Society*.

Peterson, E. G., & Hidi, S. (2019). Curiosity and interest: Current perspectives. *Educational Psychology Review*, *31*(4), 781–788. https://doi.org/10.1007/s10648-019-09513-0

Pfurtscheller, G., & Aranibar, A. (1977). Event-related cortical desynchronization detected by power measurements of scalp EEG. *Electroencephalography and Clinical Neurophysiology*, *42*(6), 817–826. https://doi.org/10.1016/0013-4694(77)90235-8

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *110*(11), 1842–1857. https://doi.org/10.1016/s1388-2457(99)00141-8

Piaget, J. (1952). *The origins of intelligence in children* (p. 419). W W Norton & Co. https://doi.org/10.1037/11494-000

Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., Johnson, R., Miller, G. A., Ritter, W., Ruchkin, D. S., Rugg, M. D., & Taylor, M. J. (2000). Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology*, *37*(2), 127–152.

Poli, F., Meyer, M., Mars, R. B., & Hunnius, S. (2022). Contributions of expected learning progress and perceptual novelty to curiosity-driven exploration. *Cognition*, *225*, 105119. https://doi.org/10.1016/j.cognition.2022.105119

Poli, F., Serino, G., Mars, R. B., & Hunnius, S. (2020). Infants tailor their attention to maximize learning. *Science Advances*, *6*(39), eabb5053. https://doi.org/10.1126/sciadv.abb5053

Quinn, P. C. (2004). Development of Subordinate-Level Categorization in 3- to 7-Month-Old Infants. *Child Development*, *75*(3), 886–899. https://doi.org/10.1111/j.1467-8624.2004.00712.x

Quinn, P. C., Eimas, P. D., & Rosenkrantz, S. L. (1993). Evidence for Representations of Perceptually Similar Natural Categories by 3-Month-Old and 4-Month-Old Infants. *Perception*, *22*(4), 463–475. https://doi.org/10.1068/p220463

Quinn, P. C., Eimas, P. D., & Tarr, M. J. (2001). Perceptual Categorization of Cat and Dog Silhouettes by 3- to 4-Month-Old Infants. *Journal of Experimental Child Psychology, 79*(1), 78–94. https://doi.org/10.1006/jecp.2000.2609

Raghavachari, S., Kahana, M. J., Rizzuto, D. S., Caplan, J. B., Kirschen, M. P., Bourgeois, B., Madsen, J. R., & Lisman, J. E. (2001). Gating of human theta oscillations by a working memory task. *Journal of Neuroscience, 21*(9), 3175–3183. https://doi.org/10.1523/JNEUROSCI.21-09-03175.2001

Raghavachari, S., Lisman, J. E., Tully, M., Madsen, J. R., Bromfield, E. B., & Kahana, M. J. (2006). Theta oscillations in human cortex during a working-memory task: Evidence for local generators. *Journal of Neurophysiology, 95*(3), 1630–1638. https://doi.org/10.1152/jn.00409.2005

Rakoczy, H., Hamann, K., Warneken, F., & Tomasello, M. (2010). Bigger knows better: Young children selectively learn rule games from adults rather than from peers. *British Journal of Developmental Psychology*, *28*(4), 785–798. https://doi.org/10.1348/026151009X479178

Rakoczy, H., Warneken, F., & Tomasello, M. (2009). Young children's selective learning of rule games from reliable and unreliable models. *Cognitive Development, 24*(1), 61–69. https://doi.org/10.1016/j.cogdev.2008.07.004

Reio, T. G., Petrosko, J. M., Wiswell, A. K., & Thongsukmag, J. (2006). The measurement and conceptualization of curiosity. *The Journal of Genetic Psychology*, *167*(2), 117–135. https://doi.org/10.3200/GNTP.167.2.117-135

Reynolds, G. D. (2015). Infant visual attention and object recognition. *Behavioural Brain Research*, *285*, 34–43. https://doi.org/10.1016/j.bbr.2015.01.015

Robitzsch, A. (2020). Why Ordinal Variables Can (Almost) Always Be Treated as Continuous Variables: Clarifying Assumptions of Robust Continuous and Ordinal

Factor Analysis Estimation Methods. *Frontiers in Education*, *5*. https://www.frontiersin.org/articles/10.3389/feduc.2020.589965

Roder, B. J., Bushnell, E. W., & Sasseville, A. M. (2000). Infants' Preferences for Familiarity and Novelty During the Course of Visual Processing. *Infancy, 1*(4), 491–507. https://doi.org/10.1207/S15327078IN0104_9

Ronfard, S., Zambrana, I. M., Hermansen, T. K., & Kelemen, D. (2018). Question-asking in childhood: A review of the literature and a framework for understanding its development. *Developmental Review*, *49*, 101–120. https://doi.org/10.1016/j.dr.2018.05.002

Rose, S. A., Gottfried, A. W., Melloy-Carminar, P., & Bridger, W. H. (1982). Familiarity and novelty preferences in infant recognition memory: Implications for information processing. *Developmental Psychology, 18,* 704–713. https://doi.org/10.1037/0012-1649.18.5.704

Rosenbaum, J. E., & Johnson, B. K. (2016). Who's afraid of spoilers? Need for cognition, need for affect, and narrative selection and enjoyment. *Psychology of Popular Media Culture, 5*, 273–289. https://doi.org/10.1037/ppm0000076

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*(2), 225–237. https://doi.org/10.3758/PBR.16.2.225

Royston, P. (2007). Profile Likelihood for Estimation and Confidence Intervals. *The Stata Journal*, *7*(3), 376–387. https://doi.org/10.1177/1536867X0700700305

Ruff, H. A., & Rothbart, M. K. (1996). *Attention in early development: Themes and variations* (pp. xv, 294). Oxford University Press.

Ruggeri, A. (2022). An introduction to ecological active learning. *Current Directions in Psychological Science*, 09637214221112114. https://doi.org/10.1177/09637214221112114

Ruggeri, A., Markant, D. B., Gureckis, T. M., Bretzke, M., & Xu, F. (2019). Memory enhancements from active control of learning emerge across development. *Cognition*, *186*, 82–94. https://doi.org/10.1016/j.cognition.2019.01.010

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*, 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Sarnthein, J., Petsche, H., Rappelsberger, P., Shaw, G. L., & von Stein, A. (1998). Synchronization between prefrontal and posterior association cortex during human working memory. *Proceedings of the National Academy of Sciences*, *95*(12), 7092–7096. https://doi.org/10.1073/pnas.95.12.7092

Saylor, M. M., & Ganea, P. A. (Eds.). (2018). *Active learning from infancy to childhood: Social motivation, cognition, and linguistic mechanisms*. Springer International Publishing. https://doi.org/10.1007/978-3-319-77182-3

Schielzeth, H., & Forstmeier, W. (2009). Conclusions beyond support: Overconfident estimates in mixed models. *Behavioral Ecology*, *20*, 416–420. https://doi.org/10.1093/beheco/arn145

Schmider, E., Ziegler, M., Danay, E., Beyer, L., & Bühner, M. (2010). Is it really robust? Reinvestigating the robustness of ANOVA against violations of the normal distribution assumption. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, *6*, 147–151. https://doi.org/10.1027/1614-2241/a000016

Sim, Z. L., Tanner, M. M., Alpert, N. Y., & Xu, F. (2015). Children Learn Better When They Select Their Own Data. *CogSci*.

Singh, A., & Manjaly, J. A. (2021). The effect of information gap and uncertainty on curiosity and its resolution. *Journal of Cognitive Psychology*, *33*, 403–423. https://doi.org/10.1080/20445911.2021.1908311

Skoczenski, A. M., & Norcia, A. M. (1998). Neural noise limitations on infant visual sensitivity. *Nature*, *391*(6668), Article 6668. https://doi.org/10.1038/35630

Slater, A. (2004). Novelty, familiarity, and infant reasoning. *Infant and Child Development*, *13*(4), 353–355. https://doi.org/10.1002/icd.356

Smith, L. B., Jayaraman, S., Clerkin, E., & Yu, C. (2018). The Developing Infant Creates a Curriculum for Statistical Learning. *Trends in Cognitive Sciences*, *22*(4), 325–336. https://doi.org/10.1016/j.tics.2018.02.004

Smith, L. B., Yu, C., & Pereira, A. F. (2011). Not your mother's view: The dynamics of toddler visual experience. *Developmental Science*, *14*(1), 9–17. https://doi.org/10.1111/j.1467-7687.2009.00947.x

Snijders, T. A. B., & Bosker, R. J. (2011). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. SAGE.

Sodian, B., Thoermer, C., Kristen, S., & Perst, H. (2012). Metacognition in infants and young children. In *Foundations of metacognition* (pp. 119–133). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199646739.003.0008

Solomon, E. A., Kragel, J. E., Sperling, M. R., Sharan, A., Worrell, G., Kucewicz, M., Inman, C. S., Lega, B., Davis, K. A., Stein, J. M., Jobst, B. C., Zaghloul, K. A., Sheth, S. A., Rizzuto, D. S., & Kahana, M. J. (2017). Widespread theta synchrony and high-frequency desynchronization underlies enhanced cognition. *Nature Communications*, *8*(1), Article 1. https://doi.org/10.1038/s41467-017-01763-2

Southgate, V., Van Maanen, C., & Csibra, G. (2007). Infant pointing: Communication to cooperate or communication to learn? *Child Development*, *78*(3), 735–740.

Spelke, E. S. (1985). Preferential-looking methods as tools for the study of cognition in infancy. In *Measurement of audition and vision in the first year of postnatal life: A methodological overview* (pp. 323–363). Ablex Publishing.

Stare, C. J., Gruber, M. J., Nadel, L., Ranganath, C., & Gómez, R. L. (2018). Curiosity-driven memory enhancement persists over time but does not benefit from post-learning sleep. *Cognitive Neuroscience*, *9*(3–4), 100–115. https://doi.org/10.1080/17588928.2018.1513399

Suffczynski, P., Kalitzin, S., Pfurtscheller, G., & Lopes da Silva, F. H. (2001). Computational model of thalamo-cortical networks: Dynamical control of alpha rhythms in relation to focal attention. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *43*(1), 25–40. https://doi.org/10.1016/s0167-8760(01)00177-5

Szumowska, E., & Kruglanski, A. W. (2020). Curiosity as end and means. *Current Opinion in Behavioral Sciences*, *35*, 35–39. https://doi.org/10.1016/j.cobeha.2020.06.008

Theobald, M., Galeano-Keiner, E., & Brod, G. (2022). Predicting vs. guessing: The role of confidence for pupillometric markers of curiosity and surprise. *Cognition & Emotion*, *36*(4), 731–740. https://doi.org/10.1080/02699931.2022.2029733

Twomey, K. E., & Westermann, G. (2018). Curiosity-based learning in infants: A neurocomputational approach. *Developmental Science*, *21*(4), e12629. https://doi.org/10.1111/desc.12629

Twomey, K. E., & Westermann, G. (2019). Building the foundations of language: Mechanisms of curiosity-driven learning. In *International handbook of language* *acquisition* (pp. 102–114). Routledge/Taylor & Francis Group. https://doi.org/10.4324/9781315110622-6

Van de Cruys, S., Damiano, C., Boddez, Y., Król, M., Goetschalckx, L., & Wagemans, J. (2021). Visual affects: Linking curiosity, Aha-Erlebnis, and memory through information gain. *Cognition*, *212*, 104698. https://doi.org/10.1016/j.cognition.2021.104698

van Lieshout, L. L. F., de Lange, F. P., & Cools, R. (2021). Uncertainty increases curiosity, but decreases happiness. *Scientific Reports*, *11*(1), Article 1. https://doi.org/10.1038/s41598-021-93464-6

van Lieshout, L. L. F., Vandenbroucke, A. R. E., Müller, N. C. J., Cools, R., & de Lange, F. P. (2018). Induction and relief of curiosity elicit parietal and frontal activity. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *38*(10), 2579–2588. https://doi.org/10.1523/JNEUROSCI.2816-17.2018

Wade, S., & Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psychonomic Bulletin & Review*, *26*, 1377–1387. https://doi.org/10.3758/s13423-019-01598-6

Walin, H., & Xu, F. (2016). Curiosity and its influence on children’s memory. *Proceedings of the 38th Annual Conference of the Cognitive Science Society*.

Wang, M. Z., & Hayden, B. Y. (2019). Monkeys are curious about counterfactual outcomes. *Cognition*, *189*, 1. https://doi.org/10.1016/j.cognition.2019.03.009

Wass, S., Porayska-Pomsta, K., & Johnson, M. H. (2011). Training Attentional Control in Infancy. *Current Biology*, *21*(18), 1543–1547. https://doi.org/10.1016/j.cub.2011.08.004

Weiss, S., Müller, H. M., & Rappelsberger, P. (2000). Theta synchronization predicts efficient memory encoding of concrete and abstract nouns. *NeuroReport*, *11*(11), 2357–2361.

White, J. K., Bromberg-Martin, E. S., Heilbronner, S. R., Zhang, K., Pai, J., Haber, S. N., & Monosov, I. E. (2019). A neural network for information seeking. *Nature Communications*, *10*(1), Article 1. https://doi.org/10.1038/s41467-019-13135-z

Wimmer, H., Hogrefe, G.-J., & Perner, J. (1988). Children's Understanding of Informational Access as Source of Knowledge. *Child Development*, *59*(2), 386–396. https://doi.org/10.2307/1130318

Wittmann, B. C., Daw, N. D., Seymour, B., & Dolan, R. J. (2008). Striatal Activity Underlies Novelty-Based Choice in Humans. *Neuron*, *58*(6), 967–973. https://doi.org/10.1016/j.neuron.2008.04.027