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# The role of curiosity in evidence-based decision-making

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# Abstract

The ability to evaluate information and engage with trustworthy information is crucial in the modern world. Epistemic curiosity is induced by information, benefits learning and is considered to drive information-seeking. Thus, understanding the associations between curiosity and information evaluation has potential to focus resources on supporting evidence-based decisions. This doctoral research consists of three sub studies and investigates the neurocognitive underpinnings of curiosity and its associations with information evaluation and usage in adults.

The first study investigated whether individual traits and thinking styles create a psychological space that could predict behavior in a decision-making task. Exploratory factor analysis using these psychological measures indicated four latent factors (pro-sociality, curiosity, open-mindedness, and cognitive skills). These factors were used to predict behavior in a task, where participants read information to take a stance on a scientific topic with complex societal impact. The information sources varied in scientific quality and social authority. Overall, information holding social authority was valued highly regardless of its scientific quality. Emotional valence and arousal were related to curiosity and pro-sociality, respectively. These results highlight the importance of curiosity and pro-sociality in engaging with and evaluating information.

Previous research indicates that curiosity boosts learning and memory and is related to eye movement patterns and neuronal activity. To allow curiosity to influence information-seeking, studies two and three utilized a realistic decision-making task to investigate the effects of curiosity and information quality on eye movements and neuronal oscillations measured with electroencephalography. Participants read statements with varying information quality. The second study showed that careful reading, as indicated by lower word-skipping rates and longer total fixation duration on words, was related to higher state curiosity. State curiosity was highest for relevant scientific information that was considered most useful and read most often. The third study used cluster-based permutation analysis to detect clusters where neuronal oscillations at alpha power differed depending on information quality. The analysis indicated two topographically distinct clusters: frontal and parietal. Further investigation showed that the deprivation sensitivity dimension of trait curiosity was associated with a decrease in alpha power at both clusters. A decrease in frontal alpha power was related to an increase in state curiosity. Prolonged information search was related to a decrease in parietal alpha power. These results suggest that alpha power is related to curiosity and the strength of cognitive engagement.

This doctoral research investigates information evaluation and usage in evidence-based decision-making and shows that curiosity is a key factor in this process. This research shows that curiosity is related to information evaluation and engagement, highlighting the importance of motivational and emotional states in evidence-based decision-making.

# Tiivistelmä

Nykyajassa on välttämätöntä kyetä arvioimaan tiedon laatua ja hyödyntämään luettavaa tietoa. Episteeminen uteliaisuus on tiedon synnyttämää ja siihen kohdistuvaa uteliaisuutta, joka edistää oppimista ja sitä pidetään tiedonhaun ajurina. Uteliaisuuden ja tiedon arvioimisen välisten yhteyksien ymmärtäminen mahdollistaa resurssien ohjaamisen tietoon pohjautuvan päätöksenteon tueksi. Tämä väitöskirjatutkimus koostuu kolmesta osatutkimuksesta, jotka selvittävät uteliaisuuden neurokognitiivisia perusteita sekä uteliaisuuden yhteyttä tiedon arviointiin ja hyödyntämiseen aikuisilla ihmisillä.

Ensimmäinen osatutkimus tutki muodostavatko yksilön psykologiset piirteet ja ajattelutyylit abstraktin psykologisen piirre-avaruuden, joka on yhteydessä toimintaan päätöksentekotehtävän aikana. Faktorianalyysia käyttäen tunnistettiin neljä piilevää tekijää (sosiaalisuutta edistävä, uteliaisuus, avarakatseisuus ja kognitiiviset taidot). Tehtävän aikana osallistujat lukivat tieteelliseltä laadultaan vaihtelevaa tietoa erilaisista lähteistä. Heidän tuli ottaa kantaa tieteelliseen aiheeseen, jolla on monitahoisia yhteiskunnallisia vaikutuksia. Tehtävän aikaisen toiminnan ja piilevien tekijöiden välisiä yhteyksiä tutkiessa havaittiin, että sosiaalisesti arvostetusta lähteestä luettua tietoa pidettiin hyvänä sen tieteellisestä laadusta riippumatta. Uteliaisuus ja sosiaalisuutta edistävä tekijä olivat yhteydessä tehtävän aikana koetun tunteen miellyttävyyteen ja voimakkuuteen. Nämä tulokset korostavat uteliaisuuden ja sosiaalisuutta edistävän tekijän tärkeyttä tiedon arvioinnissa ja hyödyntämisessä.

Uteliaisuuden on osoitettu edistävän oppimista ja muistia sekä olevan yhteydessä silmänliikkeiseen ja aivojen aktiivisuuteen. Jotta uteliaisuus vaikuttaisi tiedonhakuun, osatutkimuksissa kaksi ja kolme käytettiin tosielämän tiedonhakua ja päätöksentekoa jäljittelevää tehtävää. Tehtävässä osallistujat lukivat laadultaan vaihtelevaa tietoa. Tehtävän avulla selvitimme uteliaisuuden ja tiedonlaadun yhteyttä silmänliikkeisiin ja aivosähkökäyrällä mitattuun aivojen aktiivisuuteen. Toinen osatutkimus osoitti, että voimakkaampi tilannekohtainen uteliaisuus ja huolellinen lukeminen olivat yhteydessä toisiinsa. Lukemisen huolellisuutta arvioitiin vähäisempänä sanojen ohittamisena ja pidempänä katseen kohdistamisen kokonaiskestona yksittäisiin sanoihin. Tilannekohtainen uteliaisuus oli korkeimmillaan oleellisen tieteellisen tiedon kohdalla, jota myös pidettiin hyödyllisimpänä ja luettiin lukumäärällisesti eniten. Kolmas osatutkimus hyödynsi klusterianalyysia sellaisten elektrodien ja aikaikkunoiden tunnistamisessa, missä alfataajuudella värähtelevät aivoaallot erosivat toisistaan tiedonlaadun mukaan. Analyysin perusteella havaittiin kaksi sijainniltaan eroavaa rypästä: frontaalinen ja parietaalinen. Jatkoanalyysit osoittivat, että piirreuteliaisuuden ulottuvuuksista pakottava uteliaisuus oli yhteydessä heikompaan alfa-aktiivisuuteen kummassakin ryppäässä. Heikompi frontaalinen alfa-aktiivisuus oli yhteydessä tilannekohtaiseen uteliaisuuteen. Pitkäkestoinen tiedonhaku oli yhteydessä heikompaan alfa-aktiivisuuteen parietaalisessa ryppäässä. Nämä tulokset osoittavat, että alfa-

aktiivisuuden voimakkuus on yhteydessä uteliaisuuteen sekä kognitiivisen prosessoinnin voimakkuuteen.

Tämä väitöskirjatutkimus selvittää tiedon arviointia sekä hyödyntämistä tietoon pohjautuvassa päätöksenteossa ja osoittaa uteliaisuuden olevan merkittäjä tekijä tässä prosessissa. Tämä tutkimus korostaa motivaation ja tunnetilan merkitystä tietoon pohjautuvassa päätöksenteossa.

# List of abbreviations

| | |
|---|---|
| EEG | Electroencephalography |
| EFA | Exploratory Factor Analysis |
| FMRI | Functional magnetic resonance imaging |
| GLMM | Generalized Linear Mixed Effects Modeling |
| LMM | Linear Mixed Effects Modeling |
| PFC | Prefrontal cortex |

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# List of original publications

This dissertation is based on the following publications:

I Dawson, C., **Julku, H.**, Pihlajamäki, M., Kaakinen, J. K., Schooler, J. W., & Simola, J. (2024) Evidence-based scientific thinking and decision-making in everyday life. *Cognitive Research: Principles and Implications*, 9(1), 50. https://doi.org/10.1186/s41235-024-00578-2

II Simola, J., **Julku, H.**, Dawson, C., Österman, S., Elovaara, K., & Häikiö, T. (2026) Curiosity and evidence quality affect information seeking and eye movements during reading. *Cognition,* 274. https://doi.org/10.1016/j.cognition.2026.106598

III **Julku, H.**, Österman, S., Dawson, C., Elovaara, K., & Simola, J. (2026) Alpha oscillations are associated with curiosity during information-seeking. https://osf.io/preprints/psyarxiv/8etq5_v3 (pre-print) (In Review in *Brain Topography*)

The author contributed in the following ways:

I Participation in conceiving the research idea, designing the study, data collection, and editing the manuscript.
II Pre-processing the data and participation in editing the manuscript.
III Writing the original draft, creation of figures and tables, and conduction of generalized linear mixed effect analyses. Participation in methodology, formal analysis, validation, and data curation. Editing was done in collaboration with other authors.

Shared contributions for studies II and III (the same paradigm):
Composing stimulus materials and participation in conceptualization and study design.

The publications are referred to in the text by their roman numerals.

# 1 Introduction

Evidence-based decision-making in the modern world is difficult. Many societal and personal issues are complex, and gathering information to make a stance on a topic can be consuming. Furthermore, finding and engaging with trustworthy information is hard in the excessive information flow (Sinatra & Lombardi, 2020). Scientific information goes through a carefully controlled review process and is thought to be a preferred base for decisions affecting, for example, one's health, society, and environment. Yet scientific information may be more complicated and less engaging than non-scientific information (Faize et al., 2017). Investigating the underlying factors related to information evaluation and engagement is thus needed to provide support for people to make evidence-based decisions.

This doctoral study focuses on information evaluation and seeking while making epistemic decisions and the associations of curiosity in that process. The following sections will introduce evidence-based decision-making, curiosity, and eye movements and neuronal oscillations before briefly describing this study.

## 1.1 Evidence-based decision-making

Decision-making is a process where one collects information to select their choice of action (Davis et al., 2011; Qiu et al., 2018). Depending on the situation, the consequences of a decision may range from trivial to substantial. Decisions are affected by many different factors like prior (Lowry et al., 2022) and acquired knowledge (Cortes et al., 2021), prior beliefs (Michal et al., 2021), emotions (Lerner et al., 2015), and individual differences in executive functions, that refer to the abilities needed in managing information such as updating and inhibiting information in mind (Del Missier et al., 2010). Recent decision-making studies have utilized a novel approach using multiple psychological traits, including for example personality and thinking styles, to create latent factors that are used to predict real-life decisions, e.g., related to health or ideologies (Eisenberg et al., 2019; Zmigrod et al., 2021).

Evidence-based decision-making refers to decisions that are based on epistemic information; that is, evidence as knowledge. These types of decisions require substantial mental effort including finding the evidence, estimating its value, accommodating the new evidence to an already existing knowledge framework, re-

evaluating the framework, deciding whether more evidence needs to be collected, and finally making the decision based on the acquired evidence. These types of decisions that require evaluating and combining multiple pieces of information are called complex decisions (Davis et al., 2011; Dixon & Christoff, 2014). The decision-making process is accompanied by metacognition, the awareness of one's own cognition that is important in monitoring decision uncertainty and controlling decision adjustment (Qiu et al., 2018). Moreover, goal-directed behaviors require working memory, the active maintenance of information in memory for completing a task, which is related to the frontoparietal network that is suggested as a central node for information maintenance and manipulation (Lee et al., 2022). In addition to frontoparietal areas, temporal regions are involved in decision-making (Cortes et al., 2021). Correspondingly, Lee et al. (2022) showed that medial temporal lobe correlated with parietal lobe similarly to parietal and frontal lobe, suggesting that also medial temporal lobe is a key region in goal-directed behavior. Thus, decision-making is reflected in the engagement of multiple brain areas.

The following sub-sections will introduce information gathering and evidence evaluation in the context of evidence-based decision-making.

### 1.1.1 Information gathering

To make an informed decision, one needs to gather information. Information gathering behavior changes with the amount and quality of the information gained. The information gathering behavior for different types of decisions has been investigated using various experimental paradigms. For example, perceptual decision-making where decisions are based on evidence from perceptual stimuli (e.g., moving dots) has been studied using drift diffusion modeling. This approach investigates the threshold for gathering enough information to make a decision (Harris & Hutcherson, 2022). Another study investigated neuronal oscillations in different phases of the decision-making process: seeing the options, selecting a choice, and receiving and updating the value of the choice (Cortes et al., 2021). In that study, participants were instructed to maximize the gain of a numerical value, and they had to sample different options to learn the value of different stimuli. After gathering enough information, participants started to favor stimuli that maximized their gain. Thus, information gathering behavior changes in respect to the situation.

Decision-making and specifically information gathering strategies have been investigated with bandit tasks (Cohen et al., 2007). In bandit tasks, information is collected by selecting one source at a time. The contents of the sources are unknown to the participants; thus, they need to adapt their information-seeking strategy to be successful in the task by sampling the sources to learn their value. This sampling behavior can be contextualized as exploration, that is, changing between the sources, and exploitation as using the same source repeatedly (Mehlhorn et al.,

2015). The choice of information sampling behavior is affected, for example by the context of the environment as well as one's own ability to learn the value of gathered information (Cohen et al., 2007). Both behaviors have their pros and cons; exploration provides the opportunity to find a better source, but simultaneously risks moving to a worse one, while exploitation maximizes the use of a good source but misses the opportunity to find an even better one. Thus, understanding the underlying causes for selecting and balancing between these behaviors is an important topic that requires research on multiple levels from behavioral to neuronal processes (Cohen et al., 2007).

Bandit tasks are complex in nature, yet there are modified versions that consider additional aspects to the basic version of the task described above. A social version of this task investigates the combined effect of one's own choices together with information gathered from another person's investigations (Adrian et al., 2019). The contextual multi-armed bandit task is a version where there is an additional effect of different contexts where the gathered information is considered useful, meaning that not all information is equally valuable in every context (Schulz et al., 2015).

People are fast in learning the value of information and they use different exploration strategies depending on the quantity of available information (Wilson et al., 2014). With limited amounts of information people tend to use directed exploration, which makes the exploration process more focused leaning towards exploitation behavior, whereas with a large amount of available information random exploration is used for scanning the mass of information.

Information-seeking is affected by the subjective value of information, that reflects a person's neural response to the received information (Kobayashi & Hsu, 2019). The subjective value of information is affected by both instrumental and non-instrumental motives, where instrumental relates to the benefit value of the information, and non-instrumental refers to inner appeal towards the information, like curiosity. The decision to acquire information is mostly affected by the instrumental benefit of the information, but the decision is better predicted when non-instrumental motive is also considered. Furthermore, non-instrumental motive is sensitive to the benefit value (Kobayashi & Hsu, 2019), which is in line with the finding that curiosity and usefulness are associated with each other (Dubey et al., 2022).

Taken together, information gathering and seeking are affected by multiple matters from the amount of available information to the quality of that information.

### 1.1.2 Evidence evaluation

Evidence evaluation is an important part of evidence-based decision-making. When evaluating information, people tend to use the source of information as a cue for

estimating whether to rely on the information (Sinatra & Lombardi, 2020). This means that information from authors having high social power is often not evaluated critically enough (Ilić & Damnjanović, 2021) and this holds also for information coming from sources sharing similar personal values than the reader (Traberg & Van Der Linden, 2022). These information features are thus used as shortcuts when estimating the quality of the information. The effect of shared personal values extends also to perceiving information from an expert source as less expert and trustworthy, when their position is presented before their credentials (Andrews et al., 2025). Yet, when credentials were presented before the source author's position, the effect of shared values had no effect on perceived expertise and trustworthiness. Additionally, evaluations for the reliability, or trustworthiness, of information are affected by the publication outlet (Bråten et al., 2011; Sinatra & Lombardi, 2020). A previous study showed that young adults studying in university evaluated textbooks and articles from research centers as more trustworthy compared to articles from newspapers, corporate companies, or research magazines (Bråten et al., 2011).

The convincingness of information is evaluated intuitively, and the perceived convincingness model by Hoeken et al. (2022) suggests that evaluation of convincingness is affected by the processing effort and emotional response elicited by the information so that information that is processed more easily and elicits stronger emotional responses are considered more convincing. Thus, evidence evaluation is closely connected to emotions.

In addition to using strategies like focusing on the source features, for recognizing trustworthy information, individual differences in psychological traits and thinking styles affect evidence evaluation. These traits and thinking styles have been studied with psychological scales, and some of them are particularly associated with information evaluation and decision-making.

Actively openminded thinking is a tendency to revise one's viewpoints (Stanovich & West, 1997) and it has been shown to reduce politically motivated reasoning, the subconscious preference for information supporting one's prior beliefs, thus supporting science-supported viewpoints (Stenhouse et al., 2018).

Intellectual humility refers to one's tendency to accept that other people's beliefs could be valid and that one's own can be flawed (Krumrei-Mancuso & Rouse, 2016). Those with high intellectual humility have been shown to appreciate strong arguments more than those with low intellectual humility even when the arguments are not in line with their current beliefs (Leary et al., 2017).

Need for cognition reflects the engagement in and enjoyment of effortful thinking (Cacioppo et al., 1984). Those who are high in need for cognition are shown to be more sensitive to the quality of persuasive information than those low in need for cognition (Cacioppo et al., 1996). Furthermore, need for cognition has been

positively related to an ability to encode verbal information, that is, storing the information to one's memory for later use (Wagaman et al., 2025).

Cognitive reflection indicates one's ability to select a mathematically normative answer despite being cued with a heuristic, quick, intuitive, response (Frederick, 2005). High cognitive reflection benefits decision-making accuracy when participants are using information that has been pre-selected for their use by someone else and reduces the debilitating effect of anxiety on decision accuracy (Criado-Perez et al., 2024).

These psychological constructs portray one's willingness and capability to dismantle information and evaluate their own views critically. Additionally, evidence evaluation and related behaviors have been studied with physiological measures.

Critical reading strategy has been associated with distinct reading patterns (Tsai et al., 2022). Focusing attention, indicated by eye fixations, to those parts of the text where reasoning for the claims was provided was related to self-recognition of using critical reading strategies. Thus, participants' eye movements and self-reports on reading strategy were in line with each other.

Neuroimaging studies have connected different types of decisions (Volz et al., 2006) and stages of decision-making process (Cortes et al., 2021) with the prefrontal cortex (PFC). Studies using functional magnetic resonance imaging (fMRI) have indicated that the PFC is related to estimating the value of information (Juechems et al., 2019; Kobayashi et al., 2021; Shapiro & Grafton, 2020), specifically the right dorsolateral PFC (Kobayashi et al., 2021) and ventromedial PFC (Juechems et al., 2019; Shapiro & Grafton, 2020). An electroencephalography (EEG) study has shown that decision-making phases and the respective cognitive processes are associated with oscillatory activity in different frequency bands and topographical locations (Cortes et al., 2021). Alpha power (8–12 Hz) in the temporal cortex and coherence between right and left PFC increased when one viewed the stimulus options to choose from. At the stage where one evaluated the value of their selected option, the power of delta (1–4 Hz) and theta (4–8 Hz) oscillations in the right PFC and the coherence of theta between PFCs increased. Moreover, complex decision-making is related to lateral PFC (Dixon & Christoff, 2014) and decreases in alpha oscillations (Davis et al., 2011). These results further support the role of PFC in evaluating information value.

## 1.2 Curiosity

Curiosity has intrigued researchers for about a century. It has been shown to support decision-making as curiosity is related to estimating one's own knowledge (Goupil & Proust, 2023; Kang et al., 2009; Kim et al., 2025; Metcalfe et al., 2020;

Spitzer et al., 2024) and gathering greater amounts of information (Eschmann et al., 2023; Swirsky & Spaniol, 2024).

Curiosity has been studied in different contexts and from many different perspectives. Perceptual curiosity, the drive induced by and towards examining novel stimuli, has been studied both in humans and in other animals (Berlyne, 1954). In humans, higher perceptual curiosity leads to more extensive visual inspection of a scene (Risko et al., 2012). People experience higher perceptual curiosity when they are less confident about recognizing the stimulus (Sakaki et al., 2024). When this type of uncertainty related to perceptual curiosity is solved, memory for items that induced the curiosity is enhanced, but other stimuli presented in temporal proximity are also remembered better (Jepma et al., 2012). In other words, memory is enhanced for all perceived stimuli while the viewer is in a state of high curiosity.

When it comes to humans, curiosity has also been studied in relation to epistemic information. *Epistemic curiosity* relates to curiosity elicited by epistemic information, that is, knowledge (Berlyne, 1954; Litman et al., 2005; Litman & Spielberger, 2003). Epistemic curiosity emerges during processing of epistemic information and is considered as an activating emotion (Pekrun et al., 2017). The activating nature of curiosity is primarily related to the arousal, or intensity dimension of emotion rather than to its valence, the positive or negative direction of emotion.

Curiosity can be considered as a transient, context-dependent *state curiosity* (Berlyne, 1954; Loewenstein, 1994) that can be also referred to as epistemic state curiosity in the context of non-perceptual information such as knowledge. In addition to state curiosity, curiosity can be considered as *trait curiosity* that is a permanent tendency to experience state curiosity (Litman et al., 2005).

Epistemic state curiosity is associated with different learning strategies and epistemic beliefs (Muis et al., 2015; Pekrun et al., 2017). For example, when reading conflicting information, the idea of needing to acquire information from multiple sources, while using critical evaluation strategy, is associated with an increase in curiosity (Muis et al., 2015). Moreover, curiosity is positively related to a set of learning strategies including rehearsal, critical thinking, metacognitive self-regulation, and elaboration (Pekrun et al., 2017). Curiosity is positively associated with information seeking (asking for more information) while answering trivia questions (Vogl et al., 2020; Vogl et al., 2019). When answering those trivia questions, curiosity was also related to a high-confidence error, that is, participants thought they had answered correctly when they had not. Thus, epistemic state curiosity is related to information-seeking and evaluation behavior.

Epistemic state curiosity is related to learning and engagement in the learning process (Chevrier et al., 2019). On top of epistemic state curiosity, the positive valence and higher positive reward of the information enhance memory for that

information (Marvin & Shohamy, 2016). In short, epistemic state curiosity is associated with building understanding, that is, learning.

Epistemic trait curiosity has been studied using different dimensions that are estimated with trait curiosity scales. *Interest* and *deprivation curiosity* dimensions refer to enjoyment of finding information and a pressing need to find an answer, respectively (Litman, 2008). A more fine-grained version of trait curiosity scale, also known as the five-dimensional curiosity scale revised (5DCR), refers to interest and deprivation curiosity as *joyous exploration* and *deprivation sensitivity* (Kashdan et al., 2020). In addition to these epistemic dimensions, 5DCR scale includes *stress tolerance*, that is, an ability to manage uncertainty, *thrill seeking*, the enjoyment of unexpected, and two dimensions of social curiosity that are *overt social curiosity*, interacting with someone to understand their views, and *covert social curiosity*, using indirect methods to find information about someone.

### 1.2.1 Curiosity as a metacognitive feeling

Curiosity is considered as a drive towards information (Berlyne, 1954; Litman et al., 2005) which is caused by a gap in one's knowledge (Loewenstein, 1994). Thus, curiosity is a metacognitive feeling that requires one to recognize and evaluate their own level of knowledge (Goupil & Proust, 2023; Metcalfe et al., 2020). The link between epistemic curiosity and metacognition is further supported by the finding that the usefulness of information is positively associated with curiosity (Dubey et al., 2022). To evaluate usefulness, one must recognize the context and the relation of the information towards filling the information gap, yet at the same time being able to monitor their own understanding of this entity. Furthermore, curiosity and prior knowledge are shown to have an inverted U-shape relationship which is suggested to reflect knowledge maximization (Ten et al., 2025), that is, the greatest impact for gaining a thorough understanding about an issue. This association indicates that the lowest curiosity occurs when one has no knowledge at all, or when one has solid knowledge on a topic, while the greatest curiosity is related to mid-level knowledge. A similar pattern has been found between curiosity and confidence about one's knowledge being correct (Kang et al., 2009; Kim et al., 2025; Spitzer et al., 2024). These align with research showing that epistemic curiosity is positively related to one's feeling they almost know something, that is, when they are at the region of proximal learning (Metcalfe et al., 2020; Wade & Kidd, 2019). Thus, curiosity is strongest when one is about to reach a cohesive understanding about a topic.

The metacognitive nature of curiosity is advantageous in information processing. Indeed, curiosity has an important role in decision-making process, as higher state curiosity is associated with increased information-seeking (Swirsky & Spaniol, 2024), learning (Gruber et al., 2014; Metcalfe et al., 2021; Metcalfe et al.,

2020), and memory (Brod & Breitwieser, 2019; Gruber et al., 2014; Kang et al., 2009; Metcalfe et al., 2021; Rüterbories et al., 2024). Moreover, people feel curious towards information they perceive as important (Spitzer et al., 2024).

In addition to epistemic state curiosity, trait curiosity has been linked with information-seeking behavior. A trait curiosity measure resembling interest / joyous exploration type curiosity is associated with a deep-diving type of information-seeking, that is, revisiting the same information source that has been investigated before (Schumacher et al., 2025). Furthermore, previous studies have shown that the deprivation sensitivity dimension of trait curiosity is positively related to the frequency of finding information in real-life (Eschmann et al., 2023) and to creating a concise and thorough information network (Lydon-Staley et al., 2021). Thus, previous studies show that trait curiosity is associated with real-life information-seeking behavior.

Social contexts also affect epistemic state curiosity. Popularity of a topic has been shown to both increase and decrease one's state curiosity (Dubey et al., 2021; Swirsky & Spaniol, 2024). Young adults show a decrease in their state curiosity when the topic is unpopular among other people (Dubey et al., 2021; Swirsky & Spaniol, 2024), whereas elderly adults show an increase in their state curiosity for popular topics (Swirsky & Spaniol, 2024). Choosing to receive additional information about the topics follows the popularity of the topics, so that additional information is selected more often for popular than for unpopular topics (Dubey et al., 2021; Swirsky & Spaniol, 2024). Furthermore, when one is close to either end of curiosity spectrum, not curious at all or very curious, the perceived curiosity level of other people that differs from one's own can neutralize curiosity for the topic (Kim et al., 2025).

The metacognitive feature of epistemic state curiosity was supported in a set of studies investigating the effects of feedback and confidence on participants' curiosity (Metcalfe et al., 2023). The study indicated that curiosity vanished when people were told their knowledge was correct. However, when participants had high confidence in their answer, but they were told they were incorrect, their curiosity increased. When feedback was not provided, participants felt more curious about high confidence error answers, possibly indicating that curiosity was linked to an internal conception about the correctness of their confidence. Another study provided similar results indicating that participants' curiosity level and their ability to recognize their knowledge varied together so that curiosity decreased with greater subjective knowledge (Kim et al., 2025).

### 1.2.2 Curiosity and reward value

Neuronal underpinnings of curiosity have been mostly researched with fMRI. Studies have indicated that stronger curiosity is related to enhanced activation in

reward networks (Gruber et al., 2014; Jepma et al., 2012; Kang et al., 2009; Lau et al., 2020; Lee & Reeve, 2017; Ligneul et al., 2018) and PFC (Kang et al., 2009; Lee & Reeve, 2017). These studies have employed curiosity evoking stimuli, such as trivia questions (Gruber et al., 2014; Kang et al., 2009; Lau et al., 2020), magic tricks (Lau et al., 2020), and visual stimuli that turn from vague to clear (Chen et al., 2025; Jepma et al., 2012). The results have indicated an increase in activity at the reward network when anticipating the answer (Gruber et al., 2014) and when the uncertainty has been resolved (Jepma et al., 2012; Kang et al., 2009; Rüterbories et al., 2024), that is, when the participant receives the answer to the trivia question, or they are able to recognize the visual image.

The association between curiosity and reward has been indicated also with behavioral methods and EEG. The connection between curiosity and reward expectancy of information was studied behaviorally with a paradigm manipulating the expected information value (van Lieshout et al., 2021). Information that had positive reward expectancy, i.e., monetary gain, induced greater curiosity than information with negative expectancy, i.e., monetary loss. Moreover, greater uncertainty of the expected information value was related to enhanced curiosity. Thus, enhanced curiosity was particularly related to information with uncertain or positive expected value. Furthermore, a study investigating event-related potentials showed that information with higher reward value (indicated by greater amplitudes in event-related potentials known to reflect reward value) was associated with higher curiosity (Rüterbories et al., 2024). The authors suggested that high curiosity would be related to extended cognitive and attentional processing that depend on reward magnitude.

Curiosity can be considered as intrinsic motivation (Lee & Reeve, 2017). The neuronal correlates for desire for food and information are similar when people decide whether they are willing to take a risk of receiving an electric shock instead of the craved food or information (Lau et al., 2020). In the aforementioned study, greater state curiosity increased the willingness to receive an electric shock indicating that people are willing to suffer to relieve curiosity. Furthermore, to satisfy their curiosity, people are willing to receive harmful information, especially when they can receive the information immediately (FitzGibbon et al., 2020).

An increase in epistemic state curiosity is related to enhanced engagement in information-seeking (Metcalfe et al., 2021). This was indicated as using more time to seek information and as more active stance in solving the information gap: asking for partial hints instead of receiving the answer straight away (Metcalfe et al., 2021). Curiosity is also associated with increased investment of cognitive resources, when there is no low-effort information available (Spitzer et al., 2025). In other words, people were willing to invest additional cognitive resources to acquire information they felt curious about, but only if the investment had a true effect on the availability of the information.

A reward-learning framework for autonomous information seeking (Murayama, 2022; Murayama et al., 2019) ties the views presented in this section together. According to the framework, recognition of an information gap produces the urge to seek information, and the reward from receiving information further sustains the seeking of information to receive rewards. With this process, the knowledge base of the person builds up inducing further information gaps, thus also keeping the process of information seeking active. The situation described here referring to sustained information seeking is related to situations where information gaps can be updated, yet single information gaps can be filled during this process leading to satiation. Taken together, this section shows that curiosity, reward, and information-seeking are tightly connected.

### 1.2.3 Current gaps in curiosity research

Typically, in curiosity research, a clear information gap is presented to a participant. For example, in trivia paradigms participants are presented with trivia questions (Gruber et al., 2014; Kang et al., 2009; Lau et al., 2020) and they are expected to know or search for the right answers to these questions. Participants have been also shown magic tricks (Lau et al., 2020) or blurry images (Chen et al., 2025; Jepma et al., 2012) that slowly turn into recognizable images. The shared feature of these tasks is that there is a single correct answer. Participants rate their state curiosity either before or after they can see the answer and, in some paradigms, they can receive additional hints for solving the gap. Participants' physiological reactions elicited by curiosity can be studied at the time of anticipating or receiving the answer. These studies are excellent for studying curiosity under these strictly defined situations, yet they are relatively far from real-life situations. In real-life, finding an answer to a question often requires acquiring information from multiple sources and building understanding from their cohesion.

Some recent studies have investigated information-seeking more realistically. In these studies, curiosity was included as trait curiosity. Trait curiosity was associated with revisiting the same sources of information (Schumacher et al., 2025). Furthermore, searching for information with a focused and thorough style in an experimental task and participants' self-reported information-seeking frequency in real-life showed an association with trait curiosity (Eschmann et al., 2023). These studies showed that trait curiosity was related to more focused and frequent information-seeking behavior. Unfortunately, these studies did not include state curiosity, thus the effect of state curiosity in less controlled situations was left open.

These prior studies investigate trait curiosity using ecologically valid measures and experiments, yet state curiosity is typically studied in highly controlled experimental settings. The connecting step between strictly defined experimental studies and real-life behavior has just started to form. Thus, there is a need for more

ecologically valid experimental paradigms that could serve as a link between these prior findings. This type of experiment could also include both state and trait curiosity to investigate whether their associations with information-seeking are similar or not. A very recent study by Schumacher et al. (2026) incorporated this approach with a modified trivia paradigm, where participants first read information that included hyperlinks participants could click to reveal further information. After reading the information, participants were asked to answer trivia questions about the text content. They were not informed beforehand that they would be asked questions about the topic. Both trait and state curiosity measures were collected. The results showed that stronger state curiosity was related to higher confidence in knowing the answer and higher trait curiosity. Trait curiosity and confidence showed an interaction effect so that those with high trait curiosity showed highest state curiosity towards topics they were least confident to know the answer, and those with low trait curiosity showed higher state curiosity with increasing confidence. Thus, including both state and trait curiosity measures can reveal new nuances on the effects of curiosity.

A further difference between the studies investigating state and trait curiosity is the instrumental value of information, the benefit of the information to solve an issue. The studies traditionally used in state curiosity research involve information that has non-instrumental value for the task: the information is received at the end of the task, and it does not influence task performance. The above studies investigating the associations between information-seeking and trait curiosity may reflect instrumental value of the acquired information, as the information was not collected to solve a tight information gap, but to build a more thorough understanding about something. Considering this difference in state and trait curiosity research, it remains to be investigated whether the instrumentality of information is similarly related to state and trait curiosity. Schumacher et al. (2026) also showed that clicking the hyperlinks and the time spent reading those contents that were clicked were associated differently with state and trait curiosity. Trait curiosity was related to higher likelihood of clicking a link and longer reading time. State curiosity was associated only with reading times, but so that both the shortest and the longest reading times were associated with higher state curiosity while lower state curiosity was related to mid duration of reading times. These results indicate that instrumental information shows distinct associations with state and trait curiosity when people are seeking information for the sake of the information itself. Further studies are needed to investigate the possible differences of state and trait curiosity in relation to non-instrumental information and instrumental information when there is a specific question to be answered.

## 1.3 Studying curiosity with eye tracking and EEG

Epistemic curiosity has been studied mainly with surveys, behavioral tasks, and fMRI. There are only a few studies investigating curiosity with eye tracking and EEG, even when eye movements and neuronal oscillations have been used in studies investigating information processing. Both of these methods have high temporal resolution that allow the investigation of curiosity precisely in time. This section provides a brief overview of these methods.

### 1.3.1 Eye movements

Eye movements are often measured in reading studies, and they are considered to reflect allocation of attention (Hoffman & Subramaniam, 1995; Rayner, 1998, 2009) and are therefore excellent indicators of information sampling (Gottlieb et al., 2013). Eye movement patterns are quantified as fixations and saccades, the fast relocations of point of fixation (Liversedge & Findlay, 2000). Fixations reflect the processing of visual information in the fixated area and its close proximity. When reading, shorter words are fixated for a shorter time (Rayner et al., 2006) and skipped more often (Drieghe et al., 2004) than longer words. Also, words with high word frequency, that is, how often they occur in language, are fixated for shorter duration (Staub et al., 2010) and skipped more often (Rayner et al., 2011) than words that are not that common, that is, low word frequency.

Eye movement patterns indicating attentional allocation have been associated with both self-reported and objective usage of critical reading strategy (Tsai et al., 2022) showing that eye movements reflect allocation of cognitive resources. Perceptual curiosity has been shown to relate to broader visual investigation of a scene in a free-viewing situation (Risko et al., 2012) indicating that curiosity is related to exploring information. Moreover, epistemic state curiosity is positively related to anticipation of information as indicated by earlier gaze shifts towards the location of the upcoming information (Baranes et al., 2015). Thus, by investigating eye movements together with curiosity, it is possible to learn more about connections between curiosity, information-seeking, and allocation of cognitive resources.

### 1.3.2 Neuronal oscillations

Neuronal activity refers to communication between neurons that happen through electrical activity within neurons and chemical transmitters or electric signals in the connecting junctions. These signals can be investigated non-invasively by using EEG that records the post-synaptic potentials produced by cortical pyramidal neurons or by magnetoencephalography that records the magnetic field induced by

those electric signals. The electric currents produced by neurons are negligibly small and the measured signals at the surface of the scalp (EEG) or at close proximity to the head (magnetoencephalography) are produced by the averaged activity of millions of neurons.

Oscillations reflect periodic changes in neuronal excitability both at neuronal and circuit level and they enable further synaptic modifications, thus oscillations are an integral feature of neural system (Singer, 2018). Closely connected neurons often oscillate synchronously, thus neuronal oscillations arise from simultaneous rhythmic electrical activity of a population of neurons (Singer, 2013). These oscillations reflect neuronal processes and occur in varying amplitudes and frequency bands. Frequencies relevant to human cognition are often grouped into canonical delta (1–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–30Hz), and gamma (30–120Hz) bands.

Different oscillations have been associated with distinct functional properties. Alpha oscillations are the most abundant frequency in the awake brain. Jensen and Mazaheri (2010) hypothesized that alpha oscillations indicate active gating of information by inhibiting irrelevant information from further processing. Further work has shown that stronger oscillation power in the alpha band is related to suppression of neuronal processes indicating inhibitory control for task irrelevant stimuli (ElShafei et al., 2022; Klimesch, 2012; Prasad & Beste, 2025). A decrease in oscillation power (8–30 Hz) in turn has been suggested to indicate engagement of task-relevant cortical areas (Kielar et al., 2015). Moreover, an increase in cognitive workload is related to decreased power of alpha oscillations (Chikhi et al., 2022). Alpha oscillation power changes in relation to baseline are thus associated with either increased or decreased processing in that brain area so that increase in alpha power indicates a decrease in processing and vice versa.

EEG studies on curiosity are sparse. Previously, machine learning has been used to recognize curious states from EEG signals (Appriou et al., 2020). In that study, an EEG signal was recorded while participants answered trivia questions, and their self-reported state curiosity level was used to indicate the state of curiosity. With machine learning algorithms, the best predictive value for recognizing participants' state of curiosity was with 3- to 5-second-long time-windows at theta, alpha, and low-beta frequencies. In another study, participants answered trivia questions and rated their state curiosity while EEG was recorded (Lima & Rocha, 2019). One week later, participants were asked to recall the correct answers for the trivia questions. Frontal alpha asymmetry while doing the task correlated with remembering the correct answers, but not with the self-reported state curiosity.

Curiosity is stated to being associated with increased allocation of attentional resources (Baranes et al., 2015; Rüterbories et al., 2024; Wojtowicz & Loewenstein, 2020), leading to a suggestion that alpha oscillation power may decrease with increasing curiosity. The cortical areas showing a decrease may be related to the

nature of the stimuli piquing curiosity, that is, epistemic and perceptual stimuli may be related to different types of oscillation patterns as well as instrumental and non-instrumental information. This is an assumption that needs experimental evidence to be supported. Hence, using EEG in curiosity research has unutilized potential.

## 1.4 Current study

This doctoral research investigates the role of curiosity in evidence-based decision-making in adult participants. Two behavioral tasks were designed to investigate information evaluation and gathering. In addition, a variety of psychological measures were included, focusing specifically on curiosity. Curiosity was included in these studies as a latent cognitive factor in Study I and both as state and trait curiosity in Studies II and III. Study I employed surveys, Study II eye tracking, and Study III EEG. In addition to methodological differences, these studies focus on different time scales and temporal points. Study I has a temporal span over reading the whole information source, whereas Study II focuses on information gathering at a word level during reading. Study III investigates neural activity after reading to study further processing of the information as engagement with and evaluation of the information. The focus of this doctoral study is particularly on the neurocognitive basis of curiosity in information gathering, evaluation, and usage.

# 2 Aims

The overall aim of this doctoral study was to investigate the role of curiosity in evidence-based decision-making in adults, specifically focusing on investigating the associations between curiosity, information-seeking, and evaluation. This doctoral research includes data collected with survey, eye tracking, and EEG methodologies to investigate the role of curiosity in information-seeking and evaluation.

**Study I**. The first aim of this study was to identify latent cognitive factors related to decision-making. The second aim was to investigate whether these factors predict behavior in an evidence-based decision-making task. This study was pre-registered in two parts according to the aims.

**Study II**. This study aimed to indicate associations between curiosity and eye movements while reading information that varied in scientific quality.

**Study III**. The aim of this study was to examine whether EEG oscillation amplitudes after reading are related to information quality and curiosity.

# 3 Methods

This section provides an overview of methods used in the included studies. Detailed descriptions can be found in the respective articles. Table 1 presents the overall aim of this doctoral dissertation and the data, research questions, and statistical methods utilized in the studies.

**Table 1** The overall aim of the doctoral dissertation and the data, research question, and statistical methods in the studies.

| Overall aim | Study | Data (adult participants) | Research question | Statistical method |
|---|---|---|---|---|
| How does curiosity affect information evaluation in adults? | I | Survey and task data ($N$ = 174) | What type of latent factors are formed based on a large set of psychological variables? | Exploratory factor analysis |
| | | | Do these factors predict behavior in evidence-based decision-making task? | Linear mixed effect modeling (LMM) |
| | II | Eye movements ($n$ = 56), task data ($n$ = 59), trait curiosity scale ($n$ = 52) | Do eye movements reflect statement quality and curiosity? | LMM and generalized LMM (GLMM) |
| | III | EEG-data, task data ($N$ = 60), trait curiosity scale ($n$ = 53) | Do information quality and curiosity reflect cortical oscillation amplitudes after reading statements? | Cluster-based permutation analysis ($N$ = 60) |
| | | | | GLMM ($n$ = 53) |

## 3.1 Data acquisition and tasks

All studies followed the declaration of Helsinki and were assessed by the University of Helsinki Ethical Review Board in Humanities and Social and Behavioural Sciences. All participants provided an informed consent prior to participation in the studies.

### 3.1.1 Study I, Evidence-based decision-making task

Data used in Study I were collected online ($N$ = 174). Participants (age: $M$ = 49, $SD$ = 16.1) partook the study anonymously by using an online platform Gorilla (Cauldron Science Ltd, Cambridge, United Kingdom; https://gorilla.sc/experiment-builder). They responded to multiple questionnaires and cognitive tasks known to relate to information evaluation and decision-making. Prior research shows that latent factors based on multiple traits indicate psychological space and can predict real-life consequences (Eisenberg et al., 2019; Zmigrod et al., 2021). In this study, we investigated the effect of individuals' psychological space on an evidence-based decision-making task, thus we included a variety of questionnaires related to information evaluation and decision-making. The questionnaires included intellectual humility (Krumrei-Mancuso & Rouse, 2016), personality (Gosling et al., 2003), science attitudes (Archer et al., 2015; Nadelson et al., 2014) and curiosity (Landrum et al., 2016; Motta et al., 2021), epistemic curiosity (Litman, 2008), need for closure (Roets & Van Hiel, 2011) and cognition (Cacioppo et al., 1984), actively open-minded thinking (Haran et al., 2013), and mathematical (Fiedler et al., 2019; Morsanyi et al., 2009) and logical reasoning (Raven, 1992). The cognitive tasks included go/no-go (Stanislaw & Todorov, 1999), unusual uses task (Guilford, 1967), Navon global-local task (Navon, 1981), and Necker cube task (Necker, 1832).

In addition to responding to the questionnaires and cognitive tasks, participants partook to an evidence-based decision-making task, where they were first introduced to a topic of renewable energy sources and presented with a citizen's initiative suggesting peat as a renewable energy source. Then, they were asked to rate how familiar, interested, and curious they were about the topic and how likely they would support the initiative on a 5-point Likert-scale. In addition to these, participants rated their emotional arousal and valence with 9-point visual Self-Assessment Manikin (SAM) (Lang et al., 2005). In this task, supporting the initiative indicates they would vote against scientific consensus. After stating their stance on the initiative, participants were provided with six sources of information that were about peat. Participants could decide how carefully they read those sources. The sources were divided into two source types that were authority and personal. The authority sources were from persons or institutes that hold power in society, while personal sources reflected personal opinions. Within these two source types, the sources were divided into three quality categories: credible, non-credible, and irrelevant. Credible sources were well referenced and balanced, non-credible sources were poorly referenced or biased, and irrelevant sources were about peat but not relevant in the context of the task. After reading each of the sources, participants rated the convincingness, expertise, reliability, and shareability of the source on a 5-point Likert-scale. In addition, they answered the same topic-related and SAM ratings as at the beginning of the task after being introduced to the topic.

### 3.1.2 Studies II and III, Multi-armed bandit task

Studies II and III used a multi-armed bandit task that allowed curiosity to affect the task dynamics (Cohen et al., 2007; Schulz et al., 2015) as participants were free to decide from which sources and how many statements they selected to read. In the task, participants were presented with 18 health-related topics as claims, and their task was to collect information to respond to whether the claim was true or false. Information was available in three boxes, which all included five statements per topic/claim. Each of the boxes contained statements related to one of the following information quality categories: scientific relevant, scientific irrelevant, or non-scientific relevant. The content qualities of the boxes remained the same for a topic but were shuffled between topics. The content quality of the boxes could be discovered by sampling: by reading statements from the boxes. Participants read the statements until they reported being ready to respond or until they had read all the statements. Then, they selected an answer from four possible options. The stimuli were presented until participants indicated they had read the text by pressing a button or after 20 seconds of time. After reading each topic, participants rated their familiarity with the topic from 1 (not at all) to 4 (very much). After each statement, participants rated the usefulness of the statement to the topic, their confidence in their usefulness rating, whether the information piqued their curiosity, and the clarity of the statement on the same scale as above. The task structure is presented in Figure 1.

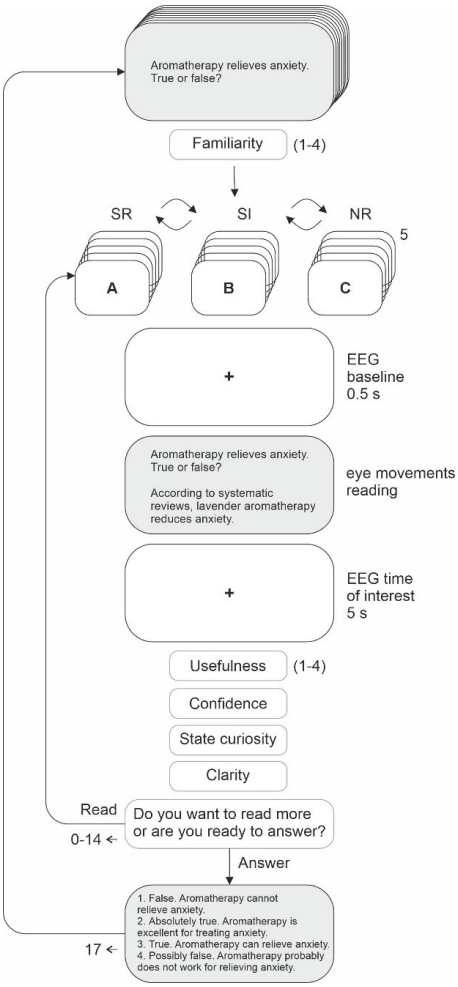



**Figure 1** Task schematics. Participants were presented with one topic (18 in total) at a time. They were asked to rate their familiarity with the topic from not at all (1) to very much (4). Participants selected a box from which a statement was presented. The statements in each box belonged to one out of the three categories: scientific relevant (SR), scientific irrelevant (SI), and non-scientific relevant (NR). Box content categories remained the same for a topic but were switched between topics. After reading a statement, participants rated the statement on its usefulness, on their confidence about the usefulness rating, state curiosity, and clarity with the same scale as familiarity. Then they decided whether they wanted to continue reading statements (up to 14 more) or whether they were ready to select an answer. After selecting an answer, a round with a new topic started (17 more rounds). Eye movements were analyzed from the time of reading the statements. EEG data were analyzed from the periods of fixation crosses before and after a statement was presented. The period before statement was used as a baseline (0.5 s) and the one after it as the window of interest (5 s).

#### 3.1.2.1 Laboratory settings

In the laboratory recording, participants were sitting comfortably in a dimly lit electronically shielded room while doing the task. Their distance was approximately 90 cm from the stimulus screen (HP LA2405x 24', 51.8 x 32.4 cm, resolution 1920x1200). The stimuli were presented on a grey background using a black sans-serif font with the letter width of approximately 0.4 degrees of visual angle.

Task timing and presentation were operated with Presentation software (version 22.1, Neurobehavioral Systems, Berkeley, USA). Participants responded by using a response pad with eight push-button keys (Cedrus RB-844, Cedrus Corporation, San Pedro, CA, USA).

During the recording, both eye movements and electroencephalography were collected. These are equivalent to the data used in Studies II and III, respectively.

#### 3.1.2.2 Eye-Tracking

Study II includes the eye movement data collected while participants ($N$ = 60, age: $M$ = 29.0, $SD$ = 7.0) were doing the multi-armed bandit task. The data was collected by using SR Research EyeLink 1000 remote eye-tracker (SR Research, Ltd., Kanata, Ontario, Canada) with a sampling rate of 1000 Hz. The eye movements analysis was restricted to the time of reading the statements.

#### 3.1.2.3 Electroencephalography

Study III uses EEG data collected while participants ($N$ = 60, age: $M$ = 29.0, $SD$ = 7.0) performed the multi-armed bandit task. The data were recorded by using 64-channel active electrode cap (actiCap) with an actiCHamp Plus amplifier (Brain Products GmbH, Gilching, Germany). For monitoring and storing the data BrainVision Recorder Professional (version 1.21.0001, Brain Products GmbH, Gilching, Germany) was used. The nominal sampling rate was 1000 Hz, and Fz was used as a reference electrode. The data were analyzed from the 5-second interval after reading the statements.

#### 3.1.2.4 Online session

One week after the laboratory session, participants were invited by e-mail to partake an online session within one week. If they had not participated within a week, one reminder e-mail was sent giving them one more week to participate. 53 participants (age: $M$ = 29.4, $SD$ = 7.4) partook the online session. On average, they responded 14 days ($SD$ = 7, range 5–38 days) after the laboratory session. The online session data were acquired using Gorilla. Multiple psychological traits and tasks were included in the online session, from which the 5DCR trait curiosity scale

(Kashdan et al. (2020), see section 1.2 Curiosity) and questions related to the multi-armed bandit task were analyzed for Studies 2 and 3. These questions included revisiting the topics as thinking or searching for more information about them after the laboratory session, and participants also responded to the same multiple choice questions as in the laboratory session.

## 3.2 Pre-processing of physiological data

### 3.2.1 Study II, Eye tracking

Eye movement data were pre-processed using SR Research DataViewer software (version 4.3.1) including drift correction and defining each word as an interest area. Fixations and saccades were detected from raw data by using the EyeLink standard threshold settings: minimum velocity of 30°/sec, minimum acceleration of 8000°/sec^2 or a minimum motion of 0.1°.

### 3.2.2 Study III, EEG

EEG data were pre-processed using EEGLAB (version 2021.1) in MATLAB (version R2023b, MathWorks). Visual inspection of the data was done to detect bad channels and noisy segments. Then, noisy data segments at the beginning and end of the recordings were removed, before down sampling the data to 500 Hz and using a band-pass filter of 1–45 Hz. Muscle and eye artifacts were removed by using an independent component analysis with ICLabel classifier (Pion-Tonachini et al., 2019) and probability interval of 0.8–1.0. Bad channels were interpolated using spherical interpolation before re-referencing data to the common average.

The epochs used in the EEG analysis were selected as follows. The period after reading was selected as a time of interest to limit eye movement artifacts caused by reading and to investigate cognitive processing after reading the text. The period before statement was selected as a baseline, as the time of the reading would have been influenced by eye movements and cognitive processing of the content, which we wanted to investigate. The fixation before statement was the neutral point before acquiring the information in the related statement. The EEG signal was segmented into 5 s epochs after reading statements and 0.5 s epochs before reading statements as a baseline (the periods when a fixation cross was presented). To both ends of these analysis windows, for the time of spectral analysis, an additional 2 s were included to avoid edge artifacts. Baseline correction was carried out for each trial using the baseline epoch as a relative baseline for the 5-second-long window of interest. Time-frequency representations (TFR) were created with FieldTrip (version 20240309). Hanning taper approach was utilized for frequencies between

1–40 Hz in steps of 1 Hz. The time window moved in steps of 50 ms and lasted for 5 cycles for epochs including edge artifact buffers.

## 3.3 Statistical analyses

### 3.3.1 Study I

Study I investigated whether multiple decision-making related thinking styles, traits, and cognitive skills form latent constructs that could predict behavior in a realistic decision-making task. The study was pre-registered in two parts. The first part aimed to detect latent factors indicating psychological profiles (https://doi.org/10.17605/OSF.IO/G2MPE), and the second part tested whether these profiles predict behavior in an evidence-based decision-making task (https://doi.org/10.17605/OSF.IO/DTQAX). All statistical analyses were run in R (R Core Team 2021), version 4.1.3.

Of the 174 participants who completed at least part of the study with valid responses, one was excluded due to exiting the study before ending the first questionnaire, and an additional two participants were excluded as they reported that they did not take the study seriously. Two participants did not provide information about their education; thus, they were excluded. A participant dataset was excluded if there was a high proportion of missing data (over 32 % for questionnaires and over 30 % for task sets), leading to exclusion of 21 participants due to missing questionnaire data and 12 participants due to missing task data.

#### 3.3.1.1 Exploratory factor analysis

Exploratory factor analysis (EFA) was used to recognize latent factors that would describe the psychological space in decision-making from the broad set of questionnaires and cognitive tasks included in the study. Creating a psychological space involves identifying and quantifying the multidimensional relationships between a large set of variables. Dimension reduction using latent variable methods can be an important step in data-driven analyses as it simplifies large datasets with potentially overlapping constructs. As in Eisenberg et al. (2019), cognitive task and questionnaire variables did not seem to create a uniform psychological space, i.e. they were not correlated likely due to the different nature of task and survey variables; thus, EFA was run solely for survey variables.

*Lavaan* package (Rosseel, 2012) was used to run EFA analysis, as it can handle both continuous and binary variables simultaneously. The Empirical Bayes Modal method was used in the extraction of the factor scores.

#### 3.3.1.2 Linear mixed effects modeling

To estimate the associations between the latent factors and task behavior in the evidence-based decision-making task, linear mixed effects modeling (LMM) was used. The analyses were run using *lme4* (Bates et al., 2015) package, version 1.1.34.

Reading rates, as words per minute, were positively skewed and thus predicted by generalized LMM with source type and quality, age, and education as independent variables together with interaction between source type and quality and a random intercept of participant. Reading rates were also predicted by curiosity factor score, source type and quality, their three-way interaction, age, and education together with participant as a random intercept. Participant was included as a random intercept to control individual differences in reading rates.

The curiosity factor score was also used to predict source expertise and reliability, topic interest and curiosity, and emotional valence. Each of these dependent variables were predicted by curiosity factor scores, source type and quality, their three-way interaction, age, and education together with a random intercept of participant. In addition to these pre-registered models, a model for emotional arousal was set with the same predicting variables.

Source convincingness and shareability, and emotional arousal were used as dependent variables predicted by pro-sociality factor scores, source type and quality, their three-way interaction, age, and education as independent variables and participant as a random intercept.

Discernment of the sources was estimated as ratings for source convincingness, expertise, and reliability. These were used as dependent variables in three different models predicted by source type and quality, their interaction, age, and education as independent variables, and participant as a random intercept.

### 3.3.2 Study II, Linear mixed effects modeling

Study II investigated the effects of curiosity and information quality on reading performance and task behavior. Statistical modeling for Study II was performed in R (R Core Team 2025), version 4.5.0. *lme4* (Bates et al., 2015) package, version 1.1.37, was used to run the statistical analyses.

From the original 60 participants, one was excluded due to misunderstanding the task instructions. The remaining 59 participants were included in the behavioral analysis. From eye movement analysis, three additional participants were excluded due to data recording issues, leading to a subsample of 56 participants. 1.7 % of data were excluded due to incorrect button presses while rating the statements. 52 participants partook the online session, thus limiting the sample size of the analysis considering trait curiosity and revisiting the topics.

Eye movements were analyzed at word-level and additional data were excluded on the following basis: calibration inaccuracies detected visually lead to exclusion

of 4.3 % of data and missing information on word frequencies lead to exclusion of 5.4 % of data. In addition, words were excluded if first-pass gaze duration was under 50 ms or over 1000 ms leading to exclusion of 0.6 % and 1.2 % of data. Those words that were skipped during the first-pass reading were excluded, representing 30.9 % of data.

LMMs were used to predict statement related ratings (usefulness, confidence in usefulness rating, state curiosity, and clarity) and proportion of statements read (within each category). Statement related ratings were predicted by information quality, time on task, and familiarity of the topic as independent variables as well as random intercepts for statement and random slopes for information quality per participant. The model predicting the proportion of statements read included information quality and state curiosity as independent variables, and random intercept for participant. Total fixation duration at word level and associations between state and trait curiosity were also investigated with LMMs. The model predicting total fixation duration included state curiosity, information quality, word frequency, and word length as independent variables together with interaction for state curiosity and information quality, random intercepts of participant, statement, and words as well as random slope of information quality per participant. State curiosity was predicted by trait curiosity dimensions as independent variables and participant as a random intercept.

Generalized linear mixed effect modeling (GLMM) was used to predict binary variables. Binomial distribution was used to predict exploration behavior in the task as changing the source of information between statements, revisiting the topics as thinking about or searching for more information about them, and skipping rates while reading. The model predicting exploration behavior included information quality, state curiosity, and time on task as independent variables and random slope of information quality per participant. Revising the topics was estimated as thinking about and searching for more information about the topics after the laboratory session and was predicted by state curiosity, familiarity, number of rounds, and trait curiosity dimensions as independent variables with participant as a random intercept. Skipping rates indicated whether the word was skipped during the first pass reading. The model predicting skipping rates included state curiosity, information quality and their interaction, word frequency, and word length as independent variables together with random intercepts of participant, statement, and words and random slope of information quality per participant. Poisson distribution was used in the analysis predicting number of rounds when gathering information in the task (i.e., the number of statements read). The model predicting number of rounds included state curiosity and familiarity as independent variables and random intercepts for topics and familiarity. The statistical models are summarized in Table 2.

Random intercepts were included to account for variability between individuals, words, statements, topics, and familiarity of the topics. Random slopes were included to account for individual differences in perceiving the quality of information categories. Time on task and familiarity were included as control variables as time on task may affect task behavior and ratings due to increasing fatigue and leaning the task features. Familiarity may affect evaluation of the ratings and revisiting the topics due to increase in knowledge and interest.

**Table 2** Model descriptions for Study II

| | Model | Dependent variable | Independent variable | Interaction | Random intercept | Random slope |
|---|---|---|---|---|---|---|
| Task behavior ($n$ = 59) | LMM | Ratings (state curiosity / usefulness / confidence on usefulness / clarity) | Information quality, time on task, familiarity | | Statement | information quality per participant |
| | LMM | Proportion of statements read | Information quality, state curiosity | | Participant | |
| | GLMM, binomial | Exploration (switch) | Information quality, state curiosity, time on task | | | Information quality per participant |
| | GLMM, Poisson | Number of rounds | State curiosity, familiarity | | Topic, familiarity | |
| Reading ($n$ = 56) | GLMM, binomial | Skipping rates | Word frequency, word length | Information quality * state curiosity | Word, statement | Information quality per participant |
| | LMM | Total fixation duration | Word frequency, word length | Information quality * state curiosity | Word, statement | Information quality per participant |
| Revisiting the topics ($n$ = 52) | GLMM, binomial | Thinking about / searching for more information | State curiosity, familiarity, number of rounds, trait curiosity dimensions | | Participant | |
| State curiosity per topic ($n$ = 52) | LMM | State curiosity | Trait curiosity dimensions | | Participant | |

LMM = linear mixed effects model, GLMM = generalized linear mixed effects model

## 3.3.3 Study III

Study III investigated whether oscillation power after reading statements is associated with information quality and curiosity.

### 3.3.3.1 Cluster-based permutation analysis

Study III used an exploratory approach and cluster-based permutation analysis was chosen to limit the sensor-frequency-time analysis space to control for excessive

testing (Maris & Oostenveld, 2007). The aim was to detect possible oscillation power differences in statement quality categories. Cluster-based permutation analysis was run for alpha-frequency band (8–12 Hz) as it showed the strongest activity in TFR. For creating clusters, Monte Carlo correction with a minimum of two neighboring channels was used. For more sensitive detection of small clusters, a significance threshold of $p$ = .01 was used for time-channel-electrode testing within categories and $p$ = .05 was used to create clusters based on the whole data (Huang & Zhang, 2017). To test the variability between quality categories, 1000 random samples were drawn.

The analysis indicated two clusters: one for difference between scientific irrelevant and non-scientific relevant statements (frontal cluster) and another for scientific relevant and non-scientific relevant statements (parietal cluster). The clusters were labeled based on their spatial locations. Then, trial-based data for all participants were exported based on the time-frequency-channel selections included in the clusters.

#### 3.3.3.2 Generalized linear mixed effects modeling

GLMM was used first to reproduce the results from cluster-based permutation analysis using R (R Core Team 2026), version 4.5.3. GLMMs were run using the *lme4* (Bates et al., 2015) package, version 2.0.1. The information quality model was run for both clusters and predicted alpha power with information quality and included participant as a random intercept. Random intercept of participant was included to account for interindividual variability in oscillation amplitudes. Then, further analyses were conducted to investigate the associations of alpha power after reading the statements with state and trait curiosity, statement related ratings, and revisiting the topics. Thus, the final model predicted alpha power with trait and state curiosity, statement ratings, revisiting the topics after the laboratory session, and statement quality while including random slopes for statement quality per participant. Again, the model was run for both clusters.

The analysis method was selected on the following basis. LMM is suggested to be used with EEG data and complex paradigms (Frömer et al., 2018), and GLMM can handle the non-normal distribution of these types of data (Bolker et al., 2009). Furthermore, our task design allowed the number of trials to vary between participants and between the stimulus categories. LMMs can consider also this type of variability, whereas ANOVA cannot.

GLMM analysis included 53 participants from the total of 60 participants, as the trait curiosity and revisiting the topics measures were acquired only from those participants. Due to an unknown technical error, statements were presented more than once in 19 occurrences, which were omitted from the data. Moreover, 1.9% of data were excluded due to incorrect button presses when rating the statements.

# 4 Results

This section describes the main results of this doctoral dissertation. Study I indicates that the latent curiosity factor is related to emotional responses and reading speed. Study II indicates that higher state curiosity is associated with more careful reading. Study III indicates that changes in cortical alpha oscillations are related to state and trait curiosity reflecting engagement in the cognitive processing of the information. Together, these results highlight the importance of curiosity in information processing and evaluation.

## 4.1 Evidence evaluation

Study I investigated whether individual psychological space that describes traits and skills related to decision-making could predict behavior in a decision-making task imitating a real-life situation.

### 4.1.1 Four factors presenting psychological space

EFA was used to investigate latent factors based on a large set of psychological variables indicating thinking styles, personality traits, and cognitive skills. The EFA indicated four latent factors that represent the dimensions of an individual psychological space: pro-sociality, curiosity, open-mindedness, and cognitive skills. *Pro-sociality* included variables reflecting an open viewpoint towards others' opinions, *curiosity* reflected a curious and engaging stance towards science, *open-mindedness* reflected the willingness to revise one's own views, and *cognitive skills* reflected logical thinking. See Table 3 for factor loadings.

Next, we used LMMs to determine whether the factors predicted behavior in the decision-making task quantified as reading rates and source evaluations. Also, the associations between the factors and emotional responses were examined. Only those results that showed a significant effect are presented here, thus open-mindedness and cognitive skills factors are not mentioned any further. GLMM was used to investigate reading rates.

**Table 3** Factor loadings for the four-factor structure.

| Variable | Pro-sociality | Curiosity | Open-mindedness | Cognitive Skills |
|---|---|---|---|---|
| Respect for other's viewpoints (IH) | **0.59** | 0.10 | -0.03 | 0.02 |
| Agreeableness (TIPI) | **0.40** | -0.26 | -0.06 | 0.07 |
| Openness (TIPI) | **0.40** | 0.31 | 0.32 | -0.22 |
| Need for closure | **-0.38** | -0.22 | -0.10 | 0.08 |
| Extraversion (TIPI) | **0.30** | 0.16 | -0.11 | -0.15 |
| Science identity (SA) | -0.15 | **0.81** | -0.22 | 0.10 |
| Need for cognition | 0.20 | **0.77** | 0.1 | -0.04 |
| Interest curiosity (EC) | 0.26 | **0.64** | 0.28 | 0.07 |
| Science curiosity | -0.12 | **0.60** | 0.09 | 0.04 |
| Deprivation curiosity (EC) | 0.02 | **0.50** | 0.24 | -0.05 |
| Importance of science (SA) | -0.24 | **0.43** | 0.21 | -0.01 |
| Independence of intellect and ego (IH) | 0.15 | **0.35** | -0.12 | -0.03 |
| Trust in science (SA) | -0.27 | **0.30** | 0.31 | -0.02 |
| Heuristic-equiprobability | -0.16 | **-0.19** | 0.13 | -0.18 |
| Openness to Revising One's Viewpoint (IH) | 0.11 | 0.10 | **0.58** | 0.14 |
| Conscientiousness (TIPI) | 0.11 | 0.23 | **-0.53** | 0.00 |
| Actively openminded thinking | -0.11 | 0.12 | **0.46** | 0.20 |
| Emotional stability (TIPI) | 0.31 | 0.09 | **-0.41** | 0.12 |
| Lack of intellectual overconfidence (IH) | 0.09 | -0.34 | **0.36** | 0.17 |
| Randomness-probability | -0.20 | 0.18 | 0.10 | **0.70** |
| Heuristic-representativeness | 0.27 | -0.12 | -0.03 | **0.66** |
| Matrix reasoning | 0.00 | 0.04 | 0.09 | **0.42** |

Multidimensional scales are shown with their original factors separately: Intellectual Humility (IH), Ten Item Personality Index (TIPI), Science Attitudes (SA), Epistemic Curiosity (EC). Loadings in bold font show factor assignments

### 4.1.2 Discerning the information sources

Overall, information holding social authority was valued highly regardless of its scientific quality; see Figure 2. The credible personal source type was rated higher than the respective authority sources, whereas the effect was the opposite for non-credible and irrelevant sources. All three ratings showed an interaction between source type and quality: convincingness ($F = 64.45$, $p < .001$), expertise ($F = 111.1$, $p < .001$), and reliability ($F = 70.03$, $p < .001$).

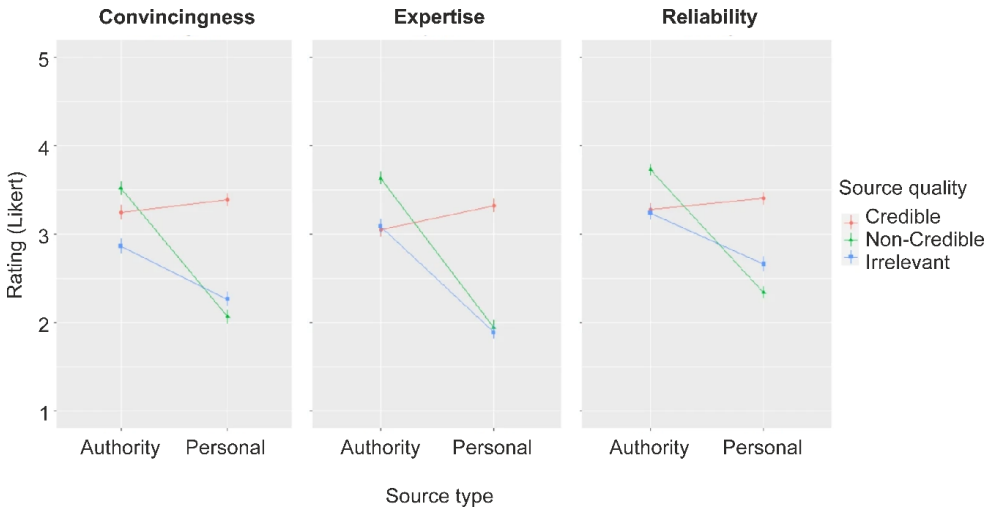



**Figure 2** Interactions of source type and source quality for ratings of convincingness, expertise and reliability. Error bars indicate standard error of the mean. Adapted from "Evidence-based scientific thinking and decision-making in everyday life" by Caitlin Dawson et al, 2024, *Cognitive Research: Principles and Implications*, Springer Nature. (https://doi.org/10.1186/s41235-024-00578-2). CC BY.

### 4.1.3 Curiosity and reading rates

Reading rates, as words per minute, varied based on source quality ($\chi^2 = 106.96$, $p < .001$) and authority ($\chi^2 = 79.53$, $p < .001$) so that authority sources were read the longest. Pairwise testing showed that the non-credible sources were read the fastest and irrelevant sources the slowest with credible sources in between, see Table 4.

**Table 4** Pairwise contrasts between levels of source quality for reading rates (words per minute), averaged over the levels of the source type and education.

| Contrast | Estimate | *SE* | *df* | *z-ratio* | *p* |
|---|---|---|---|---|---|
| Credible – Non-credible | -0.25 | 0.067 | Inf | -3.65 | < .001 *** |
| Credible – Irrelevant | 0.46 | 0.066 | Inf | 7.032 | < .001 *** |
| Non-credible – Irrelevant | 0.70 | 0.067 | Inf | 10.50 | < .001 *** |

P value adjustment: Tukey method for 3 tests. Tests are performed on the log scale.
***Indicates $p < .001$

Reading rates were also predicted by a model including curiosity factor scores. Higher scores for curiosity factor were related to higher reading rates, that is, faster reading, for both credible and for the personal irrelevant sources, see Figure 3. Additionally, there were interactions at non-credible quality level between curiosity

factor score and source quality ($\chi^2 = 15.12$, $p < .001$) indicating that for non-credible sources curiosity affected both source types similarly. There were also interactions at personal and non-credible levels between source type and quality ($\chi^2 = 8.23$, $p = .016$). This indicates that the personal non-credible source showed a different association with curiosity than the other two personal sources.




**Figure 3** Interactions between source type and source quality, and source quality and curiosity factor scores for reading rates. Shaded area indicates confidence intervals. Outlying data points have been cropped ($n$=60 or 8%). Adapted from "Evidence-based scientific thinking and decision-making in everyday life" by Caitlin Dawson et al, 2024, *Cognitive Research: Principles and Implications*, Springer Nature. (https://doi.org/10.1186/s41235-024-00578-2). CC BY.

### 4.1.4 Curiosity and pro-sociality predict emotional arousal

Emotional valence and arousal were related to curiosity ($\beta = 0.34$, $p = 0.037$) and pro-sociality ($\beta = 0.43$, $p = 0.01$), respectively. Curiosity factor scores and emotional valence showed a nonlinear relationship, so that strongest and weakest valence were related to highest curiosity factor scores and mid-level valence was related to lowest curiosity factor scores, see Figure 4. Emotional arousal was positively associated with curiosity factor scores ($\beta = 0.47$, $p = 0.003$), so that arousal increased together with factor scores, see Figure 5.

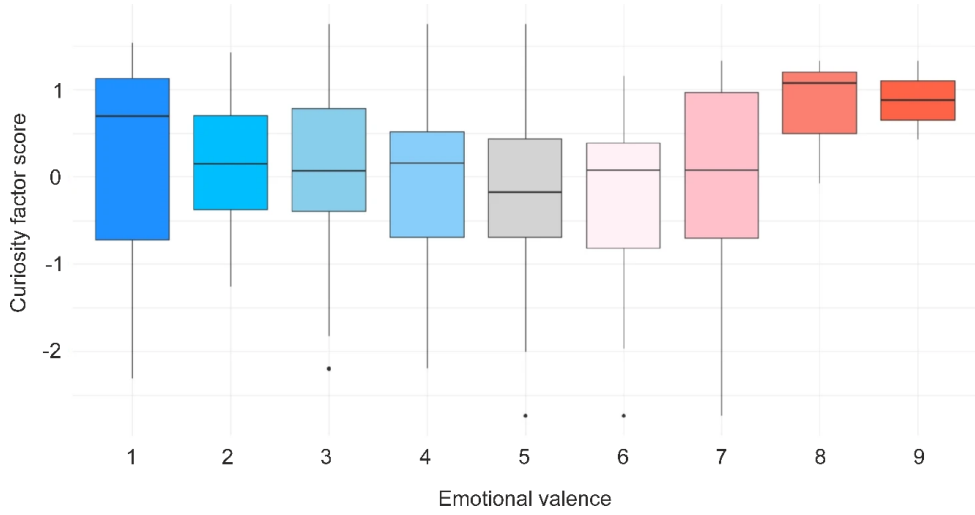



**Figure 4** Nonlinear relationship of curiosity factor scores and emotional valence ratings, rated on a 9-point Self-Assessment Manikin with endpoints Unpleasant (1) to Pleasant (9). Adapted from "Evidence-based scientific thinking and decision-making in everyday life" by Caitlin Dawson et al, 2024, *Cognitive Research: Principles and Implications*, Springer Nature. (https://doi.org/10.1186/s41235-024-00578-2). CC BY.

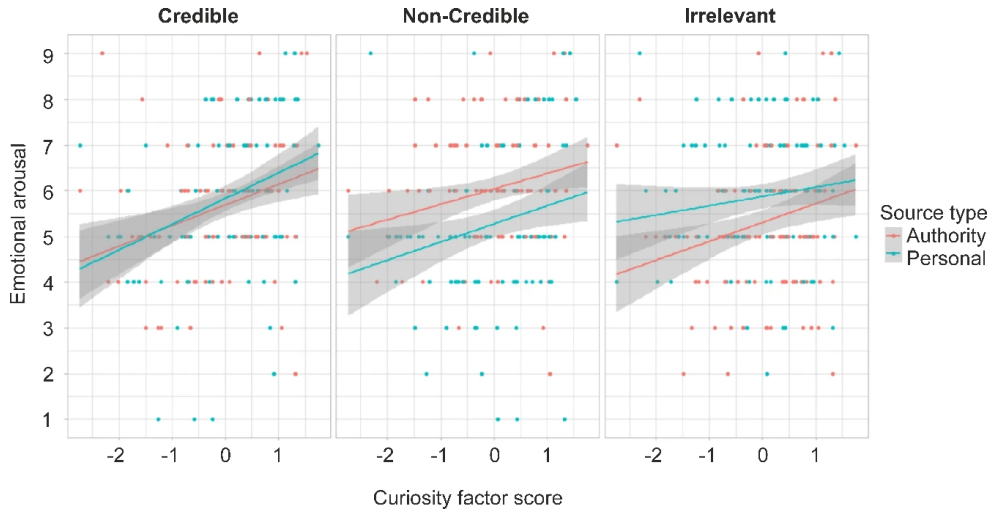



**Figure 5** Higher curiosity factor scores predicted higher emotional arousal ratings, rated on a 9-point Self-Assessment Manikin with endpoints Peaceful (1) to Agitated (9). Shaded area indicates confidence intervals. Adapted from "Evidence-based scientific thinking and decision-making in everyday life" by Caitlin Dawson et al, 2024, *Cognitive Research: Principles and Implications*, Springer Nature. (https://doi.org/10.1186/s41235-024-00578-2). CC BY.

## 4.2 Curiosity and eye movements

Study II investigated whether eye movements during reading reflect statement quality and curiosity. The following results indicate that both information quality and curiosity were associated with reading behavior.

### 4.2.1 Information-seeking behavior

After reading each of the statements (see Figure 1 for task schematics), participants rated statement related state curiosity, usefulness, confidence on the usefulness rating, and clarity. State curiosity differed between the information quality categories (SR vs SI: $\beta = -0.52$, $p < .001$; SR vs NR: $\beta = -0.79$, $p < .001$; SI vs NR: $\beta = -0.27$, $p < .001$). State curiosity was highest for the SR statements and lowest for NR statements (Figure 6a). Statement usefulness was predicted by information quality so that SR statements were rated most useful with no difference between SI and NR statements (SR vs SI: $\beta = -1.23$, $p < .001$; SR vs NR: $\beta = -1.33$, $p < .001$), see Figure 6b. Participants' confidence in their usefulness rating was lowest for SI statements (SI vs SR: $\beta = 0.20$, $p = .002$; SI vs NR: $\beta = 0.21$, $p = .003$) with no difference between SR and NR statements (Figure 6c). Statement clarity was highest for NR statements (NR vs SR: $\beta = -0.18$, $p = .008$; NR vs SI: $\beta = -0.25$, $p < .001$) with no difference between SR and SI statements (Figure 6d).

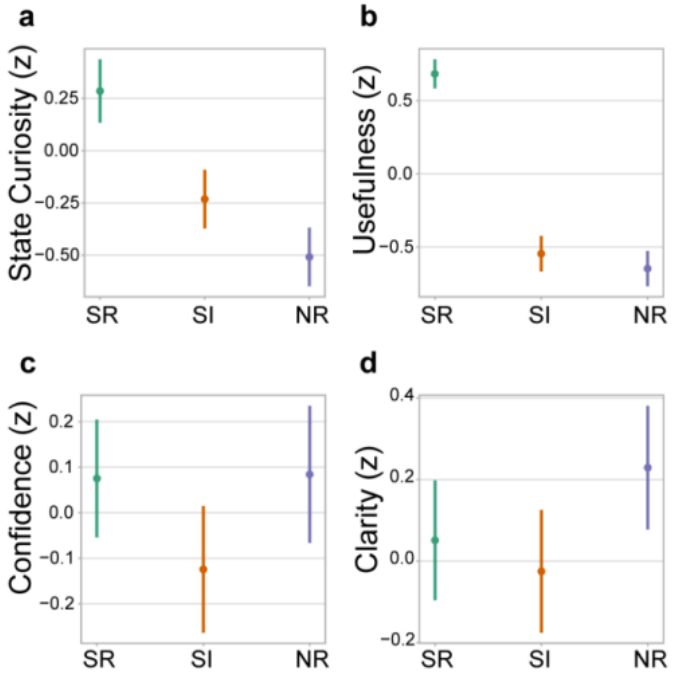



**Figure 6** Rating results. Model predictions for a) state curiosity, b) usefulness, c) confidence, and d) clarity ratings across the evidence quality categories: SR = scientific relevant (green), SI = scientific irrelevant (orange), NR = non-scientific relevant (purple), controlling for the effect of time on task and familiarity with the topics. Error bars denote 95% confidence intervals (CI), n=59. Copied from "Curiosity and evidence quality affect information seeking and eye movements during reading" by Jaana Simola et al, 2026, *Cognition*, Elsevier. (https://doi.org/10.1016/j.cognition.2026.106598). CC BY.

The investigation of information seeking behavior indicated that the proportion of statements read (from all statements within a category) was greatest for SR statements (SR vs SI: $\beta$ = -0.06, p = .007; SR vs NR: $\beta$ = -0.07, p = .008) with no difference between SI and NR statements (Figure 7a). SR statements were exploited, that is, selected continuously, more often than NR statements (SR vs NR: $\beta$ = 0.70, p = .031) indicated by fewer switches of statement categories between statements read (Figure 7b). Moreover, switching behavior decreased with time on task (Figure 7c).

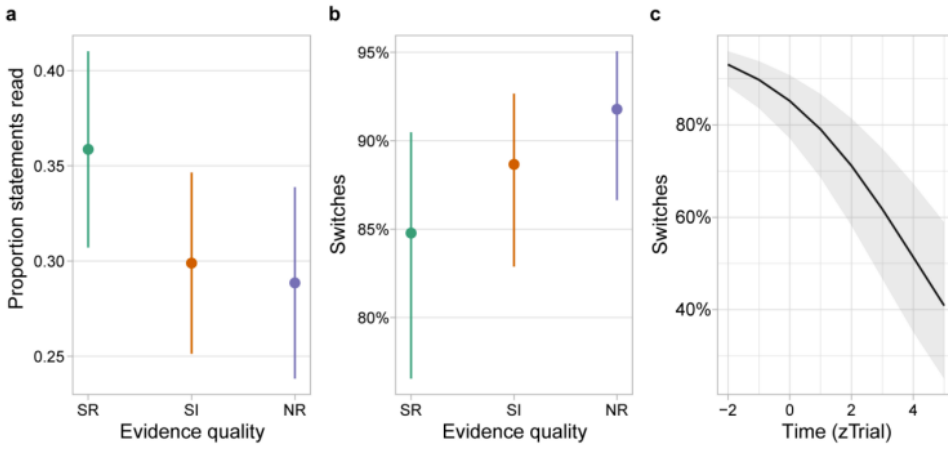



**Figure 7** Information-seeking results. a) Predicted proportion of statements read varied across the evidence quality categories and was highest for the SR statements. Predicted probability of exploration (i.e., switches between the boxes) indicated that exploration varied across b) the evidence quality categories and was lower for SR than NR statements and c) decreased over time-on-task ($p < .001$). SR = scientific relevant (green), SI = scientific irrelevant (orange), NR = non-scientific relevant (purple). Error bars and shading denote 95% confidence intervals (CI), n=59. Copied from "Curiosity and evidence quality affect information seeking and eye movements during reading" by Jaana Simola et al, 2026, *Cognition*, Elsevier. (https://doi.org/10.1016/j.cognition.2026.106598). CC BY.

### 4.2.2 State curiosity and statement quality are associated with more careful reading

The investigation of eye movement data revealed that during the first-pass reading, higher word skipping rates were observed for SR than SI and NR statements (SR vs SI: $\beta = -0.23$, $p = .002$; SR vs NR: $\beta = -0.26$, $p = .001$) with no difference between SI and NR statements, see Figure 8a. Overall, higher state curiosity ratings were related to lower word skipping rates ($\beta = -0.05$, $p = .018$), see Figure 8b.

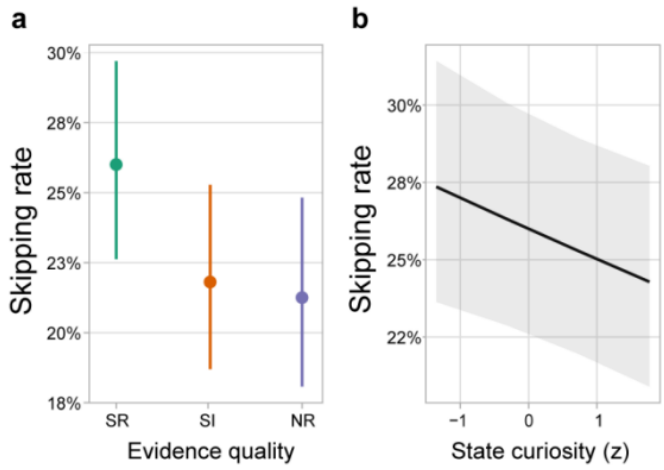



**Figure 8** Skipping rates. Predicted skipping rates a) varied across the evidence quality categories and were highest for the SR statements and b) decreased with increasing state curiosity (p = .018). SR = scientific relevant (green), SI = scientific irrelevant (orange), NR = non-scientific relevant (purple). Error bars and shading denote 95% confidence intervals (CI), n=56. Copied from "Curiosity and evidence quality affect information seeking and eye movements during reading" by Jaana Simola et al, 2026, *Cognition*, Elsevier. (https://doi.org/10.1016/j.cognition.2026.106598). CC BY.

The investigation of total fixation duration indicated an interaction for state curiosity and evidence (statement) quality, see Figure 9. Total fixation duration differed between the quality categories so that SR statements were fixated the longest, then SI statements, and NR statements were fixated the shortest (SR vs NR: β = -0.08, $p$ = .003; SI vs NR: β = -0.07, $p$ = .028). Curiosity was associated with an increase in total fixation duration (β = 0.02, $p$ = .001). However, an interaction between state curiosity and statement quality indicated a greater increase for SI and NR than SR statements (SR: β = 0.02, $p$ = .001; SI: β = 0.05, $p$ < .001; NR: β = 0.06, $p$ < .001). Moreover, the total fixation durations between quality categories varied more when state curiosity was low than when it was high.

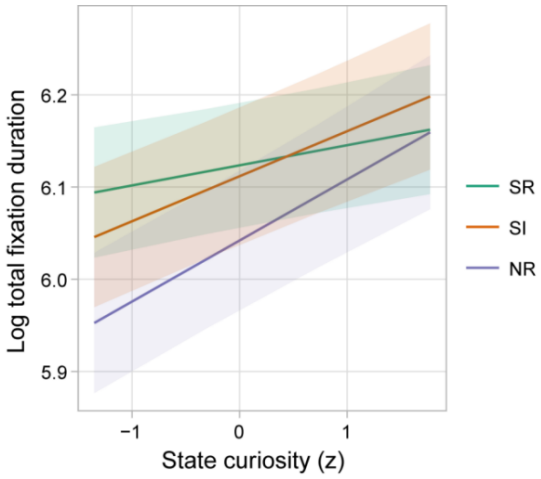



**Figure 9** Total fixation duration as a function of state curiosity across the evidence quality categories. SR = scientific relevant (green), SI = scientific irrelevant (orange), NR = non-scientific relevant (purple). Shaded areas denote 95% CI, n=56. Copied from "Curiosity and evidence quality affect information seeking and eye movements during reading" by Jaana Simola et al, 2026, *Cognition*, Elsevier. (https://doi.org/10.1016/j.cognition.2026.106598). CC BY.

### 4.2.3 Trait curiosity and information-seeking

Study II also examined whether information-seeking behavior in the task was related to trait curiosity. Information-seeking was estimated as number of rounds and exploration. Trait curiosity was not associated with information-seeking in the task.

We investigated also whether revisiting the task topics after the laboratory session was related to state and trait curiosity, topic familiarity, and number of rounds per topic. Revisiting the topics was operationalized as thinking about and searching for more information about the topics after the laboratory session. Trait curiosity dimensions joyous exploration ($\beta = 11.72$, $p = .025$) and deprivation sensitivity ($\beta = 15.91$, $p < .001$) were positively and thrill seeking ($\beta = -15.20$, $p < .001$) negatively related to thinking about the topics.

To investigate associations between state and trait curiosity, the mean state curiosity scores for each topic were predicted by mean scores for trait curiosity dimensions. Thrill seeking dimension of trait curiosity correlated negatively with state curiosity ($\beta = -0.19$, $p = .002$) while none of the other trait curiosity dimensions were related to state curiosity.

## 4.3 Curiosity and alpha oscillations

Study III investigated whether neuronal activity after reading statements was associated with statement quality and curiosity. Neuronal oscillations were investigated after reading, as we were interested in whether statement quality and curiosity were related to sustained cognitive processing of the information content. First, the association between oscillation power and statement quality was investigated. Cluster-based permutation analysis on alpha frequency band indicated two clusters with significant differences between statement categories. A *frontal* cluster showed a difference between SI and NR statements at frequencies 11–12 Hz, at time window of 4.55–4.7 s, and at electrodes AFz, AF8, Fz, F2, F4, F6, F8, FC4, FC6, and FT8. A *parietal* cluster showed a difference between SR and NR statements, at frequencies 9–12 Hz, time-window of 4.4–4.85 s, and at electrodes CPz, CP1, CP3, Pz, P1, P3, P5, P7, POz, PO3, and PO7. The clusters are visualized in Figure 10. The data from these clusters were exported for further statistical analysis with GLMMs.

The information quality model started the GLMM analysis and indicated that for both clusters alpha power was stronger after reading NR statements when compared to SR statements (frontal: $\beta = 0.119$, $p = .014$; parietal $\beta = 0.102$, $p = .046$). There was no difference between NR and SI statements, when NR was used as a baseline. After these results reproducing the findings from cluster-based permutation test on a more limited dataset, the more comprehensive GLMM analyses were conducted.

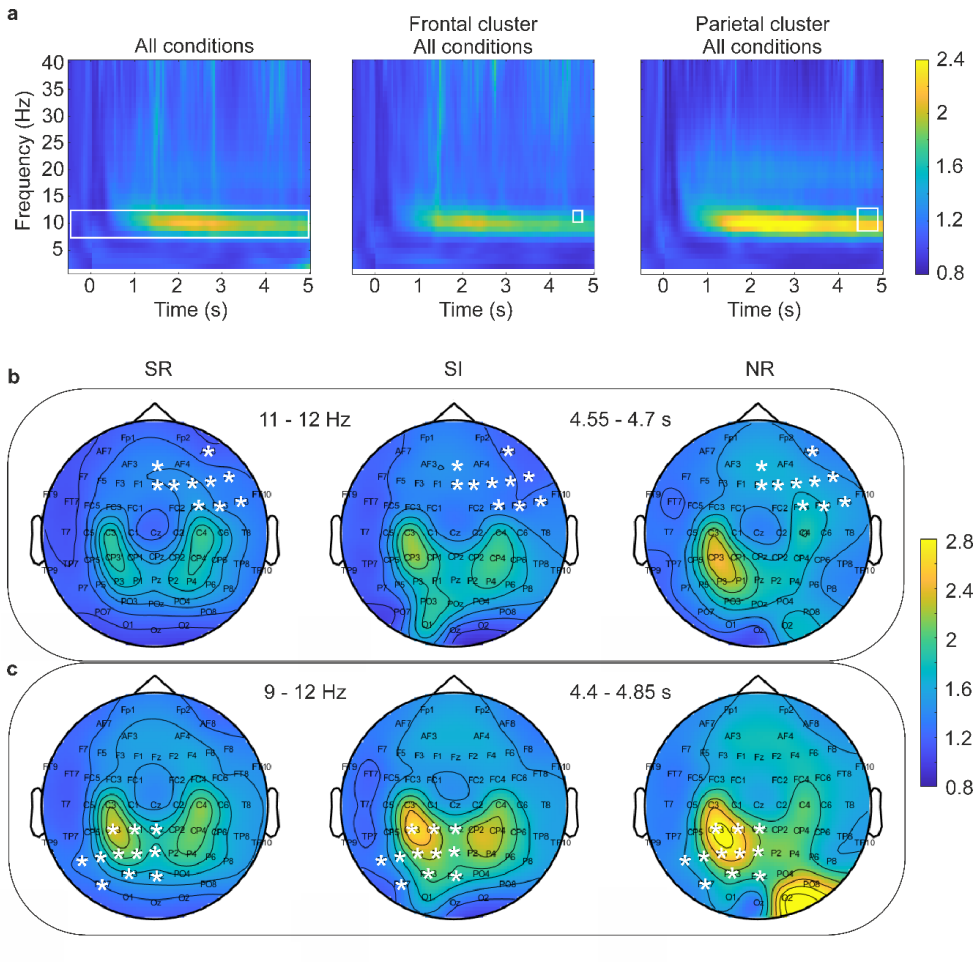



**Figure 10** Cluster visualization. A) Time-Frequency Representations (TFR) for all conditions. Left: all channels and conditions, the white square indicates 8–12 Hz, that relates to alpha oscillations and was used as a frequency selection in cluster-based permutation analysis. Center and right: TFRs for channels included in the frontal (center) and parietal clusters (right). White squares indicate the time and frequency range of the clusters. Color scale represents oscillation power in relation to baseline in all TFRs. B) and C) Topography of mean alpha power for clusters indicated by the cluster-based permutation analysis. B) Topography of mean oscillation amplitudes over frequencies 11–12 Hz and timepoints 4.55–4.7 s from the cluster labeled as frontal. C) Topography of mean oscillation amplitudes over frequencies 9–12 Hz and timepoints 4.4–4.85 s from the cluster labeled as parietal. White asterisks indicate electrodes included in the clusters. Columns from left to right indicate information quality categories: SR = scientific relevant, SI = scientific irrelevant, NR = non-scientific relevant. The color scale represents oscillation power in relation to baseline.

### 4.3.1 Alpha oscillations are associated with curiosity and searching for more information

GLMM analyses indicated that an increase in deprivation sensitivity dimension of trait curiosity was related to a decrease in alpha power in both frontal ($\beta$ = -0.198, $p$ = .004) and parietal ($\beta$ = -0.243, $p$ = .005) clusters. Furthermore, a decrease in frontal alpha power ($\beta$ = -0.082, $p$ < .001) was related to an increase in state curiosity. A decrease in parietal alpha power ($\beta$ = -0.539, $p$ = .015) was associated with searching for more information about the task topics on participants' own time. The results for frontal and parietal clusters are presented in Tables 5 and 6, respectively.

**Table 5** Fixed and random effects for the model predicting frontal alpha power. glmer(pwr_mean ~ zjoy + zdep + zstress + zthrill + zosoc + zcsoc + zCur + zClar + zUseful + zConf + think + search + quality + (quality | ID), family = Gamma(link = "log")). Quality baseline = Scientific Relevant.

| Fixed effects | Estimate | *SE* | *t* | *p* |
|---|---|---|---|---|
| **(Intercept)** | **0.724** | **0.091** | **7.970** | **< .001** |
| joyous exploration (zjoy) | 0.015 | 0.064 | 0.243 | .808 |
| **deprivation sensitivity (zdep)** | **-0.198** | **0.068** | **-2.898** | **.004** |
| stress tolerance (zstress) | -0.036 | 0.062 | -0.583 | .560 |
| thrill seeking (zthrill) | -0.042 | 0.064 | -0.661 | .509 |
| overt social curiosity (zosoc) | 0.042 | 0.062 | 0.676 | .499 |
| covert social curiosity (zcsoc) | 0.101 | 0.060 | 1.676 | .094 |
| **state curiosity (zCur)** | **-0.082** | **0.022** | **-3.782** | **< .001** |
| clarity (zClar) | -0.001 | 0.020 | -0.058 | .954 |
| usefulness (zUseful) | 0.043 | 0.025 | 1.711 | .087 |
| confidence (zConf) | 0.018 | 0.020 | 0.895 | .371 |
| think | -0.098 | 0.132 | -0.740 | .459 |
| search | -0.223 | 0.176 | -1.264 | .206 |
| qualitySI | 0.050 | 0.060 | 0.840 | .401 |
| qualityNR | 0.113 | 0.068 | 1.662 | .096 |
| Random effects | Variance | *SD* | correlation | |
| (Intercept: ID) | 0.142 | 0.377 | | |
| Slope \| ID: qualitySI | 0.043 | 0.207 | -0.29 | |
| Slope \| ID: qualityNR | 0.081 | 0.284 | -0.18 | 0.11 |

$N_{observations}$ = 4409, $N_{ID}$ = 53, Marginal $R^2$ / Conditional $R^2$ 0.082 / 0.234

*Note.* SI = Scientific Irrelevant, NR = Non-scientific Relevant

**Table 6** Fixed and random effects for the model predicting parietal alpha power. glmer(pwr_mean ~ zjoy + zdep + zstress + zthrill + zosoc + zcsoc + zCur + zClar + zUseful + zConf + think + search + quality + (quality | ID), family = Gamma(link = "log")). Quality baseline = Scientific Relevant.

| Fixed effects | Estimate | *SE* | *t* | *p* |
|---|---|---|---|---|
| **(Intercept)** | **0.874** | **0.110** | **7.946** | **< .001** |
| joyous exploration (zjoy) | -0.016 | 0.080 | -0.195 | .845 |
| **deprivation sensitivity (zdep)** | **-0.243** | **0.086** | **-2.833** | **.005** |
| stress tolerance (zstress) | -0.107 | 0.078 | -1.364 | .173 |
| thrill seeking (zthrill) | -0.011 | 0.080 | -0.142 | .887 |
| overt social curiosity (zosoc) | 0.068 | 0.078 | 0.865 | .387 |
| covert social curiosity (zcsoc) | 0.070 | 0.076 | 0.920 | .358 |
| state curiosity (zCur) | -0.026 | 0.021 | -1.240 | .215 |
| clarity (zClar) | 0.027 | 0.020 | 1.395 | .163 |
| usefulness (zUseful) | 0.021 | 0.024 | 0.845 | .398 |
| confidence (zConf) | -0.001 | 0.019 | -0.067 | .946 |
| think | 0.207 | 0.166 | 1.249 | .212 |
| **search** | **-0.539** | **0.221** | **-2.438** | **.015** |
| qualitySI | 0.110 | 0.066 | 1.669 | .095 |
| qualityNR | 0.101 | 0.067 | 1.519 | .129 |
| Random effects | Variance | *SD* | correlation | |
| (Intercept: ID) | 0.239 | 0.489 | | |
| Slope \| ID: qualitySI | 0.094 | 0.306 | -0.23 | |
| Slope \| ID: qualityNR | 0.090 | 0.301 | 0.11 | 0.43 |

$N_{observations}$ = 4409, $N_{ID}$ = 53, Marginal $R^2$ / Conditional $R^2$ 0.124 / 0.369

*Note.* SI = Scientific Irrelevant, NR = Non-scientific Relevant

# 5 Discussion

Prior research has indicated that curiosity plays a vital role in information-seeking (Eschmann et al., 2023; Lydon-Staley et al., 2021; Swirsky & Spaniol, 2024) and engagement with information (Chevrier et al., 2019). Curiosity is perceived as intrinsic motivation (Lee & Reeve, 2017) and it drives the use of attentional resources (Baranes et al., 2015). Furthermore, epistemic curiosity is considered as a metacognitive feeling (Goupil & Proust, 2023; Metcalfe et al., 2020) that enhances learning (Chevrier et al., 2019; Gruber et al., 2014; Metcalfe et al., 2021; Metcalfe et al., 2020).

This doctoral study investigated the role of curiosity in information-seeking and evaluation in evidence-based decision-making with adult participants. The research focus was on information quality, curiosity, and their interplay. Study I investigated the latent structure of individuals' psychological space and its effects on behavior in an online behavioral decision-making task. Studies II and III investigated the effects of curiosity and information quality in an information-seeking task using eye tracking in Study II and EEG in Study III.

The results of these three studies indicate that different aspects of curiosity are linked to information quality, stronger engagement with information, and sustained cognitive engagement with the topics.

## 5.1 Information quality

Study I showed that source authority affected reading times, that is, authority sources were read longer than personal sources. Furthermore, irrelevant sources were read for the longest, following with credible sources, and non-credible sources were read for the shortest time. Moreover, participants discerned personal sources more carefully than authority sources. This was indicated in the differences in rating the sources. The non-credible authority source was consistently rated higher than credible and irrelevant authority sources on convincingness, expertise, and reliability. Whereas personal sources were rated as expected, that is, the credible source as the most convincing, reliable, and expert. Previous studies have indicated that social authority of the source, that is, how much expertise and power the source holds, is a strong cue for information value (Ilić & Damnjanović, 2021; Kiili et al., 2008) possibly leading to careless information discernment shown here.

Study II indicated that SR statements were read the most often, rated as the most useful, and that the SR quality category was exploited the most. The switching behavior decreased with increasing task duration. A previous study has indicated that as trials progressed, the participants were increasingly selecting the stimuli with higher value (Cortes et al., 2021). Thus, participants may have learned to select the most useful source for the task, leading to a decrease in switching behavior.

Study III indicated two topographically distinct clusters that showed differences in alpha power between information quality categories. The GLMM analysis aimed to reproduce the information quality results and showed that for both clusters (frontal and parietal) alpha power was stronger for NR than SR statements. Prior studies have suggested that stronger alpha oscillations reflect inhibition of irrelevant information (ElShafei et al., 2022; Klimesch, 2012; Prasad & Beste, 2025) and that weaker alpha power indicates cognitive engagement (Kielar et al., 2015) and higher cognitive load (Chikhi et al., 2022). According to these prior studies, stronger alpha power for NR statements in relation to SR statements may indicate weaker cognitive engagement with the information content of NR statements. SR statements were rated as the most useful, possibly indicating that NR statements were recognized as less valuable for the task and thus inhibited from further processing. Moreover, clarity ratings were the highest for NR statement, likely reflecting lower cognitive load.

Further analysis with a more comprehensive model including both state and trait curiosity, statement quality and ratings, and revisiting the topics showed that information quality was no longer a significant predictor for alpha power. These results show that a decrease in alpha power is related to state curiosity, deprivation sensitivity, and revisiting the topics by searching for more information. The decrease in alpha power with increasing state curiosity, deprivation sensitivity, and searching for more information may indicate stronger cognitive engagement with the information content.

Lateral PFC is suggested to relate to abstract value of information (Dixon & Christoff, 2014). This could be related to our result in frontal cluster showing a decrease in alpha power with increased state curiosity.

## 5.2 Curiosity and attentional focus in reading

The results of Studies I and II showed partly mixed results when it came to reading the sources. Study I showed that the higher curiosity factor score was associated with faster reading of high-quality information, whereas Study II indicated more careful reading with state curiosity. In Study I, curiosity factor scores were non-linearly related to valence so that both ends of the valence-scale, that is, unpleasant and pleasant, were related to higher curiosity factor scores. As the curiosity factor score includes both dimensions of interest/deprivation trait curiosity (Litman,

2008), this feature could relate to the unpleasant feelings related to the coercing need to solve an issue (deprivation curiosity) and to the joy of finding information (interest curiosity) (Litman, 2005; Litman, 2008). Thus, the reading speed in Study I may be affected by the deprivation dimension of curiosity leading to faster information intake due to the need to solve the issue quickly. It is also possible that the interest dimension of curiosity directs the reader to encounter as much information as possible, leading to faster reading. Latent curiosity factor included also positive attitudes towards science, science curiosity, and need for cognition, which all indicate positive approach towards scientific information even when it can be complex and sometimes inconsistent. Thus, these features indicate a straightforward approach towards science-related information. Overall, the curiosity factor suggests a tendency to consume information more quickly.

Moreover, Study I showed an association between higher curiosity factor score with greater emotional arousal, possibly indicating increased vigilance. Similar results were found also for pro-sociality. Emotional arousal is linked to increased attention (Zsidó, 2024), thus linking curiosity and pro-sociality to focused attention, possibly reflecting the lure of the information.

Study II showed that SR statements received the greatest attentional investments, indicated by longest total fixation durations. Epistemic state curiosity was related to more careful reading indicated by lower word skipping rates and longer total fixation duration on words. Moreover, state curiosity interacted with statement quality. The effect of state curiosity on total fixation duration was stronger for the SI and NR statements than for the SR statements. The rating results showed differences in state curiosity between the statement quality categories so that participants rated curiosity the highest for SR statements, then SI statements, and the lowest for NR statements. This may indicate that the level of state curiosity was already high for the SR statements. Thus, the increase in curiosity had a stronger effect on total fixation duration for the SI and SR statements. In line with prior studies (Chevrier et al., 2019; Metcalfe et al., 2021), the results of Study II suggest that epistemic state curiosity is related to greater engagement with information as indicated by more careful reading.

The results of Studies I and II suggest that when it comes to reading, epistemic state and trait curiosity may be associated in a different manner. Epistemic state curiosity was related to stronger engagement with the text indicated by increase in total fixation duration, whereas latent curiosity factor including epistemic trait curiosity measures was associated with shorter reading times of the high-quality information. The text lengths also varied between the tasks, so that Study I had longer texts in relation to Study II, thus in addition to possible differences related to state and trait dimensions the results may indicate differences in reading strategies related to text types.

## 5.3 Frontal alpha reflects epistemic state curiosity

Previous research has linked state curiosity and brain activity in frontal areas with reward processing and metacognition.

Epistemic state curiosity is positively associated with the reward value of information (Rüterbories et al., 2024) and previous fMRI results have indicated that activity in frontal areas is related to the subjective value of information (Juechems et al., 2019; Kobayashi et al., 2021; Shapiro & Grafton, 2020). Moreover, greater usefulness of information is related to increased curiosity (Dubey et al., 2022). The results of Study II indicate that participants were able to recognize SR statements as the most valuable source of information, as in addition to rating them as most useful, they read these statements most often and exploited this source category the most. Furthermore, SR statements received the highest state curiosity ratings. Study III shows a decrease in frontal alpha power associated with an increase in epistemic state curiosity, possibly indicating active processing of information that is considered valuable.

Epistemic state curiosity is related to metacognitive self-regulation (Chevrier et al., 2019; Goupil & Proust, 2023; Pekrun et al., 2017), the ability to recognize one's knowledge and use that understanding to guide further information-seeking and usage. Neuroimaging studies using fMRI have localized metacognitive processing mostly to frontal cortex, but also to temporal/parietal areas (Fleur et al., 2021; Vaccaro & Fleming, 2018). During perceptual and value-based decision-making tasks metacognitive processing is associated specifically with the right PFC (Vaccaro & Fleming, 2018), similar to the location of our frontal cluster. Furthermore, metacognitive processing, as metacognitive control of decision adjustment and metacognitive monitoring of decision uncertainty, is associated with activity in the frontal cortex when re-evaluating decisions (Qiu et al., 2018). This suggests that frontal cortex is related to metacognitive processing of estimating the certainty of knowledge and the need to adjust it. Study III showed that higher state curiosity was related to a decrease in frontal alpha power which is previously shown to indicate stronger cognitive engagement (Kielar et al., 2015) and higher cognitive load (Chikhi et al., 2022). Together, these prior and new results suggest that frontal alpha power after reading indicates stronger cognitive engagement as metacognitive processing that is enhanced by an increase in epistemic state curiosity.

With this paradigm, it is unfeasible to distinguish whether our EEG results are related to reward value or metacognition. However, it is possible that the decrease in frontal alpha power related to an increase in epistemic state curiosity reflects both. The enhanced reward value may promote further metacognitive processing for the related information.

## 5.4 Trait curiosity and revisiting the topics

Studies II and III also investigated whether participants revisited the topics introduced in the multi-armed bandit task. Revisiting was defined as thinking about and searching for more information about the topics after the laboratory session. Previous research has indicated that higher deprivation sensitivity is related to revisiting prior concepts and creating concise and thorough information networks (Lydon-Staley et al., 2021). Furthermore, deprivation sensitivity and joyous exploration are positively associated with the frequency of finding information in real-life (Eschmann et al., 2023).

Study II investigated whether revisiting the topics after the laboratory session was predicted by state and trait curiosity, topic familiarity, and number of statements read per topic during the task in laboratory. In line with prior findings (Lydon-Staley et al., 2021), thinking about the topics was positively related to joyous exploration and deprivation sensitivity and negatively to thrill seeking.

Interestingly, Study III showed that a decrease in parietal alpha power was related to searching for more information about the topics and to an increase in deprivation sensitivity. As the decrease in alpha power is considered to reflect greater engagement with information content (Kielar et al., 2015), searching for more information is likely related to stronger engagement during the task. Similarly, higher deprivation sensitivity may be associated with stronger cognitive engagement with statement content. Previous research has made a distinction between curiosity- and interest-based information-seeking; information-seeking that ends when an answer is found represents curiosity, while prolonged information-seeking represents interest (Hidi & Renninger, 2019). Thus, a decrease in parietal alpha power may represent growing interest in the topic indicated as searching for more information afterwards. Stronger deprivation sensitivity was related to a decrease in both parietal and frontal alpha power suggesting a tendency to engage with information.

Prolonged cognitive engagement was reflected in revisiting the topics introduced in Studies II and III. Study II showed that trait curiosity was related to thinking about the topics so that deprivation sensitivity and joyous exploration increased and thrill-seeking decreased thinking about the topics. Study III indicated that both increased deprivation sensitivity and searching for more information were associated with a decrease in parietal alpha power, suggesting stronger engagement in processing the information. The parietal cortex has been shown to have an important role when performing a task simultaneously combining attentional and semantic memory, that is, long-term memory with semantic information demands (Capotosto et al., 2023). Furthermore, parietal activity has been linked to working memory (Champod & Petrides, 2010; Lee et al., 2022), a short-term memory storage limited in capacity. Thus, parietal alpha may also indicate stronger cognitive engagement during the task and thus explain revisiting

to search for more information. Higher deprivation sensitivity was related to a decrease in alpha power both at frontal and parietal clusters, possibly enhancing processing of epistemic information in general.

Together, these results suggest that trait curiosity, specifically deprivation sensitivity, is related to prolonged engagement with the task topics. The prolonged engagement may indicate sustained state curiosity (rather than interest) as the version of multi-armed bandit task used here did not reveal the correct answers on the topics. Alternatively, continuous information search was a built-in feature of our task, which might have induced interest in the topics. It is suggested that curiosity would be a special case of interest, and the important distinction would be state vs. trait instead of curiosity vs. interest (Pekrun, 2019). Our results indicate that trait curiosity is reflected in oscillatory activity together with either state curiosity or prolonged information engagement depending on the brain area.

## 5.5 Methodological approaches

Together, these studies combined different approaches to curiosity research. In addition to state and trait curiosity, we approached curiosity as a latent construct formed from various curiosity related psychological traits and thinking styles. We included different methods, i.e., exploratory factor analysis, eye movements, and EEG, which have been rarely used in curiosity research. Furthermore, we utilized two tasks that were designed to resemble information-seeking in real-life decision-making. The shared characteristic of the tasks was participants' ability to decide how deeply they wanted to engage with the information content. In the evidence-based decision-making task, participants could decide how carefully they read the information presented to them. In the multi-armed bandit task, participants could choose both the source and number of statements they read.

Previously, exploratory factor analysis has been used to form latent factors based on multiple psychological traits and these latent factors were used to predict behavioral outcomes (Eisenberg et al., 2019; Zmigrod et al., 2021). A similar approach has been used to study curiosity, but the latent factors were built from behavioral tasks, and these factors were predicted by trait curiosity dimensions (Jach et al., 2024). Study I applied the approach and showed that latent curiosity factor predicted reading behavior and emotional responses in the evidence-based decision-making task utilizing real-life text stimuli.

Studies II and III included curiosity both as state and trait curiosity. In curiosity research, often only state (Gruber et al., 2014; Kang et al., 2009; Lau et al., 2020; Marvin & Shohamy, 2016; Metcalfe et al., 2021) or trait (Eschmann et al., 2023; Lydon-Staley et al., 2021; Schumacher et al., 2025) curiosity is included. Our approach allowed us to assess curiosity both as context-dependent and as a permanent tendency simultaneously. By including both state and trait curiosity can

reveal possible interactions and differences between these measures, like indicated by Schumacher et al. (2026). Similarly to prior studies, we used curiosity in predicting behavioral and physiological outcomes.

In Studies II and III, we utilized the multi-armed bandit task, where participants could choose the number and source of statements they read. Even though participants were encouraged to seek information to decide their stance on a topic, they were also informed that they could read as many or few statements they wanted. This freedom was incorporated as we wanted to allow participants' inner states to have an influence on the number and source of information they read. A similar idea has been used in curiosity study, where participants could decide either to receive hints to solve an issue by themselves or to receive the answer directly (Metcalfe et al., 2021). Typically, in epistemic curiosity studies, participants are asked whether they feel curious about the answer (Brod & Breitwieser, 2019; Gruber et al., 2014; Jepma et al., 2012; Kang et al., 2009; Lau et al., 2020; Ligneul et al., 2018; Rüterbories et al., 2024); however, we asked whether the information piqued their curiosity. In Studies II and III, we did not inform the participants about the right answers as we did not want to interfere with their information-seeking behavior. This prevents us from comparing our curiosity results directly with prior studies. Nonetheless, in the context of evidence-based decision-making, this approach is more realistic as the participants must defer the weight of the evidence by themselves. The same idea of weighing the evidence by a participant was implemented in the evidence-based decision-making task in Study I.

In addition to using a novel task to investigate curiosity, Studies II and III employed methods rarely used in curiosity research. Prior research has indicated that anticipatory saccades towards the answer are related to epistemic curiosity (Baranes et al., 2015). Our focus was on investigating whether eye movements during reading were related to information quality and curiosity. The results of Study II indicate that curiosity is related to eye movement patterns when acquiring information opening new venues for including curiosity in reading and information evaluation research.

The number of EEG studies on curiosity is even scarcer than those investigating eye movements. In Study III, we investigated whether oscillation amplitudes after reading are associated with information quality and curiosity. We chose to investigate the time after reading, as curiosity has been associated with better learning (Chevrier et al., 2019; Gruber et al., 2014; Metcalfe et al., 2020) and memory (Brod & Breitwieser, 2019; Gruber et al., 2014; Kang et al., 2009; Rüterbories et al., 2024), suggesting a prolonged processing for the information content. The results of Study III indicate that epistemic curiosity, as state curiosity and trait deprivation sensitivity, is reflected in alpha oscillations after reading. Thus, further research of curiosity in neural oscillations may unravel how curiosity relates to epistemic information processing.

Together, the results from all three studies suggest that curiosity can and should be investigated with different methods and curiosity measures. Our results indicate that despite the measure of curiosity being used (latent factor, state curiosity, or trait curiosity) curiosity was beneficial for estimating the information quality and engaging with the content. Latent curiosity factor scores provide an overall view to curiosity and using the dimensions of trait curiosity instead capture finer details in relation to curiosity as a broader tendency. State curiosity seems to reach differences in the immediate effects of curiosity, that is during the task. Whereas trait curiosity could be better suited for estimating long-lasting effects of curiosity. A similar idea has been presented previously, where state vs trait has been proposed as a more suitable approach than the curiosity vs interest separation (Pekrun, 2019).

Often in curiosity research, participants are provided with clear information gaps that can be filled during the task. In those tasks, the information itself is the prize and has no instrumental value for the task. Both tasks utilized in our studies incorporated complex topics that required conjoining multiple pieces of information, thus the information had instrumental value for the task. This approach has a different view to interconnections between curiosity and information as curiosity is traditionally studied in relation to anticipating the information, but our focus was on curiosity in relation to information being already held. Regarding the nature of our tasks, our results show that curiosity relates to information processing and engagement when there is no clear answer available. This highlights the role of curiosity in evaluating and processing information while making evidence-based decisions in real-life.

## 5.6 Limitations

The two experimental paradigms included in this doctoral study had a realistic-like setup. Although, they had a crucial difference that has not been discussed earlier and may affect the comparison of the results. In Study I, the evidence-based decision-making task was implemented on an online platform, whereas in Study II (and III) the multi-armed bandit task took place in laboratory surroundings. This difference might influence reading and task behavior. Even though participants were aware of participating in a scientific study in both cases, the laboratory environment might have affected their behavior more as the feeling of being observed can be stronger. This might have guided participants to put emphasis on reading the stimuli more carefully in Study II.

We decided to measure state curiosity using a single item. Especially in the multi-armed bandit task participants performed multiple ratings repeatedly. Therefore, we limited the number of ratings to take into account participants' resources. Nevertheless, including a multi-item state curiosity measure (e.g.,

Pekrun et al., 2017; Schmidt & Rotgans, 2021) could have improved the reliability of our results. Further studies investigating state curiosity as one of the key concepts are encouraged to consider including a multi-item measure of state curiosity.

Previous studies using bandit paradigms have shown that the amount of available information is related to information seeking behavior so that exploration is more likely to happen with greater amount of available information (Brown et al., 2022; Wilson et al., 2014) and towards information sources with unknown contents (Hogeveen et al., 2022). In our version of the multi-armed bandit task, the number of statements per topic was limited to 15, possibly affecting information gathering in our participants. Furthermore, people are fast at learning the value of information (Wilson et al., 2014) and in our version of the task, there was no variability in the value of the statements within each information quality category. Together, these might have limited participants' willingness to seek further information.

The studies included in this dissertation were based on data collected from highly educated participants. This type of bias in the sample is common in experimental studies, and it may also bias the results. Additionally, participants in this study had the physical features that are expected as a norm in these types of experiments. Nevertheless, it is important to acknowledge that the design of equipment and software, such as EEG caps, eye tracking equipment, and algorithms, are designed for western features. These caps have been criticized for being ill-fitting (Choy et al., 2022; Mlandu et al., 2024) and the eye tracking software has been shown to have difficulties in recognizing pupils in a wider variety of eye shapes than considered typically western, further causing a bias towards educated, western participants.

These studies were carried out in Finland, which is a northern welfare country that has provided free nine-year-long compulsory education for all children since the 1970's. Currently free education is provided for all underaged people in all social classes. People in general are literate (OECD, 2024), and science is perceived positively in Finnish society (Eurobarometer, 2021). Furthermore, social context has an influence on experienced curiosity (Dubey et al., 2021; Kim et al., 2025; Swirsky & Spaniol, 2024) and as participants voluntarily participated in scientific research, the results may have a bias towards favoring scientific information. These results may therefore reflect the effects of social structures that have supported both curiosity and academic skills.

The studies included in this doctoral dissertation provide important additions to current literature and motivate further research to consider social factors to investigate whether the same connections apply to various populations.

## 5.7 Recapitulation

The overall aim of this doctoral dissertation was to investigate how curiosity affects information evaluation in adults. Collectively, Studies I, II, and III indicate that curiosity is related to allocation of cognitive resources. This was indexed by enhanced emotional arousal and faster reading (Study I), more careful reading indicated by lower skipping rates and longer total fixation durations measured as eye movements during reading (Study II), as well as decreases in alpha oscillation power after reading (Study III).

This work extends prior curiosity studies in four following ways. First, curiosity was related to information having instrumental value for making decisions on complex topics. Thus, curiosity is not only related to anecdotal information, but to building a more comprehensive understanding. Second, curiosity and information quality showed interactions with each other. Study I indicated that increases in curiosity factor scores were related to faster reading. This effect was greater for personal than authority sources, and reading speed of non-credible sources was least affected by curiosity factor scores. Study II showed that statements were read more carefully with increasing state curiosity, with the slightest effect on SR statements. Thus, information quality is an important factor when estimating the effects of curiosity on reading behavior. Additionally, the choice of text type and curiosity measure can affect the direction of the associations between reading behavior and curiosity. Third, curiosity is not only relevant while interacting with the information but also to cognitive processing of the information after reading. This was shown by associations between epistemic state and trait curiosity with cortical alpha power after reading. Fourth, the results were acquired while participants were doing decision-making tasks with instrumental value toward a realistic goal. Participants could decide how carefully to read and/or how much information they acquired. Thus, the results reflect curiosity in relatively natural situations.

Together, these findings highlight the robustness of associations between curiosity, instrumental information, and allocation of cognitive resources. These findings motivate future studies to investigate curiosity while making evidence-based decisions. The studies should include multiple measures for curiosity but also to extend methodologies to eye tracking, EEG, and robust analytical methods that allow for complex modeling. It is worth investigating further whether and how curiosity affects information processing and evaluation in realistic decision-making.

These findings suggest that curiosity may help to direct cognitive resources when evaluating information having potential instrumental value.

# 6 Conclusions

This work highlights the importance of curiosity on information-seeking, evaluation, and processing. Here, curiosity was associated with the intensity and valence of emotional responses while reading information. Furthermore, curiosity was related to engagement with information reflected as more careful reading, revisiting the topics on participants' own time, and neuronal oscillations indicating engagement in processing. Thus, curiosity had broad and long-lasting associations with information evaluation and engagement. Curiosity was investigated as a broad latent construct and as state and trait curiosity. By using a broad set of methods, this work shows robustly that curiosity is an important factor in epistemic environments and further in evidence-based decision-making. This work provides novel inputs to curiosity research by using experiments resembling real-life situations. Furthermore, together the studies show that curiosity can and should be studied at different levels, that is, as a broad latent construct and as state and trait level. The results are complementary to each other and highlight the benefits of curiosity on information processing and evaluation.

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# References


Adrian, J. A., Siddharth, S., Baquar, S. Z. A., Jung, T.-P., & Deák, G. (2019). Decision-making in a social multi-armed bandit task: Behavior, electrophysiology and pupillometry. *arXiv preprint arXiv:1905.07474*. https://doi.org/10.48550/arXiv.1905.07474

Andrews, E. A., Walter, N., & Atad, E. (2025). Should we retire the concept of source credibility? An experimental exploration of when credibility is (and is not) useful. *Science Communication*, 10755470251334094. https://doi.org/10.1177/10755470251334094

Appriou, A., Ceha, J., Pramij, S., Dutartre, D., Law, E., Oudeyer, P.-Y., & Lotte, F. (2020). Towards measuring states of epistemic curiosity through electroencephalographic signals. 2020 ieee international conference on systems, man, and cybernetics (smc),

Archer, L., Dawson, E., DeWitt, J., Seakins, A., & Wong, B. (2015). "Science capital": A conceptual, methodological, and empirical argument for extending bourdieusian notions of capital beyond the arts. *Journal of Research in Science Teaching*, *52*(7), 922-948. https://doi.org/10.1002/tea.21227

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., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of statistical software*, *67*, 1-48. https://doi.org/10.18637/jss.v067.i01

Berlyne, D. E. (1954). A theory of human curiosity. *British journal of Psychology*, *45*(3).

Bolker, B. M., Brooks, M. E., Clark, C. J., Geange, S. W., Poulsen, J. R., Stevens, M. H. H., & White, J.-S. S. (2009). Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in ecology & evolution*, *24*(3), 127-135. https://doi.org/10.1016/j.tree.2008.10.008

Brod, G., & Breitwieser, J. (2019). Lighting the wick in the candle of learning: generating a prediction stimulates curiosity. *NPJ science of learning*, *4*(1), 17. https://doi.org/10.1038/s41539-019-0056-y

Brown, V. M., Hallquist, M. N., Frank, M. J., & Dombrovski, A. Y. (2022). Humans adaptively resolve the explore-exploit dilemma under cognitive constraints: Evidence from a multi-armed bandit task. *Cognition*, *229*, 105233. https://doi.org/10.1016/j.cognition.2022.105233

Bråten, I., Strømsø, H. I., & Salmerón, L. (2011). Trust and mistrust when students read multiple information sources about climate change. *Learning and instruction*, *21*(2), 180-192. https://doi.org/10.1016/j.learninstruc.2010.02.002

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological bulletin*, *119*(2), 197. https://doi.org/10.1037/0033-2909.119.2.197

Cacioppo, J. T., Petty, R. E., & Feng Kao, C. (1984). The efficient assessment of need for cognition. *Journal of personality assessment*, *48*(3), 306-307. https://doi.org/10.1207/s15327752jpa4803_13

Capotosto, P., Sulpizio, V., Galati, G., & Baldassarre, A. (2023). Visuo-spatial attention and semantic memory competition in the parietal cortex. *Scientific Reports*, *13*(1), 6218. https://doi.org/10.1038/s41598-023-33533-0

Champod, A. S., & Petrides, M. (2010). Dissociation within the frontoparietal network in verbal working memory: a parametric functional magnetic resonance imaging study. *Journal of Neuroscience*, *30*(10), 3849-3856. https://doi.org/10.1523/JNEUROSCI.0097-10.2010

Chen, X., Twomey, K. E., Hayes, M., & Westermann, G. (2025). The limits of curiosity? New evidence for the roles of metacognitive abilities and curiosity in learning. *Metacognition and Learning*, *20*(1), 1. https://doi.org/10.1007/s11409-024-09407-9

Chevrier, M., Muis, K. R., Trevors, G. J., Pekrun, R., & Sinatra, G. M. (2019). Exploring the antecedents and consequences of epistemic emotions. *Learning and instruction*, *63*, 101209. https://doi.org/10.1016/j.learninstruc.2019.05.006

Chikhi, S., Matton, N., & Blanchet, S. (2022). EEG power spectral measures of cognitive workload: A meta-analysis. *Psychophysiology*, *59*(6), e14009. https://doi.org/10.1111/psyp.14009

Choy, T., Baker, E., & Stavropoulos, K. (2022). Systemic racism in EEG research: considerations and potential solutions. *Affective science*, *3*(1), 14-20. https://doi.org/10.1007/s42761-021-00050-0

Cohen, J. D., McClure, S. M., & Yu, A. J. (2007). Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1481), 933-942. https://doi.org/10.1098/rstb.2007.2098

Cortes, P. M., García-Hernández, J. P., Iribe-Burgos, F. A., Hernández-González, M., Sotelo-Tapia, C., & Guevara, M. A. (2021). Temporal division of the decision-making process: An EEG study. *Brain Research*, *1769*, 147592. https://doi.org/10.1016/j.brainres.2021.147592

Criado-Perez, C., Jackson, C., Minbashian, A., & Collins, C. G. (2024). Cognitive reflection and decision-making accuracy: Examining their relation and boundary conditions in the context of evidence-based management. *Journal of Business and Psychology*, *39*(1), 249-273. https://doi.org/10.1007/s10869-023-09883-x

Davis, C. E., Hauf, J. D., Wu, D. Q., & Everhart, D. E. (2011). Brain function with complex decision making using electroencephalography. *International journal of psychophysiology*, *79*(2), 175-183. https://doi.org/10.1016/j.ijpsycho.2010.10.004

Del Missier, F., Mäntylä, T., & Bruine de Bruin, W. (2010). Executive functions in decision making: An individual differences approach. *Thinking & Reasoning*, *16*(2), 69-97. https://doi.org/10.1080/13546781003630117

Dixon, M. L., & Christoff, K. (2014). The lateral prefrontal cortex and complex value-based learning and decision making. *Neuroscience & Biobehavioral Reviews*, *45*, 9-18. https://doi.org/10.1016/j.neubiorev.2014.04.011

Drieghe, D., Brysbaert, M., Desmet, T., & De Baecke, C. (2004). Word skipping in reading: On the interplay of linguistic and visual factors. *European Journal of Cognitive Psychology*, *16*(1-2), 79-103. https://doi.org/10.1080/09541440340000141

Dubey, R., Griffiths, T. L., & Lombrozo, T. (2022). If it's important, then I'm curious: Increasing perceived usefulness stimulates curiosity. *Cognition*, *226*, 105193. https://doi.org/10.1016/j.cognition.2022.105193

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

Eisenberg, I. W., Bissett, P. G., Zeynep Enkavi, A., Li, J., MacKinnon, D. P., Marsch, L. A., & Poldrack, R. A. (2019). Uncovering the structure of self-regulation through data-driven ontology discovery. *Nature communications*, *10*(1), 2319. https://doi.org/10.1038/s41467-019-10301-1

ElShafei, H. A., Zhou, Y. J., & Haegens, S. (2022). Shaping information processing: The role of oscillatory dynamics in a working memory task. *Eneuro*, *9*(5). https://doi.org/10.1523/ENEURO.0489-21.2022

Eschmann, K. C., Pereira, D. F., Valji, A., Dehmelt, V., & Gruber, M. J. (2023). Curiosity and mesolimbic functional connectivity drive information seeking in real life. *Social Cognitive and Affective Neuroscience*, *18*(1), nsac050. https://doi.org/10.1093/scan/nsac050

Eurobarometer, S. (2021). European citizens' knowledge and attitudes towards science and technology. *Eurobarometer. Accessed November*, *4*, 2021.

Faize, F. A., Husain, W., & Nisar, F. (2017). A critical review of scientific argumentation in science education. *Eurasia Journal of Mathematics, Science and Technology Education*, *14*(1), 475-483. https://doi.org/10.12973/ejmste/80353

Fiedler, D., Sbeglia, G. C., Nehm, R. H., & Harms, U. (2019). How strongly does statistical reasoning influence knowledge and acceptance of evolution? *Journal of Research in Science Teaching*, *56*(9), 1183-1206. https://doi.org/10.1002/tea.21547

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

Fleur, D. S., Bredeweg, B., & van den Bos, W. (2021). Metacognition: ideas and insights from neuro-and educational sciences. *NPJ science of learning*, *6*(1), 13. https://doi.org/10.1038/s41539-021-00089-5

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, *19*(4), 25-42. https://doi.org/10.1257/089533005775196732

Frömer, R., Maier, M., & Abdel Rahman, R. (2018). Group-level EEG-processing pipeline for flexible single trial-based analyses including linear mixed models. *Frontiers in neuroscience*, *12*, 48. https://doi.org/10.3389/fnins.2018.00048

Gosling, S. D., Rentfrow, P. J., & Swann Jr, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in personality*, *37*(6), 504-528. https://doi.org/10.1016/S0092-6566(03)00046-1

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. (2023). Curiosity as a metacognitive feeling. *Cognition*, *231*, 105325. https://doi.org/10.1016/j.cognition.2022.105325

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

Guilford, J. P. (1967). The nature of human intelligence.

Haran, U., Ritov, I., & Mellers, B. A. (2013). The role of actively open-minded thinking in information acquisition, accuracy, and calibration. *Judgment and Decision making*, *8*(3), 188-201. https://doi.org/10.1017/S1930297500005921

Harris, A., & Hutcherson, C. A. (2022). Temporal dynamics of decision making: A synthesis of computational and neurophysiological approaches. *Wiley Interdisciplinary Reviews: Cognitive Science*, *13*(3), e1586. https://doi.org/10.1002/wcs.1586

Hidi, S. E., & Renninger, K. A. (2019). Interest development and its relation to curiosity: Needed neuroscientific research. *Educational Psychology Review*, *31*(4), 833-852. https://doi.org/10.1007/s10648-019-09491-3

Hoeken, H., Fikkers, K., Eerland, A., Holleman, B., van Berkum, J., & Pander Maat, H. (2022). The Perceived Convincingness Model: why and under what conditions processing fluency and emotions are valid indicators of a message's perceived convincingness. *Communication Theory*, *32*(4), 488-496. https://doi.org/10.1093/ct/qtac019

Hoffman, J. E., & Subramaniam, B. (1995). The role of visual attention in saccadic eye movements. *Perception & psychophysics*, *57*(6), 787-795. https://doi.org/10.3758/BF03206794

Hogeveen, J., Mullins, T. S., Romero, J. D., Eversole, E., Rogge-Obando, K., Mayer, A. R., & Costa, V. D. (2022). The neurocomputational bases of explore-exploit decision-making. *Neuron*, *110*(11), 1869-1879. e1865. https://doi.org/10.1016/j.neuron.2022.03.014

Huang, G., & Zhang, Z. (2017). Improving sensitivity of cluster-based permutation test for EEG/MEG data. 2017 8th International IEEE/EMBS Conference on Neural Engineering (NER),

Ilić, S., & Damnjanović, K. (2021). The effect of source credibility on bullshit receptivity. *Applied Cognitive Psychology*, *35*(5), 1193-1205. https://doi.org/10.1002/acp.3852

Jach, H. K., Cools, R., Frisvold, A., Grubb, M. A., Hartley, C. A., Hartmann, J., Hunter, L., Jia, R., de Lange, F. P., & Larisch, R. (2024). Individual differences in information demand have a low dimensional structure predicted by some curiosity traits. *Proceedings of the National Academy of Sciences*, *121*(45), e2415236121. https://doi.org/10.1073/pnas.2415236121

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in human neuroscience*, *4*, 186. https://doi.org/10.3389/fnhum.2010.00186

Jepma, M., Verdonschot, R. G., Van Steenbergen, H., Rombouts, S. A., & 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

Juechems, K., Balaguer, J., Castañón, S. H., Ruz, M., O'Reilly, J. X., & Summerfield, C. (2019). A network for computing value equilibrium in the human medial prefrontal cortex. *Neuron*, *101*(5), 977-987. e973. https://doi.org/10.1016/j.neuron.2018.12.029

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T.-y., & 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

Kashdan, T. B., Disabato, D. J., Goodman, F. R., & McKnight, P. E. (2020). The Five-Dimensional Curiosity Scale Revised (5DCR): Briefer subscales while separating overt and covert social curiosity. *Personality and individual differences*, *157*, 109836. https://doi.org/10.1016/j.paid.2020.109836

Kielar, A., Panamsky, L., Links, K. A., & Meltzer, J. A. (2015). Localization of electrophysiological responses to semantic and syntactic anomalies in language comprehension with MEG. *NeuroImage*, *105*, 507-524. https://doi.org/10.1016/j.neuroimage.2014.11.016

Kiili, C., Laurinen, L., & Marttunen, M. (2008). Students evaluating Internet sources: From versatile evaluators to uncritical readers. *Journal of Educational Computing Research*, *39*(1), 75-95. https://doi.org/10.2190/EC.39.1.e

Kim, S., Harris, P. L., & Néher, B. (2025). Curiosity can influence metacognitive processes. *Metacognition and Learning*, *20*(1), 1-22. https://doi.org/10.1007/s11409-025-09444-y

Klimesch, W. (2012). Alpha-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

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., Lee, S., Filipowicz, A. L., McGaughey, K. D., Kable, J. W., & Nassar, M. R. (2021). Dynamic representation of the subjective value of information. *Journal of Neuroscience*, *41*(39), 8220-8232. https://doi.org/10.1523/JNEUROSCI.0423-21.2021

Krumrei-Mancuso, E. J., & Rouse, S. V. (2016). The development and validation of the comprehensive intellectual humility scale. *Journal of personality assessment*, *98*(2), 209-221. https://doi.org/10.1080/00223891.2015.1068174

Landrum, A., Hilgard, J., Akin, H., Li, N., & Kahan, D. M. (2016). Measuring interest in science: The science curiosity scale. Proceedings of the Annual Meeting of the Cognitive Science Society,

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2005). *International affective picture system (IAPS): Affective ratings of pictures and instruction*

*manual*. NIMH, Center for the Study of Emotion & Attention Gainesville, FL.

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*(5), 531-543. https://doi.org/10.1038/s41562-020-0848-3

Leary, M. R., Diebels, K. J., Davisson, E. K., Jongman-Sereno, K. P., Isherwood, J. C., Raimi, K. T., Deffler, S. A., & Hoyle, R. H. (2017). Cognitive and interpersonal features of intellectual humility. *Personality and Social Psychology Bulletin*, *43*(6), 793-813. https://doi.org/10.1177/0146167217697695

Lee, B., Kim, J. S., & Chung, C. K. (2022). Parietal and medial temporal lobe interactions in working memory goal-directed behavior. *Cortex*, *150*, 126-136. https://doi.org/10.1016/j.cortex.2022.02.005

Lee, W., & Reeve, J. (2017). Identifying the neural substrates of intrinsic motivation during task performance. *Cognitive, Affective, & Behavioral Neuroscience*, *17*, 939-953. https://doi.org/10.3758/s13415-017-0524-x

Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. *Annual review of psychology*, *66*(1), 799-823. https://doi.org/10.1146/annurev-psych-010213-115043

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

Lima, G., & Rocha, F. (2019). Curiosity, frontal EEG asymmetry, and learning. Proceedings of the Annual Meeting of the Cognitive Science Society,

Litman, J. (2005). Curiosity and the pleasures of learning: Wanting and liking new information. *Cognition and Emotion*, *19*(6), 793-814. https://doi.org/10.1080/02699930541000101

Litman, J., Hutchins, T., & Russon, R. (2005). Epistemic curiosity, feeling-of-knowing, and exploratory behaviour. *Cognition & Emotion*, *19*(4), 559-582. https://doi.org/10.1080/02699930441000427

Litman, J. A. (2008). Interest and deprivation factors of epistemic curiosity. *Personality and individual differences*, *44*(7), 1585-1595. https://doi.org/10.1016/j.paid.2008.01.014

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

Liversedge, S. P., & Findlay, J. M. (2000). Saccadic eye movements and cognition. *Trends in cognitive sciences*, *4*(1), 6-14. https://doi.org/10.1016/S1364-6613(99)01418-7

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological bulletin*, *116*(1), 75.

Lowry, M., Trivedi, N., Boyd, P., Julian, A., Treviño, M., Lama, Y., Heley, K., & Perna, F. (2022). Making decisions about health information on social media: a mouse-tracking study. *Cognitive Research: Principles and Implications*, *7*(1), 68. https://doi.org/10.1186/s41235-022-00414-5

Lydon-Staley, D. M., Zhou, D., Blevins, A. S., Zurn, P., & Bassett, D. S. (2021). Hunters, busybodies and the knowledge network building associated with

deprivation curiosity. *Nature Human Behaviour*, *5*(3), 327-336. https://doi.org/10.1038/s41562-020-00985-7

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG-and MEG-data. *Journal of neuroscience methods*, *164*(1), 177-190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Marvin, C. B., & Shohamy, D. (2016). Curiosity and reward: Valence predicts choice and information prediction errors enhance learning. *Journal of experimental psychology: General*, *145*(3), 266. https://doi.org/10.1037/xge0000140

Mehlhorn, K., Newell, B. R., Todd, P. M., Lee, M. D., Morgan, K., Braithwaite, V. A., Hausmann, D., Fiedler, K., & Gonzalez, C. (2015). Unpacking the exploration–exploitation tradeoff: a synthesis of human and animal literatures. *Decision*, *2*(3), 191. https://doi.org/10.1037/dec0000033

Metcalfe, J., Kennedy-Pyers, T., & Vuorre, M. (2021). Curiosity and the desire for agency: wait, wait… don't tell me! *Cognitive Research: Principles and Implications*, *6*, 1-8. https://doi.org/10.1186/s41235-021-00330-0

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

Metcalfe, J., Vuorre, M., Towner, E., & Eich, T. S. (2023). Curiosity: The effects of feedback and confidence on the desire to know. *Journal of experimental psychology: General*, *152*(2), 464. https://doi.org/10.1037/xge0001284

Michal, A. L., Zhong, Y., & Shah, P. (2021). When and why do people act on flawed science? Effects of anecdotes and prior beliefs on evidence-based decision-making. *Cognitive Research: Principles and Implications*, *6*(1), 28. https://doi.org/10.1186/s41235-021-00293-2

Mlandu, N., McCormick, S. A., Davel, L., Zieff, M. R., Bradford, L., Herr, D., Jacobs, C. A., Khumalo, A., Knipe, C., & Madi, Z. (2024). Evaluating a novel high-density EEG sensor net structure for improving inclusivity in infants with curly or tightly coiled hair. *Developmental Cognitive Neuroscience*, *67*, 101396. https://doi.org/10.1016/j.dcn.2024.101396

Morsanyi, K., Primi, C., Chiesi, F., & Handley, S. (2009). The effects and side-effects of statistics education: Psychology students'(mis-) conceptions of probability. *Contemporary Educational Psychology*, *34*(3), 210-220. https://doi.org/10.1016/j.cedpsych.2009.05.001

Motta, M., Chapman, D., Haglin, K., & Kahan, D. (2021). Reducing the administrative demands of the science curiosity scale: a validation study. *International Journal of Public Opinion Research*, *33*(2), 215-233. https://doi.org/10.1093/ijpor/edz049

Muis, K. R., Pekrun, R., Sinatra, G. M., Azevedo, R., Trevors, G., Meier, E., & Heddy, B. C. (2015). The curious case of climate change: Testing a theoretical model of epistemic beliefs, epistemic emotions, and complex learning. *Learning and instruction*, *39*, 168-183. https://doi.org/10.1016/j.learninstruc.2015.06.003

Murayama, K. (2022). A reward-learning framework of knowledge acquisition: An integrated account of curiosity, interest, and intrinsic–extrinsic rewards. *Psychological Review*, *129*(1), 175. https://doi.org/10.1037/rev0000349

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

Nadelson, L., Jorcyk, C., Yang, D., Jarratt Smith, M., Matson, S., Cornell, K., & Husting, V. (2014). I just don't trust them: the development and validation of an assessment instrument to measure trust in science and scientists. *School science and mathematics*, *114*(2), 76-86. https://doi.org/10.1111/ssm.12051

Navon, D. (1981). The forest revisited: More on global precedence. *Psychological Research*, *43*(1), 1-32. https://doi.org/10.1007/BF00309635

Necker, L. A. (1832). LXI. Observations on some remarkable optical phænomena seen in Switzerland; and on an optical phænomenon which occurs on viewing a figure of a crystal or geometrical solid. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *1*(5), 329-337. https://doi.org/10.1080/14786443208647909

OECD. (2024). Do adults have the skills they need to thrive in a changing world?: Survey of adult skills 2023, OECD skills studies. In: OECD Publishing Paris.

Pekrun, R. (2019). The murky distinction between curiosity and interest: State of the art and future prospects. *Educational Psychology Review*, *31*(4), 905-914. https://doi.org/10.1007/s10648-019-09512-1

Pekrun, R., Vogl, E., Muis, K. R., & Sinatra, G. M. (2017). Measuring emotions during epistemic activities: The epistemically-related emotion scales. *Cognition and Emotion*, *31*(6), 1268-1276. https://doi.org/10.1080/02699931.2016.1204989

Prasad, S., & Beste, C. (2025). Distinct roles of alpha and theta oscillations in information-seeking in cognitive control. *Journal of Neurophysiology*, *134*(4), 1174-1184. https://doi.org/10.1152/jn.00205.2025

Qiu, L., Su, J., Ni, Y., Bai, Y., Zhang, X., Li, X., & Wan, X. (2018). The neural system of metacognition accompanying decision-making in the prefrontal cortex. *PLoS biology*, *16*(4), e2004037. https://doi.org/10.1371/journal.pbio.2004037

R Core Team. *R: A language and environment for statistical computing*. In R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Raven, J. R., J C; Court, J H. (1992). *Manual for raven's progressive matrices and vocabulary: Standard progressive matrices*. Oxford Psychologists Press.

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological bulletin*, *124*(3), 372. https://doi.org/10.1037/0033-2909.124.3.372

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *The quarterly journal of experimental psychology*, *62*(8), 1457-1506. https://doi.org/10.1080/17470210902816461

Rayner, K., Reichle, E. D., Stroud, M. J., Williams, C. C., & Pollatsek, A. (2006). The effect of word frequency, word predictability, and font difficulty on the eye movements of young and older readers. *Psychology and Aging*, *21*(3), 448. https://doi.org/10.1037/0882-7974.21.3.448

Rayner, K., Slattery, T. J., Drieghe, D., & Liversedge, S. P. (2011). Eye movements and word skipping during reading: effects of word length and predictability. *Journal of Experimental Psychology: Human Perception and Performance*, *37*(2), 514. https://doi.org/10.1037/a0020990

Risko, E. F., Anderson, N. C., Lanthier, S., & Kingstone, A. (2012). Curious eyes: Individual differences in personality predict eye movement behavior in scene-viewing. *Cognition*, *122*(1), 86-90. https://doi.org/10.1016/j.cognition.2011.08.014

Roets, A., & Van Hiel, A. (2011). Item selection and validation of a brief, 15-item version of the Need for Closure Scale. *Personality and individual differences*, *50*(1), 90-94. https://doi.org/10.1016/j.paid.2010.09.004

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of statistical software*, *48*, 1-36. https://doi.org/10.18637/jss.v048.i02

Rüterbories, T., Mecklinger, A., Eschmann, K. C., Crivelli-Decker, J., Ranganath, C., & Gruber, M. J. (2024). Curiosity satisfaction increases event-related potentials sensitive to reward. *Journal of Cognitive Neuroscience*, *36*(5), 888-900. https://doi.org/10.1162/jocn_a_02114

Sakaki, M., Ten, A., Stone, H., & Murayama, K. (2024). Role of metacognitive confidence judgments in curiosity: Different effects of confidence on curiosity across epistemic and perceptual domains. *Cognitive science*, *48*(6), e13474. https://doi.org/10.1111/cogs.13474

Schmidt, H. G., & Rotgans, J. I. (2021). Epistemic curiosity and situational interest: Distant cousins or identical twins? *Educational Psychology Review*, *33*(1), 325-352. https://doi.org/10.1007/s10648-020-09539-9

Schulz, E., Konstantinidis, E., & Speekenbrink, M. (2015). Learning and decisions in contextual multi-armed bandit tasks. Proceedings of the Annual Meeting of the Cognitive Science Society,

Schumacher, A., Kammerer, Y., Scharinger, C., Gottschling, S., Hübner, N., Tibus, M., Kasneci, E., Appel, T., Gerjets, P., & Bardach, L. (2025). How do intellectually curious and interested people learn and attain knowledge? A focus on behavioral traces of information seeking. *European Journal of Personality*, 08902070241309124. https://doi.org/10.1177/08902070241309124

Schumacher, A., Spitzer, M. W., Jach, H. K., Kammerer, Y., Scharinger, C., & Bardach, L. (2026). From clicks to curiosity: Exploring self-directed information seeking as a behavioral manifestation of curiosity. *Journal of Experimental Psychology: Applied*. https://doi.org/10.1037/xap0000568

Shapiro, A. D., & Grafton, S. T. (2020). Subjective value then confidence in human ventromedial prefrontal cortex. *Plos one*, *15*(2), e0225617. https://doi.org/10.1371/journal.pone.0225617

Sinatra, G. M., & Lombardi, D. (2020). Evaluating sources of scientific evidence and claims in the post-truth era may require reappraising plausibility judgments. *Educational Psychologist*, *55*(3), 120-131. https://doi.org/10.1080/00461520.2020.1730181

Singer, W. (2013). Cortical dynamics revisited. *Trends in cognitive sciences*, *17*(12), 616-626. https://doi.org/10.1016/j.tics.2013.09.006

Singer, W. (2018). Neuronal oscillations: unavoidable and useful? *European Journal of Neuroscience*, *48*(7), 2389-2398. https://doi.org/10.1111/ejn.13796

Spitzer, M. W., Strittmatter, Y., Marti, M., Schumacher, A., & Bardach, L. (2025). Curiosity overpowers cognitive effort avoidance tendencies. *Cognition*, *262*, 106167. https://doi.org/10.1016/j.cognition.2025.106167

Spitzer, M. W. H., Janz, J., Nie, M., & Kiesel, A. (2024). On the interplay of curiosity, confidence, and importance in knowing information. *Psychological Research*, *88*(1), 101-115. https://doi.org/10.1007/s00426-023-01841-9

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior research methods, instruments, & computers*, *31*(1), 137-149. https://doi.org/10.3758/BF03207704

Stanovich, K. E., & West, R. F. (1997). Reasoning independently of prior belief and individual differences in actively open-minded thinking. *Journal of educational psychology*, *89*(2), 342. https://doi.org/10.1037/0022-0663.89.2.342

Staub, A., White, S. J., Drieghe, D., Hollway, E. C., & Rayner, K. (2010). Distributional effects of word frequency on eye fixation durations. *Journal of Experimental Psychology: Human Perception and Performance*, *36*(5), 1280. https://doi.org/10.1037/a0016896

Stenhouse, N., Myers, T. A., Vraga, E. K., Kotcher, J. E., Beall, L., & Maibach, E. W. (2018). The potential role of actively open-minded thinking in preventing motivated reasoning about controversial science. *Journal of Environmental Psychology*, *57*, 17-24. https://doi.org/10.1016/j.jenvp.2018.06.001

Swirsky, L. T., & Spaniol, J. (2024). Moderators of curiosity and information seeking in younger and older adults. *Psychology and Aging*. https://doi.org/10.1037/pag0000847

Ten, A., Oudeyer, P.-Y., Sakaki, M., & Murayama, K. (2025). The curious U: Integrating theories linking knowledge and information-seeking behavior. *Open Mind*, *9*, 1763-1785. https://doi.org/10.1162/OPMI.a.41

Traberg, C. S., & Van Der Linden, S. (2022). Birds of a feather are persuaded together: Perceived source credibility mediates the effect of political bias on misinformation susceptibility. *Personality and individual differences*, *185*, 111269. https://doi.org/10.1016/j.paid.2021.111269

Tsai, M.-J., Wu, A.-H., Bråten, I., & Wang, C.-Y. (2022). What do critical reading strategies look like? Eye-tracking and lag sequential analysis reveal attention to data and reasoning when reading conflicting information. *Computers & Education*, *187*, 104544. https://doi.org/10.1016/j.compedu.2022.104544

Vaccaro, A. G., & Fleming, S. M. (2018). Thinking about thinking: A coordinate-based meta-analysis of neuroimaging studies of metacognitive judgements. *Brain and neuroscience advances*, *2*, 2398212818810591. https://doi.org/10.1177/2398212818810591

van Lieshout, L. L., Traast, I. J., de Lange, F. P., & Cools, R. (2021). Curiosity or savouring? Information seeking is modulated by both uncertainty and valence. *Plos one*, *16*(9), e0257011. https://doi.org/10.1371/journal.pone.0257011

Vogl, E., Pekrun, R., Murayama, K., & Loderer, K. (2020). Surprised–curious–confused: Epistemic emotions and knowledge exploration. *Emotion*, *20*(4), 625. https://doi.org/10.1037/emo0000578

Vogl, E., Pekrun, R., Murayama, K., Loderer, K., & Schubert, S. (2019). Surprise, curiosity, and confusion promote knowledge exploration: Evidence for robust effects of epistemic emotions. *Frontiers in psychology*, *10*, 2474. https://doi.org/10.3389/fpsyg.2019.02474

Volz, K. G., Schubotz, R. I., & von Cramon, D. Y. (2006). Decision-making and the frontal lobes. *Current opinion in neurology*, *19*(4), 401-406. https://doi.org/10.1097/01.wco.0000236621.83872.71

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

Wagaman, B. N., Ikonomou, V. C., Campbell, I. A., Borgogna, N. C., Aita, S. L., Elliot, E., & Hill, B. D. (2025). Context matters: Need for Cognition moderates immediate story recall but not other types of memory tests. *Personality and individual differences*, *247*, 113458. https://doi.org/10.1016/j.paid.2025.113458

Wilson, R. C., Geana, A., White, J. M., Ludvig, E. A., & Cohen, J. D. (2014). Humans use directed and random exploration to solve the explore–exploit dilemma. *Journal of experimental psychology: General*, *143*(6), 2074. https://doi.org/10.1037/a0038199

Wojtowicz, Z., & Loewenstein, G. (2020). Curiosity and the economics of attention. *Current opinion in behavioral sciences*, *35*, 135-140. https://doi.org/10.1016/j.cobeha.2020.09.002

Zmigrod, L., Eisenberg, I. W., Bissett, P. G., Robbins, T. W., & Poldrack, R. A. (2021). The cognitive and perceptual correlates of ideological attitudes: a data-driven approach. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1822). https://doi.org/10.1098/rstb.2020.0424

Zsidó, A. N. (2024). The effect of emotional arousal on visual attentional performance: a systematic review. *Psychological Research*, *88*(1), 1-24. https://doi.org/10.1007/s00426-023-01852-6