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The Curious Gaze: Investigating the Effect of Curiosity on Information-Seeking Behaviour and Eye Movements

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Objectives. Making decisions requires the ability to seek out and use reliable information. Curiosity, as an intrinsic desire to know, is believed to be an important motivation for information seeking. Curiosity is not only a personality trait that reflects the tendency to experience new but also a cognitive state that arises from the information gap. The reward learning framework, which underscores the rewarding value of information, provides a fresh theoretical perspective for understanding curiosity. The purpose of this thesis is to investigate the role of curiosity in information-seeking process. Specifically, it aims to examine how curiosity influences information-seeking behaviour and eye movements, and to explore the relationship between trait and state curiosity within this context.

Methods. The sample comprised 52 participants who took part in a laboratory experiment and an online survey. The experiment involved a reading-based decision-making task, in which participants were required to read health-related arguments from three categories: *scientific relevant (SR)*, *scientific irrelevant (SI)*, and *non-scientific relevant (NR)*. Eye movements were recorded during reading, while state curiosity was self-reported after each argument. In the survey session, participants’ trait curiosity levels were measured using the Five-Dimensional Curiosity Scale Revised (5DCR). Data preparation and analysis was conducted using R software. Statistical analyses included Spearman’s correlation, as well as linear and generalized linear mixed-effects models.

Results and conclusions. State curiosity was associated with total fixation duration, but the effects interacted with information quality. For high quality (SR) arguments, the total fixation duration was overall longer regardless of state curiosity levels, whereas for low quality (SI and NR) arguments, total fixation duration increased with higher levels of state curiosity. As for the effects of trait curiosity, overt social curiosity was associated with more persistent information-seeking style, while stress tolerance was related to a quicker and more decisive reader. In addition, thrill-seeking tendency exhibited a negative effect on state curiosity during health-related decision-making. Overall, this study provides new insights into the role of curiosity in information-seeking process, and indicates the importance of curiosity in supporting public evidence-based decision-making.

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1 Introduction

Have you ever hesitated about getting vaccinated? Have you ever struggled with which financial products to buy or which school to choose for your children? Making decisions in this modern society is not an easy task. Entangled in a maze of complex, controversial and even misleading information, responsible decision-making requires the ability to seek out, recognize, and use reliable information. For a long time, understanding the mechanisms of information-seeking process has been an important aim across various fields including education, psychology, and neuroscience (FitzGibbon et al., 2020). An important fact is that information-seeking is often motivated by curiosity, an intrinsic desire to know (Litman, 2019). Curiosity is a force behind search; a motivation for acquiring new knowledge. While numerous theories have delved into the nature and structure of curiosity, its effect on information-seeking and its role in evidence-based decision-making remain largely unexplored.

This thesis aims to investigate the role of curiosity in information-seeking process. Understanding how people use information of varying scientific quality to make health-related decisions and recognizing the role of curiosity in this process is pivotal for supporting the public in making sound and science-based decisions. Curiosity is distinguished as trait curiosity and state curiosity. Trait curiosity is a stable personality tendency to experience something new. In the current study, trait curiosity was measured by the Five-Dimensional Curiosity Scale Revised (Kashdan et al., 2020). State curiosity refers to a temporary cognitive state triggered by salient information (Gottlieb et al. 2013), which contains inherent rewarding value according to the reward-learning framework of knowledge acquisition (Murayama et al., 2019). Another foundational theory for understanding state curiosity is Loewenstein's (1994) information gap theory. According to this theory, curiosity arises from the gap between what people already know and what they want to know.

Instead of examining curiosity through trivia questions (Kang et al., 2009) or blurred images (Jepma et al., 2012), the current study explores curiosity in a bandit task in which participants were required to choose arguments of varying scientific quality to make health-related decisions. During the decision-making task, participants information-seeking behaviour was observed, and their eye movements were recorded.

Behavioural analyses reveal individuals’ strategies in collecting information for making decisions; whereas eye movement measures provide real-time and objective insights into how individuals process information (Lai et al., 2013; Tsai et al., 2022). Eye movement works as a window for the underlying cognitive processes (Gottlieb et al., 2013), and reveals how people distribute their attention during reading (Tsai et al., 2022). By analysing the behavioural and eye-tracking data, this thesis will provide new insight into the effect of both trait and state curiosity on individuals' information-seeking.

This thesis will present prior theories about curiosity in Chapter 2, followed by introducing the basic components of eye movements and their connection to curiosity in Chapter 3. Chapter 4 will introduce the research task and research questions, while Chapter 5 will describe the procedures and analysis methods. The results from behavioural and eye movement analyses will be presented in Chapter 6 and further discussed in the final Chapter 7.

2 Curiosity and information seeking

Curiosity has a central role in diverse intellectual behaviours such as learning and development (Shin et al., 2019). However, to date, our understanding of the nature and underlying causes of curiosity is limited (Litman, 2019). One reason is that there is no single and uniform definition of curiosity (Kidd & Hayden, 2015), making it difficult to measure or distinguish it from other variables in empirical studies. In fact, for a long time, curiosity has been viewed as synonymous and overlapping with the concept of “interest” (Rotgans & Schmidt, 2014; Renninger & Hidi, 2016), resulting in the interchangeable usage of these two terms in both scholarly literature and daily conversations (Grossnickle, 2016; Shin et al., 2019). As Murayama and colleagues (2019) have claimed, both curiosity and interest are naïve or folk concepts, and providing objective definitions for subjective feelings appears to be a challenging task.

Among various definitions of curiosity, one common ground is understanding curiosity as “a desire for new information” (Litman, 2019; Gruber et al., 2019). In contrast with extrinsic information seeking such as studying for a test or fulfilling other obligations, curiosity refers to the intrinsic desire to acquire new information (Gottlieb et al., 2013). This “desire to know” is inherently bounded and explained by a human’s natural need for sense making - an inclination to understand, interpret, and create meaning from the world around us. Curiosity and information-seeking phenomena reflect this fundamental need for sense-making (Lowenstein, 1994, p.84). Curiosity thus serves an important function in motivating information-seeking and knowledge acquisition (Kidd & Hayden, 2015).

To better understand the role of curiosity in information-seeking process, this chapter will review various theories concerning its underlying causes, different dimensions or types of curiosity, and its impact on decision-making.

2.1 The roots of curiosity

Over the past decades, various psychological studies and theories have helped us to understand curiosity and its underlying causes. Stepping into the 21st century, the development of neuroscience has also provided essential discoveries about the mechanisms of curiosity from the neurocognitive perspective. This section will review different theories about the root causes of curiosity.

2.1.1 Drive theory

Curiosity has been viewed as a drive, which has many similarities with primary drives such as hunger and fear (Berlyne, 1954). Like hunger drives people to eat, curiosity motivates humans to seek out new stimuli. According to Berlyne, the “curiosity drive” can be activated by external novel, complex, surprising, ambiguous, and variable stimuli. Depending on the different types of stimuli, curiosity can be further divided into two categories: perceptual curiosity and epistemic curiosity. Perceptual curiosity is elicited by sensory stimuli, whereas epistemic curiosity refers to a desire to seek new knowledge or semantic, symbolic information (Berlyne, 1954).

The drive theory has contributed valuable investigations about characteristics and causes of curiosity. However, the drive-based accounts of curiosity encounter a paradox when considering people’s voluntary exposure to curiosity (Loewenstein, 1994, p.84). In Berlyne’s view, the activation of curiosity drive is always accompanied by the arousal of an aversive feeling, which drives people to gain new information. If curiosity brings a purely aversive feeling, it would be difficult to explain why people consistently and intentionally seek out and engage in curiosity-motivated situations rather than completely avoiding them (Loewenstein, 1994; Gruber et al., 2019).

2.1.2 Information gap theory

Instead of viewing curiosity as a drive, Loewenstein (1994) proposed an integrative hypothesis called the information gap theory, explaining the situational determinants of curiosity as a temporary state. According to Loewenstein (1994), a state of curiosity arises from the gap between what people already know and what they want to know. It is triggered when an individual’s goal or “informational reference point" is elevated above the person's current level of knowledge (p.87). Curiosity is, thus, evoked by both external and internal factors (p.92). It not only needs novel, complex, or ambiguous stimuli to highlight the missing information, but also requires people to have metacognitive ability to monitor their knowledge capacity and thus identify the magnitude of the information gap (Litman, 2019).

Once the existence of an information gap is perceived, a sensation of deprivation curiosity is elicited and it motivates people to acquire missing information to resolve the recognized discrepancy, close the gap, and eliminate the feeling of deprivation (Loewenstein, 1994, p.87). However, what is the relationship between the magnitude of the information gap and curiosity? Empirical studies present conflicting perspectives regarding the optimal size of the information gap for triggering curiosity. Some suggested that individuals experience greater curiosity when the information gap is on the verge of closing, for example during the "tip-of-the-tongue" state (Litman et al., 2005). Whilst other research indicated that an intermediate level of gap fosters the strongest curiosity. For instance, studies have uncovered a reversed U-shaped curve between curiosity and individuals' confidence levels in knowing the answer (Kang et al., 2009; Baranes et al., 2015), as it's hard to be curious about things people don't understand at all, while extensive knowledge leads to saturation.

Information gap theory explains the motivational power of specific state curiosity during information seeking. After individuals obtain sufficient information to bridge the gap, their curiosity will be satiated. The process of satisfying curiosity, according to Loewenstein (1994, p.90), is inherently pleasant, like getting a reward. This pleasant feeling explains the paradox encountered by the drive theory: why individuals willingly seek out exposure to curiosity.

2.1.3 The reward learning perspective

The idea that the process of satisfying curiosity is rewarding and pleasurable is supported by neurocognitive research. For example, the results from functional magnetic resonance imaging (fMRI) showed that the left caudate nucleus, which is located within the dorsal striatum, increased activation in high-compared to low-curiosity states during trivia question presentations (Kang et al., 2009). Given that the dorsal striatum has been demonstrated to have a crucial role in reward processing and expectation by a substantial body of research (Hare et al., 2008; Delgado et al., 2003), these findings were interpreted to support the idea of curiosity as anticipation of rewarding information, triggering the brain’s reward circuitry (Kang et al., 2009). In other words, curiosity works via the reward-related brain regions to seek out new information (Cervera et al., 2020). As the object of epistemic curiosity, information is considered as an indirect reward, which may share many commonalities with primary rewards such as food and water (Kidd & Hayden, 2015).

Based on the emerging consensus that information contains inherent rewarding value, recent studies have adopted a reward learning perspective to understand curiosity and knowledge acquisition. An innovative account called “a reward-learning framework of autonomous knowledge acquisition” was proposed on the basis of reward-learning or reinforcement-learning model, emphasizing reward processing as the core of the knowledge acquisition process (Murayama et al., 2019). According to this framework, the “expected” rewarding value of new information motivates people to initiate information-seeking behaviour. When the information gap is successfully closed by new knowledge, the felt rewarding experience would then strengthen future information-seeking activity, thus formulating the positive loop for consistent knowledge acquisition (Murayama et al., 2019).

The reward-learning perspective argues that, during the state of uncertainty, the expected rewarding value of information is influenced by learning progress, reward history, and other contextual factors such as information utility and the level of uncertainty (FitzGibbon et al., 2020). These perspectives reflect a subjective evaluation of the possible quality of the outcome, which is called cognitive desire by Berridge (2009). Cognitive desire represents one’s expected pleasantness during anticipation, however, it may be less convincing when talking about people’s risk-related or negative information seeking. Therefore, another mechanism – incentive salience - was recognized to explain the strong motivational power of curiosity (Berridge, 2004). Incentive salience is a feeling of "wanting" or "desire", meaning a purely motivational urge for new information (FitzGibbon et al., 2020). Unlike "liking" which is an immediate hedonic pleasure after consumption, "wanting" of incentive salience is beyond sensory experience and gives motivational magnet property to the stimuli, making the reward attractive and desirable (Berridge, 2004).

According to Murayama (2019), "wanting" and "liking" represent two distinct components of expected reward value in the reward-learning framework. Both cognitive desire and incentive salience are essential factors that support people's information-seeking behaviour (FitzGibbon et al., 2020).

2.2 Dimensionality of Curiosity

After reviewing theories about the underlying causes of curiosity, let's shift our focus to its structure. Curiosity, as a multifaceted psychological construct, encompasses various types and facets. Numerous theories have been proposed concerning its categorization. This section will introduce some views on the dimensionality of curiosity.

2.2.1 Interest- and deprivation curiosity

Curiosity is characterized by co-existence of aversive and pleasant feelings (Litman & Jimerson, 2004), suggesting a distinction between deprivation and interest curiosity. According to Litman (2008), these two types of curiosity reflect different motives for acquiring new information and engaging in exploration. Interest-type (I-type) curiosity refers to the desire for new information simply out of individuals' enjoyment or interest, which involves positive affect such as the anticipated pleasure of learning new things (Litman, 2008). By contrast, deprivation-type (D-type) curiosity is driven by anxiety, frustration, and the need to reduce uncertainty caused by missing key information (Litman, 2008). D-type curiosity is activated when individuals realize the lack of specific information (Litman, 2019). This status of "unknown" can elicit a sense of deprivation, which motivates people to spend time and energy finding specific solutions to eliminate the bothersome feeling of ignorance. On the contrary, the I-type of curiosity can be evoked without the perception of missing information. It is conceptualized as a more relaxed attitude towards information seeking with the purpose of joy and pleasantness (Litman, 2019).

Based on the distinction between interest and deprivation curiosity, Litman and colleagues developed the 10-item 2-factor Epistemic Curiosity scale, measuring individual tendency in terms of I- and D- type curiosity (Litman, 2008).

2.2.2 The five-dimensional model of curiosity

To better understand the structure of curiosity, Kashdan and colleagues (2018) synthesized diverse aspects of curiosity and proposed a five-factor model. According to this model, curiosity is constructed by five separate dimensions: joyous exploration, deprivation sensitivity, stress tolerance, thrill seeking, and social curiosity (Kashdan et al., 2018, 2020).

The first two dimensions of this model reflect different emotional experiences of curiosity: joyous exploration represents the pleasurable feeling of finding something intriguing; deprivation sensitivity refers to the frustration or anxiety caused by the existence of the information gap, which is similar to Litman’s I/D-distinction of curiosity. However, curiosity is not a purely emotional experience, it also requires cognitive judgements. The following two dimensions reflect two cognitive judgments involved in curiosity: the stress tolerance subscale evaluates people’s dispositional tendency to cope with distress when exploring the new, while thrill seeking reflects the willingness to accept risks to acquire new experiences. The fifth dimension – social curiosity, addresses how individuals feel curious about other people. Interpersonal interaction is one key aspect of daily life, and most human behaviour is displayed in the social context (Reis et al.,2000). Social curiosity includes overt approaches, such as directly asking and observing what people are doing, and covert strategies, like hearing and gathering second-hand information about others’ lives. (Kashdan et al., 2018, 2020).

Based on this multidimensional model, Kasdan et al. (2018) created the five-dimensional curiosity scale (5DC), comprising five subscales, each corresponding to a distinct facet of curiosity. Subsequently, the scale was developed to distinguish between overt and covert social curiosity, which is known as the five-dimensional curiosity scale revised (5DCR) (Kashdan et al., 2020).

The 5DCR was used in the current study, as it comprehensively encompasses various facets of trait curiosity, particularly the cognitive dimensions. Given the study's focus on information-based decision-making, which inherently involves cognitive processes, the 5DCR provides a suitable framework for evaluating participants' trait curiosity levels.

2.2.3 Relationship between trait and state curiosity

Some theories treat curiosity as a stable personality trait, reflecting individuals' natural inclination to experience new things (Gruber et al., 2019). For example, Litman's I/D-type curiosity is positively related to the "Openness to Experience" trait – one of the crucial components of Big Five personality traits (Litman, 2019; Gruber & Ranganath, 2019). However, other studies view curiosity as a temporary cognitive state, which refers to state curiosity (Loewenstein, 1994). It is a short-term psychological state that involves epistemic emotions such as enjoyment and confusion (Renninger & Hidi, 2016).

It is assumed that individuals' inherent levels of trait curiosity influence both the frequency and intensity of state curiosity experience (Grossnickle, 2016; Shin et al., 2019). Individuals high in trait curiosity are expected to experience state curiosity more frequently, and in diverse situations, since they are more inclined to notice, seek out, and interact with curiosity-evoking stimuli (Kashdan et al., 2004; Naylor, 1981; Grossnickle, 2016). Similarly, according to Spielberger's state-trait theory of emotion and personality, people high in a particular trait (curiosity, in this case) are also more likely to experience the corresponding states with greater intensity (Spielberger, 1972). These theories suggested that although trait and state curiosity are two separate constructs, they are closely related.

Several empirical studies over the past two decades have examined the correlation between trait and state curiosity. For example, a correlation between state and trait curiosity ($r = .52$) was found in a study investigating the effect of curiosity on the genesis of intimacy (Kashdan & Roberts, 2004). Another strong correlation between state and trait curiosity ($r = .78$) was reported in a study of affect and job performance (Reio & Callahan, 2004). Similar results were also reported in a study about curiosity and well-being, where state curiosity was correlated ($r = .42$) with trait curiosity (Kashdan & Steger, 2007). Also, Litman and colleagues (2005) showed that in curiosity-arousing situations, individuals' trait curiosity was significantly related to state epistemic curiosity ($r = .24$).

Although the strength of correlation varied, previous studies indicate an association between the trait and state curiosity. However, it is unclear to what extent individual variations in trait curiosity influence people's state curiosity experiences, especially in the information-seeking process. In addition, as previous studies tend to consider trait curiosity as a unitary characteristic (Kashdan & Roberts, 2004; Reio & Callahan, 2004), the effect of different dimensions of trait curiosity has been unexplored. Thus, there is a need for empirical evidence to elucidate and fully understand the relationship between different dimensions of trait curiosity and state curiosity during information seeking.

2.3 Curiosity in decision making

Decision making concerns making choices among several desirable options (Edwards, 1954), and it is a fundamental aspect of human daily life. From selecting financial investments to pondering vaccine acceptance, or even thinking about what to eat for lunch, individuals are consistently involved in the complex process of decision making. There are plenty of theories about decision making across economics, sociology, and psychology (Edwards, 1954). This section will not go into the various accounts of how people make decisions, for those are beyond the scope of the current study. Instead, this section focuses on examining the role of curiosity in the decision-making process.

Curiosity, the intrinsic desire for new information, is believed to play a vital role in the decision-making process, both emotionally and cognitively.

On the one hand, decision making can be emotional (Van Dijk & Zeelenberg, 2007). Curiosity, as a desire to know, is an emotionally arousing state that triggers information-seeking behaviour (Reio & Callahan, 2004). Recent research has demonstrated that the motivational force of curiosity can be so strong that it can overcome regret aversion in decision-making (Van Dijk & Zeelenberg, 2007). Regret arises when the outcome of a chosen option is worse than expectations; individuals may experience regret, even if the outcome aligns with expectations, due to wondering whether another option would have been better (Schwarz, 2000). Regret aversion refers to the tendency to protect oneself from regret by selecting certain alternatives or avoiding additional information that could lead to regret. Curiosity and regret aversion are two opposing emotional forces during decision making, pulling individuals between seeking and avoiding unknown information (Van Dijk & Zeelenberg, 2007). The discovery that curiosity can counteract regret aversion in decision-making suggests that curiosity, regarded as a positive emotional-motivational factor (Kashdan et al., 2004), significantly influences people's behaviour during the decision-making process.

On the other hand, decision making also involves cognitive functions, such as analytical thinking and reasoning ability. As earlier mentioned, curiosity is a cognitive desire that involves cognitive processes (Berridge, 2009). For example, curiosity can be regarded as one of the dispositional dimensions of critical thinking (Facione,1990). One thinking disposition examined in the California Critical Thinking Disposition Inventory (Facione et al., 2001) is called inquisitiveness, evaluating individuals’ curiosity for learning new knowledge (Li, 2021). Additionally, research showed that curiosity is also related to individuals’ need for cognition, which refers to people’s innate inclination to actively participate in and enjoy thinking (Olson, 1984). Bavoľár and Miháľ (2019) demonstrated a positive correlation between both curiosity and the need for cognition with the rational decision-making style, as evaluated by the General Decision-Making Style inventory. This style features a comprehensive information search and logical assessment of alternatives (Scott & Bruce, 1995). These findings indicated the potential advantage of curiosity in facilitating thoughtful decision-making.

In addition, neurocognitive research has also provided evidence regarding the cognitive mechanisms underlying curiosity. For example, studies have shown activation of the anterior cingulate cortex during states of curiosity (Jepma et al., 2012), a region related to controlling, error monitoring, and cost-benefit calculating (Apps et al., 2016; Cervera et al., 2020). According to Cervera et al. (2020), curiosity involves self-motivated learning, in which people need to manage their demands and interests to have the largest benefits of information.

The need for executive control involved in curiosity can be better understood if we consider the process of curiosity-driven information-seeking to always accompany with a trade-off between exploration and exploitation behaviour (Hills et al., 2015). Exploration means sampling or gathering information from uncertain or varying quality sources, whereas exploitation involves using the information from a proven reliable source (March, 1991). Deciding between exploring risky yet possibly more profitable options, or exploiting the familiar but maybe suboptimal options is a challenging problem in decision-making, known as the exploration versus exploitation problem (Cohen et al., 2007; Hills et al., 2015). Decision-making requires the balance between exploration and exploitation, to achieve more efficient information seeking.

Curiosity, serving as both an epistemic emotion and a cognitive function, is expected to impact individuals' behaviour during decision-making. However, empirical evidence on this matter is lacking, particularly concerning exploration and exploitation behaviours within the context of information-seeking. Furthermore, distinguishing between the effects of trait and state curiosity on decision-making remains unclear.

3 Eye movements, attention, and curiosity

One of the primary ways humans acquire information about our changing surroundings is by using our eyes to look around. The eye-tracking method offers real-time, immediate, and objective insights into how individuals process information (Lai et al., 2013; Tsai et al., 2022). As suggested by Gottlieb et al. (2013), "the oculomotor system may be an excellent model system for understanding information seeking" (p.6). Eye movements serve as a window for individuals' underlying cognitive processes and visual attention. This part will introduce the basic components of eye movements, examine how eye movements work as an indicator of mental processes, particularly attention, and review its connection to curiosity.

3.1 Basic components of eye movements

Saccades and fixations are two basic components of eye movements. During reading, our eyes do not move smoothly and continuously from line to line but jump quickly from one point to another (Reichle et al., 1998). This is because of the limitation of the physiological structure of human eyes - only words falling on the fovea of the retina have the maximum visual acuity (Conklin et al., 2019b). The rapid, ballistic jump of eyes are known as saccades. People cannot obtain and encode any information during saccades because the eyes move so quickly (Rayner, 2009; Conklin et al., 2019a).

The interval between saccades is called a fixation, and it is characterized by a relatively stable eye gaze. According to the immediacy assumption (Just & Carpenter, 1980), during fixation, people can see texts clearly and process information from the fixation point. Among fixation measures, the location and the duration of fixations are two commonly used variables (Reichle et al., 1998). The location of fixation indicates where people look, whereas the duration of fixation tells about the time spent on a given fixation location, for example on a word. In a review of eye-tracking studies in educational science spanning the years 2000 to 2012, Lai et al. (2013) found that temporal measures of eye movements (i.e., fixation duration) were the most frequently used indices, indicating “when” and for “how long” people look at a specific part of the stimulus.

The duration of fixation is one essential metric in the current study, and it is used to assess participants’ reading behaviour. Previous research has demonstrated that the fixation duration on words is influenced by multiple factors, including word frequency, word length, age of acquisition, and predictability (Reichle et al., 1998; Conklin et al., 2019b). Specifically, studies have consistently demonstrated that readers tend to look longer at low-frequency words, compared to high-frequency ones (Rayner, 1998), and tend to have longer fixation durations on longer words (Rayner et al., 2011).

3.2 Eye movement as an indicator of ongoing cognition

For decades, eye-tracking studies have been based on the “eye-mind hypothesis”. According to this hypothesis, eye movements can reveal the underlying cognitive process, since there is a tight link between what one is looking at and what one is thinking about (Just & Carpenter, 1980).

The eye-mind hypothesis is supported by many empirical studies, especially those investigating reading. For example, research has found that when readers go back and reread the text (known as regression), it often indicates difficulties in understanding (Rayner, 1998). This line of findings suggested that eye movements can serve as signals that reflect cognitive processes during reading.

Instead of a passive input stage, eye movements involve active control and are deployed to sample visual information effectively (Gottlieb et al., 2013). Visual attention is believed to play a central role in eye movement control (Hoffman & Subramaniam, 1995) and is recognized to be critical in guiding information sampling (Cardoso-Leite & Bavelier, 2014). In essence, eye movements reveal how visual attention is distributed across stimuli.

Attention is commonly understood as a selection process (Orquin & Mueller Loose, 2013). Previous literature has distinguished two types of attention: bottom-up and top-down attention (Corbetta & Shulman, 2002; Cardoso-Leite & Bavelier, 2014; Pinto et al., 2013). The former is stimulus-driven attention, which is automatic and involuntary. It is usually attracted by unexpected salient stimuli such as a sudden loud noise. On the contrary, top-down attention refers to goal-oriented, voluntarily directed, self-controlled allocation of attention. Attention, especially top-down attention is essential in enhancing memory and learning. For example, participants remembered more letters from positions that they had been told to attend to, which indicated that attention determined what information could be encoded and memorized across eye movement (Irwin & Gordon, 1998).

More importantly, research has demonstrated that the covert attention system plays a vital role in guiding overt eye movements (Hoffman, 2016). In other words, our attention automatically precedes eye movements to a target location (Irwin & Gordon, 1998). For example, Hoffman and Subramaniam (1995) showed that people could not look at one location while attending to another, suggesting the close connection between visuospatial attention and voluntary saccadic eye movements. This also makes eye movement analysis an important approach to understanding human attention.

Eye movements are also driven by individual factors. On the one hand, people's general gaze patterns can be explained by environmental factors, including visual saliency (Orquin & Mueller Loose, 2013) and task relevance (Gottlieb et al., 2013; Hayhoe, 2000). These stimulus- and task related variables reveal some general principles that are similar across different observers. On the other hand, there are stable stimulus-independent individual differences in eye movements. For example, fixation durations and saccade amplitudes were correlated within individuals across various tasks (Andrews & Coppolla, 1999), and different types of images (Castelhano & Henderson, 2008). Several observer-level factors were investigated to explain the individual differences, such as cultural background (Chua et al.,2005), typicality of social development (Riby & Hancock, 2008), and personality – among which importantly curiosity.

3.3 Eye movements and curiosity

According to Risko et al. (2012), curiosity can be used to predict eye movement behaviour. In a free viewing task study, Risko et al. (2012) showed that participants' trait perceptual curiosity scale score (PC; Collins et al., 2004) correlated with the number of regions visited (r= .36). That is, people with higher trait perceptual curiosity tended to look at more regions of scenes. To the best of my knowledge, this is the first empirical study that has investigated the relationship between curiosity and eye movements, and that demonstrated an effect of trait curiosity on eye-moving patterns.

Additional empirical research conducted by Baranes et al. (2015) demonstrated that one's state curiosity can also influence gaze patterns, especially the gaze positions. In their study, participants' eye movements were tracked when reading trivia questions and, after a short delay, were presented with the answers visually. The findings indicated that a higher level of state curiosity is linked to an earlier anticipatory shift of gaze toward the answer location. In other words, when curiosity was high, participants' gaze converged faster and stayed longer in the expected answer area (Baranes et al., 2015), which implies that eye movements can serve as indicators of state curiosity levels.

It is not surprising that curiosity, as the intrinsic motivation to seek out information, is related to people's eye movements that mirror the information-sampling process. Both curiosity and eye movements are vital in people's information-gathering and cognitive processes. While a few studies have touched upon this topic (Risko et al., 2012; Baranes et al., 2015), there remains a notable scarcity of empirical research examining the relationship between curiosity and eye movements. Our understanding of how curiosity affects eye movements, particularly in the context of reading and information-seeking processes, remains relatively poor.

4 Present study

The aim of the present study is to investigate the effect of curiosity on people's information-seeking and eye movement patterns during reading-based decision-making tasks. This study also investigates the relationship between state and trait curiosity in information acquiring process.

The research questions are:

1. How does state and trait curiosity influence people's information-seeking performance in a decision-making task?
2. What is the relationship between state and trait curiosity in the information-seeking process?
3. How does state and trait curiosity affect eye movements while reading health-related arguments in a decision-making task?

Based on existing literature, curiosity motivates information-seeking behaviour. Previous research has also indicated a distinct but closely related relationship between state and trait curiosity. Moreover, studies have shown that eye movements reveal state curiosity and can be predicted by trait curiosity level (Risko et al., 2012; Baranes et al., 2015). Therefore, drawing from the existing literature, the hypotheses for the present study are:

H1.1: Higher state curiosity would be associated with more active information-seeking performance, such as a greater number of argument readings.
H1.2: Higher trait curiosity would also predict more active information-seeking performance, with the effects varying among five dimensions.
H2: The level of trait curiosity would influence the experience of state curiosity in information-seeking.
H3.1: State curiosity would affect fixation patterns during reading arguments with varying quality.
H3.2: Different types of trait curiosity would also lead to different fixation patterns.

5 Method

The present study is part of a larger collaborative project, FINSCI, funded by the Strategic Research Council (SRC) within the Research Council of Finland. In this era of increasingly abundant and mixed information, FINSCI aims to investigate and foster Finnish residents' science capital, to help with science learning and knowledge-based decision-making. The current study used quantitative data collected in the FINSCI project with the questionnaire and eye-tracking method. The study included two experimental sessions: one laboratory experiment and one online survey experiment.

5.1 Participants

Sixty-one participants (44 female, 14 male, 3 non-binary, 19-46 years, mean age 28,2 years, SD 6,9 years) were recruited through student email lists, noticeboard advertisements, and word of mouth for laboratory experiments. All participants were Finnish-speaking adults and had normal or corrected-to-normal vision. They were free of neurological history and had no current medication affecting the central nervous system. Each participant gave informed, written consent via electronic documentation prior to taking part in any research activities and was compensated with a movie ticket (10€).

One week after the experiment, participants received a follow-up online survey. Fifty-four individuals out of the initial group responded to this survey. They were compensated with an additional movie ticket (10€).

Considering the data integrity, the data from 54 participants who completed both the experiment and the follow-up self-report survey were assessed. Two individuals within this subset were excluded for specific reasons. One was removed due to a misunderstanding of the task, which could have affected data quality. The other one was excluded for having a pre-existing neurological condition, a predefined exclusion criterion for this study. As a result, the final sample for this study comprises 52 participants (39 female, 11 male, 2 non-binary) with an age range of 19 to 46 years (mean age 29,4 years, SD 7,4 years).

The final dataset from 52 participants was used for the behavioural analyses. However, more participants had to be excluded from the eye movement analyses because of poor-quality eye-tracking data. For two participants, data were excluded due to fixation detection problems. In another case, a combination of issues, including strong diagonal drift and random fixation patterns, led to the exclusion of a participant's data. As a result, data from 49 participants (37 female, 10 male, 2 non-binary, 19-46 years, mean age 30,0 years, SD 7,3 years) were used for eye-tracking analyses.

5.2 Ethical Considerations

The experiment was performed in accordance with the Declaration of Helsinki and was reviewed by the University of Helsinki Ethical Review Board in Humanities and Social and Behavioural Sciences.

5.3 Laboratory Experiment

5.3.1 Study Design

The current experiment was a reading-based decision-making task designed as a contextual multi-armed bandit task, a concept originating from Robbins (1952). Analogous to gamblers deciding which slot machine to play to maximize their rewards, this task provides a context in which individuals need to choose among different options to optimize their outcomes (Bergemann & Valimaki, 2006; Schulz et al., 2015). Multi-armed bandit task provides a helpful framework for assessing learning and decision-making (Schulz et al., 2015). In the current version of this task, participants were free to choose information from three labelled boxes - A, B, and C, to answer health-related questions. Respectively, the boxes contained arguments from three distinct categories: i) *scientific relevant*, ii) *scientific irrelevant*, and iii) *non-scientific relevant*. The varying quality of information between these categories provides different utility for answering the questions, and thus leads to the uncertain value of rewards. In essence, participants were challenged to make optimized decisions to gather reliable information. Health-related topics were used to create a meaningful context for exploring people's scientific-based decision-making in daily life.

5.3.2 Material: Health-related questions and arguments

A total of eighteen health-related questions were used in the present study. The topics of these questions were sourced from Juhani Knuuti's book, Kauppatavarana terveys (translated into English as Health as a Commodity), which was published in 2020. Knuuti is a medical doctor and professor in Finland. According to Knuuti, the unreliability of information and people's cognitive biases towards science has caused challenges to public health (Knuuti, 2020).

In his book, Knuuti analysed 71 health topics based on scientific literature. These topics spanned a broad spectrum, including facets such as disease prevention, disease diagnosis, environmental risks, and various disease treatments. With the interest of exploring how people make evidence-based decisions in daily life, 18 topics that specifically pertain to daily health and have considerable scientific research were selected for this study. An example question is: "Aromaterapia lievittää ahdistusta. Totta vai tarua?" (In English: Aromatherapy relieves anxiety. True or false?").

Moreover, Knuuti evaluated and interpreted hundreds of health claims regarding these topics, which are sometimes even contradictory. On the basis of these health claims, 15 arguments were formulated for each question. Based on argumentation theory (Hoeken et al. 2012; Van Eemeren et al. 2009), the arguments were categorized into three types (5 for each category). The first category is called *scientific relevant (SR)*, and it contains arguments relevant to the specific health topic that were based on scientific research or authorities (e.g., "Based on a systematic review published in 2020, aromatherapy reduces anxiety in patients undergoing heart surgery."). The second category is *scientific irrelevant (SI)*, containing arguments based on scientific evidence but not relevant to this topic (e.g., "Based on studies, there are no significant side effects from aromatherapy."). The third category is *non-scientific relevant (NR)*, which refers to arguments containing information that is not based on research evidence, although relevant to the topic (e.g., “According to the aromatherapist, aromatherapy lifts the mood and relieves anxiety.”). All questions and arguments were presented in Finnish.

After a preliminary classification of arguments, a pilot testing for the argument categories was carried out on an online platform “RedCap”. Respondents were required to categorize the arguments into those three predefined categories, as well as offer comments related to the arguments. The arguments were presented in 4 segments of which participants could complete as many as they could. As a result, 12 participants finished the pilot test for one segment, and 8 for each other three segments. Based on their feedback, slight modifications were made to improve the argument readability and classification reliability.

5.3.3 Procedures

The laboratory study was carried out in the Cognitive Brain Research Unit (CBRU) in the Faculty of Medicine, University of Helsinki. During the experiment, participants were seated in a dimly lit room, approximately 90 cm from a 24-inch HP LA2405x monitor with a resolution of 1920x1200. Participants’ eye movements during the task were recorded with an SR Research EyeLink 1000 remote eye-tracker (SR Research, Ltd., Kanata, Ontario, Canada) at a sampling rate of 1000 Hz. Stimulus timing was controlled, using the Presentation® software (Version 22.1, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com). Before data collection, all participants gave written consent forms through the Red Cap e-consent framework.

The 18 questions used in this study were separated into four blocks, each consisting of 4 or 5 questions. A brief task practice was conducted to familiarize participants with the task. To guarantee the accuracy and precision of the eye-tracking data, the eye tracker was calibrated, and calibration accuracy was validated using a 9-point grid before each recording block. In a validation step, the calibration was repeated until the average error for all points was less than 1° and in most cases less than 0.5°. Calibration sessions were applied to every participant before each recording block. The presentation order of the blocks was counterbalanced across participants to control for the influence of fatigue. Between the blocks, participants were allowed to have a short break.

After the calibration and task instruction in Finnish, participants were presented with a series of 18 health-related questions on the computer screen. After each question, they were required to choose information from three boxes, which contained information with three different quality levels – *scientific relevant*, *scientific irrelevant*, and *non-scientific relevant*. For each question, the correspondence between the three boxes and the three types of information was random, and participants were not aware of the classification of the three types of information beforehand. There were five pieces of arguments in each box, and participants were free to read as many as they wanted. They were also free to proceed to answer the multiple-choice question when they felt they had collected enough information related to the topic. Figure 1 shows the general paradigm of the current experiment.

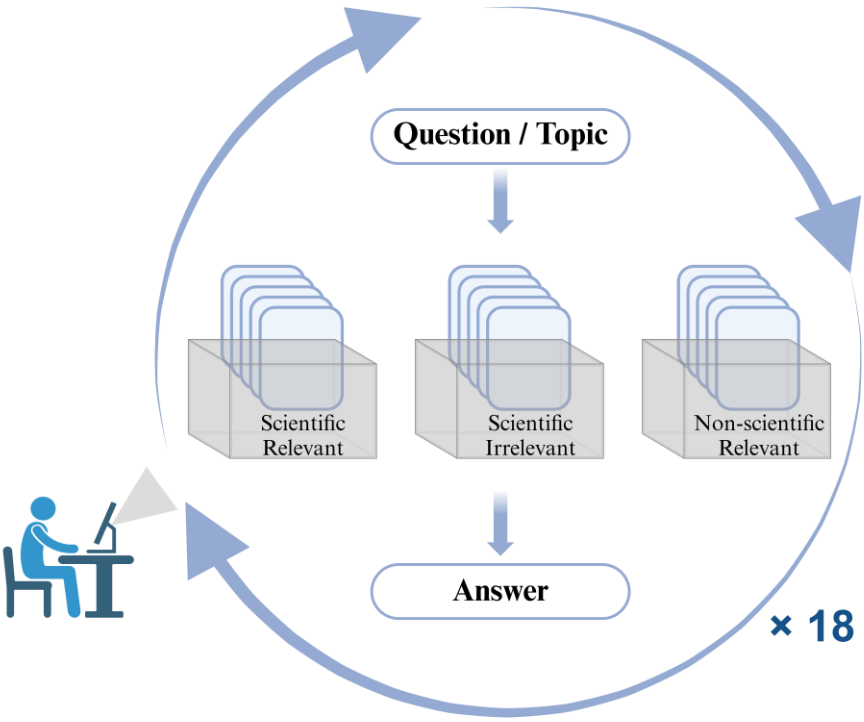

Figure 1. Experimental paradigm.

Besides reading arguments, participants were also required to provide various ratings for each question and argument. Figure 2 presents an example trial sequence for one question. All texts were presented originally in Finnish, and they were translated into English for Figure 2. Firstly, a health-related question was presented in the upper middle part of the screen, followed by a 5-second central fixation cross on a grey background. Participants were then asked to rate their familiarity with the given topic, from 1(not at all) to 4 (very familiar). After a 0.5-second fixation cross, three blue boxes labelled A, B, and C were presented on the screen. Participants chose a box by pressing the corresponding button on the response pad. As a result, an argument from this box was presented in the middle of the screen until response or for a maximum duration of 20 seconds, with the question also presented in the upper middle part of the screen. After reading each argument, participants were asked to provide subjective ratings on the usefulness of the information, confidence on the usefulness rating, the level of curiosity that the information piqued, and how easy it was to comprehend the information, from 1 (not at all) to 4 (very useful, very confident, very curious, very easy to comprehend). Between each rating, a 0.5-second fixation cross was presented. After completing the four ratings for each argument, participants were asked whether they wanted to read more arguments or give an answer. If they chose to read more arguments (by pressing 1), they were presented with the three blue boxes again and repeated the process of choosing a box, reading an argument, and giving four ratings. If participants felt they had collected enough information and chose to answer the question (by pressing 2), then multiple-choice answer options were presented, and they could indicate their answer by pressing a number corresponding to the answer options on the response pad.

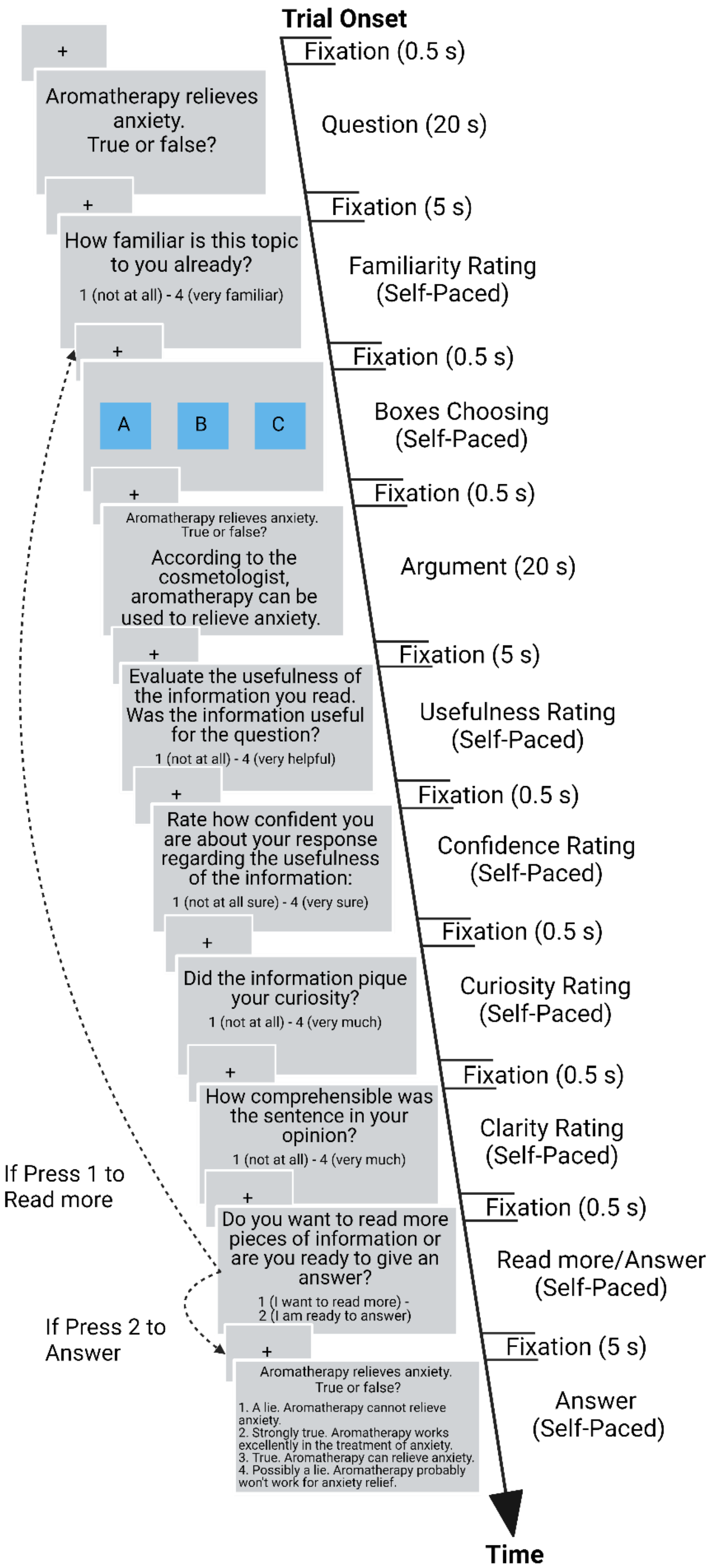

Figure 2. Trial sequence for an example question, from the presentation of the question to a decision to give an answer.

5.4 Online Experiment

One week after the laboratory experiment, a link to an online platform was sent to all participants, including surveys of the trait curiosity, memory recall test, other personality traits, and cognitive tasks that were used in other studies.

Levels of trait curiosity were measured using the Five-Dimensional Curiosity Scale Revised (5DCR), invented by Kashdan et al. (2020). The scale evaluates five dimensions of trait curiosity: joyous exploration, deprivation sensitivity, stress tolerance, thrill seeking, and social curiosity. The fifth dimension is further separated into overt social curiosity and covert social curiosity subscales, resulting in 6 subscales in total in this version. Each subscale in 5DCR consists of 4 items, resulting in a total of 24 statements. Participants were required to rate the degree to which the statements described them, using a seven-point Likert scale ranging from 1 (does not describe me at all) to 7 (completely describes me). This scale has been reported to have strong reliability (ω > .80 for all six subscales) and good construct validity by Kashdan et al. (2020) with participants from the United States.

In the current study, the 5DCR was translated from English into Finnish for data collection. The 24 items were computed into 6 composite variables representing 6 facets of curiosity. To evaluate the internal consistency of the 5DCR in the Finnish version, McDonald's omega (ω) was calculated. We chose ω rather than the widely used Cronbach's alpha (α) because α assumes tau equivalence meaning that each item contributes equally, which is not the case in 5DCR (Grüning & Lechner, 2023). The values of ω ranged from adequate (Min= .70) to good internal consistency (Max= .82) (Table 1). Considering the limited sample size (N=52), these results were quite acceptable.

Table 1. The composite variables, number of the variables used to compute it, example of the statements in English, and the McDonald's omega (ω).

Composite variable	Variables used (*n*)	Example of the statements	McDonald's omega (ω)
Joyous Exploration	4	*"I enjoy learning about subjects that are unfamiliar to me."*	.70
Deprivation Sensitivity	4	*"I feel frustrated if I can't figure out the solution to a problem, so I work even harder to solve it."*	.70
Stress Tolerance	4	*"I cannot handle the stress that comes from entering uncertain situations"*	.75
Thrill Seeking	4	*"Risk-taking is exciting to me."*	.79
Overt Social Curiosity	4	*"I ask a lot of questions to figure out what interests other people."*	.82
Covert Social Curiosity	4	*"I seek out information about the private lives of people in my life."*	.70

5.5 Data Analysis

5.5.1 Data preparation

Eye tracking data were pre-processed with SR Research DataViewer software (SR Research Ltd., version 4.3.1), including drift corrections on both vertical and horizontal planes, and setting up interest areas, such that each word in arguments constructed an area of interest (AOI). In the current study, a fixation was defined as a period that was neither a saccade nor a blink– a saccade was identified using Eyelink's standard algorithm with the following thresholds: minimum velocity of 30°/sec, minimum acceleration of 8000 °/sec^2 or a minimum motion of 0.1°; whereas a blink is detected when the saccade detector doesn't detect the pupil data for three or more consecutive samples.

The data were analysed on the word level. Based on the fixation events, five standard dependent variables were exported to assess eye movements during reading. These variables included: *first fixation duration* (the duration of the first fixation on the target word during the first pass reading), *gaze duration* (summed first-pass fixations duration on the target word before exiting the word for the first time), *regression path duration* (summed duration of fixations from the first fixation on the target word until it is exited to the right for the first time, including fixations made during regressions and the saccades), *total fixation duration* (the sum of all fixations on the target word), and *skipping probability* (the probability that the target word was skipped during the first pass reading) (Rayner, 1998; Rayner, 2009; Rayner et al., 2011). The duration variables were chosen as they represent different aspects of word processing. It is also important to note that these metrics exclusively account for fixations that land in interest areas; fixations outside of these areas are not considered in these analyses.

Regarding the questionnaire data, the average item score of each dimension in 5DCR was calculated for each participant. The score for Stress Tolerance items was calculated reversely based on Kashdan's scoring instruction (Kashdan et al., 2020).

Data was combined in software R after the pre-processing by using participant and argument ID to join the eye tracking data, behavioural data, demographic information, and curiosity measures. To control for the effect of word frequency on reading patterns, both lemma frequency and surface frequency for each Finnish word were added to the combined dataset, derived from Finnish Internet Parsebank, a mass-scale corpus of Internet Finnish (Ginter & Laippala, 2017). Lemma frequency refers to the frequency of the core or base form of words, whereas the surface frequency looks at the certain inflected form of words as they appear in the text (Jurafsky et al., 2002).

After the data combination, outliers were removed. For example, trials with incorrect button presses to the subjective rating scores were removed, including 1.81% of the data. Then, several variables were log-transformed due to skewness, including the word frequency, the proportion of arguments read, and four eye-tracking variables about processing duration - first fixation duration, gaze duration, regression path duration, and total fixation duration.

Additional data preparation was done for the dataset exclusively used for eye movement analyses, to improve the reliability of eye-tracking analyses meanwhile keeping the data integrity of the behavioural analyses. Firstly, 6.7% of the data was excluded because of missing word frequency information. Then, the z-score transformation was applied to standardize several variables, including state curiosity, word length, and word frequency. Thirdly, in analyses for fixation durations, 42.63% of the words were excluded because they were skipped by participants during first-pass reading; in addition, 1.16% of the data was removed due to short gazes (gaze durations less than 50ms), 1.14% of the data was excluded due to long gazes (gaze durations longer than 1000ms).

5.5.2 Statistical Analyses

Spearman's correlation analysis

Spearman's rank correlation is one of the most commonly used correlation methods, aiming to assess the strength of association between two variables (Hauke & Kossowski, 2011). As a nonparametric statistical method, Spearman's rank correlation does not require a normal distribution of variables or a linear relationship between them (Hauke & Kossowski, 2011). Besides, different from Pearson's product-moment correlation, Spearman's rank correlation is based on the ranks of the data rather than the actual values themselves. Therefore, it can also be applied to data measured on ordinal scales, not just limited to interval scales (Hauke & Kossowski, 2011).

In the current study, due to the non-normal distribution of some variables and the mix of interval and ordinal scale measurements, Spearman's rank correlation approach was adopted. The correlation analysis was computed in R, using the *cor()* function from the base R package.

Linear and generalized linear mixed-effects models

Both linear mixed-effects models (LMMs) and generalized linear mixed-effects models (GLMMs) are linear regressions that model the relationship between one dependent variable (or response variable) and two or more independent variables (or explanatory variables). The linear and generalized linear mixed-effects model is a good approach for the current analyses because they are particularly appropriate for hierarchical datasets and unbalanced designs (Frömer et al., 2018).

The hierarchical or multilevel datasets mean that the observations are placed at various hierarchies or levels in the data. One type of hierarchical dataset can be caused by repeated measures. The repeated-measures data is featured by the dependent variable being measured multiple times on the same participant under different conditions, across levels of a repeated-measures factor (or factors) (West et al., 2022). In the current study, each participant read multiple arguments on 18 topics. Both argument type and topic are repeated-measures factors. The result of repeated measures is a two-level dataset. Level 1 is the repeated measures for each participant, such as the argument type in the current study, explaining within-participant variation. Level 2 is the participant level, such as trait curiosity measures, describing the between-participant variation (West et al., 2022).

The unbalanced design feature of the current study also indicates that LMMs and GLMMs are a good approach. Compared with traditional repeated-measure ANOVAs which have limitations on assuming the equal number and quality of individual items that are included into averages, the linear and generalized linear mixed-effects model is advantageous in performing analyses at a single trial level, thus taking all data into account (Pinheiro & Bates, 2000; Frömer et al., 2018). This means that LMMs and GLMMs are especially suitable for unbalanced designs - the dataset that includes unequal numbers of observations for each participant (Fröber, 2017; Frömer et al., 2018), which was the case in the current study. In the current experiment, participants had the freedom to decide how many arguments they wanted to read, resulting in large variability in observations among and between individuals. The LMMs and GLMMs are also robust in dealing with missing values (Pinheiro & Bates, 2000). In this case, LMMs and GLMMs allow taking individual differences into account in repeated-measured data. Therefore, linear and generalized linear mixed-effects models are adopted in the current analysis.

The models are called “mixed-effects” models because as an extension of standard linear regression, the linear and generalized mixed-effects model incorporates both fixed effects and random effects.

The fixed effects describe the systematic or constant influence of one or more independent variables (or called covariates) on the dependent variable. The meaning of fixed effects is shown in the regression coefficients, illustrating the expected change in the dependent variable associated with one unit change of the independent variable, assuming other covariates remain the same. In addition to the independent or explanatory variables, there is also a type of factor called the control variable. They are also included in the model to control for the unexplained variance statistically, although they are not directly helpful for predicting the response variables.

On the other hand, random effects are associated with one or more random factors, which account for random deviation (West et al., 2022). Random effects are usually determined by experimental design (Gomes, 2022). In the repeated-measures data set, the variable that identifies level 2 data is often regarded as a random factor. Thus, the participant ID, each argument and word are considered random factors in the current analysis. Another noteworthy matter is that different from fixed effects, random effects only explain the random variation of dependent variables within certain individuals, not for the entire population. In other words, random effects explain the systematic individual differences (Frömer et al., 2018).

The generalized linear mixed-effects model is a more general form of the linear mixed-effects model. They share fundamental components, including fixed effects and random effects. However, LMM only applies to the dataset in which dependent variables follow the Gaussian (normal) distribution, such as the variables about processing duration in reading, whereas the generalized linear mixed-effects model can tolerate various distributions of the dependent variable, such as binomial and Poisson distributions (Gomes, 2022).

The binomial distribution is characterized by only two possible outcomes. In the current study, participants' switch (exploration) behaviour (whether participants turn to another source of information during reading) and skipping probability (whether participants skip the target word on first-pass reading or not) follow binomial distribution, since they have only two possibilities: 1 for switching or skipping, and 0 for not switching or not skipping. The Poisson distribution reflects the probability of a certain event occurring within a given time interval. For example, the number of arguments read by each participant on each question takes the values 1,2,…,15, and therefore it follows the Poisson distribution as counting data. For these variables, the generalized linear mixed-effects models are adopted.

5.5.3 Model specification in the current study

The statistical analyses were conducted using R-Studio (Version 4.2.3; R Core Team, 2023). The linear and generalized linear mixed models were conducted using the *lmer()* and *glmer()* functions respectively, from the lme4 package (Bates et al., 2015). One advantage of *lmer()* and *glmer()* formulas is including both fixed and random effects in one expression. The expression on the left of the tilde symbol represents the response variable, while the right side includes the predictors and random effects. The simplest formula for random effect is written as (1 | g), indicating the random intercept for each level of the grouping factor g (Gałecki & Burzykowski, 2013, Bates et al., 2015).

Behavioural analyses

The first research question concerned the effect of curiosity on participants' performance in the reading task. Participants' task performance was assessed using three variables: *the number of arguments read per topic*, *the proportion of arguments read for each category* (calculated by dividing the actual count by 90

- the total number of arguments per category), and the *switching probability* (defined as a change to another category after reading the last argument, instead of continuing to read the argument within the same category).

Separate LMMs or GLMMs were employed for each dependent variable. For each model, to answer the first question about the effect of curiosity on information-seeking performance, state curiosity and all dimensions of trait curiosity were included as fixed factors.

Specifically, due to the Poisson distribution, a GLMM was computed for analysing the number of arguments read. Besides the state and trait curiosity, participants' familiarity rating on each topic was also included as a control variable. Each topic and participant ID were considered as random factors. The formula is as follows:

Number ~ StateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + Familiarity + (1 | Topic) + (1 | ID)

Note: StateCur = state curiosity; cur_joy = joyous exploration; cur_dep = deprivation sensitivity; cur_stress = stress tolerance; cur_thrill = thrill seeking; cur_Osoc = overt social curiosity; cur_Csoc = covert social curiosity. This also applies to the following models.

In the models for proportion and switching probability, in addition to state and trait curiosity, fixed effects factors also encompass the argument type, aiming to account for differences in information quality. Familiarity, along with other ratings related to the argument such as confidence and clarity, were incorporated as control variables. The usefulness rating was excluded due to its strong correlation with the state curiosity rating ($r = 0.58$, $p < 0.001$). A random intercept for participant ID was added to explain within-participant variation. Each argument was also considered as a random effect in the model for switching probability. The formula is as follows:

Proportion / Switches~ StateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + argument type + Confidence + Clarity + Familiarity + (1 | Argument) + (1 | ID)

In addition, to answer research question 2 about the influence of trait curiosity on state curiosity in the reading context, another linear mixed-effect model was employed. The formula also parallels the above one, with state curiosity being a response variable instead of the predictor. This model also controlled for the effects of argument type, confidence, clarity and topic familiarity.

StateCur ~ cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + argument type + Confidence + Clarity + Familiarity + (1 | Argument) + (1 | ID)

Eye movement analyses

The third research question is about the effects of curiosity on participants' eye movements during reading. Five eye movement measures were examined as dependent variables (DV): *first fixation duration*, *gaze duration*, *regression path duration*, *total fixation duration*, and *skipping probability*.

Four separate linear mixed-effects models were computed for the duration measures. One generalized linear mixed effects model was performed for skipping probability, which follows the binary distribution. For each model, fixed effects include state curiosity (z-scored), all dimensions of trait curiosity, and argument type. The interaction between state curiosity and argument type is also included to account for the influence of state curiosity across different levels of argument type. Besides, word length (z-scored), and Lemma word frequency (log-transformed and z-scored) were added to the model as control variables. Random effects include participant ID, argument, and word.

The formula for these five models is as follows:

*DV ~ argument type*zStateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + zLength + zlogFrequency + (1 | word) + (1 | Argument) + (1 | ID)*

In both behavioural and eye movement analyses models, the 95% confidence intervals for the contrasts were computed using Wald estimation. The estimation of model fitting was performed with the REML (Restricted (or Residual) Maximum Likelihood) argument, which aims to maximize the likelihood of the residuals, capturing the uncertainty introduced by random effects (West et al., 2022; Bates et al., 2015; Gałecki & Burzykowski, 2013). Besides, the model comparison was conducted using the likelihood ratio test with the *anova()* command in R, with a low p-value indicating the significant difference between compared models. Lower values on AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion) also indicate better model fit.

6 Results

6.1 Behavioural results

This section addresses the first two research questions: the effect of curiosity on participants' performance in the reading task (question one), and the relationship between state and trait curiosity (question two).

6.1.1 Number of arguments read

On average, participants read 4.92 ± 3.22 (standard deviation, SD) out of 15 arguments on each topic, ranging from 1 to 15. Figure 3 displays the number of arguments read on each topic for all participants.

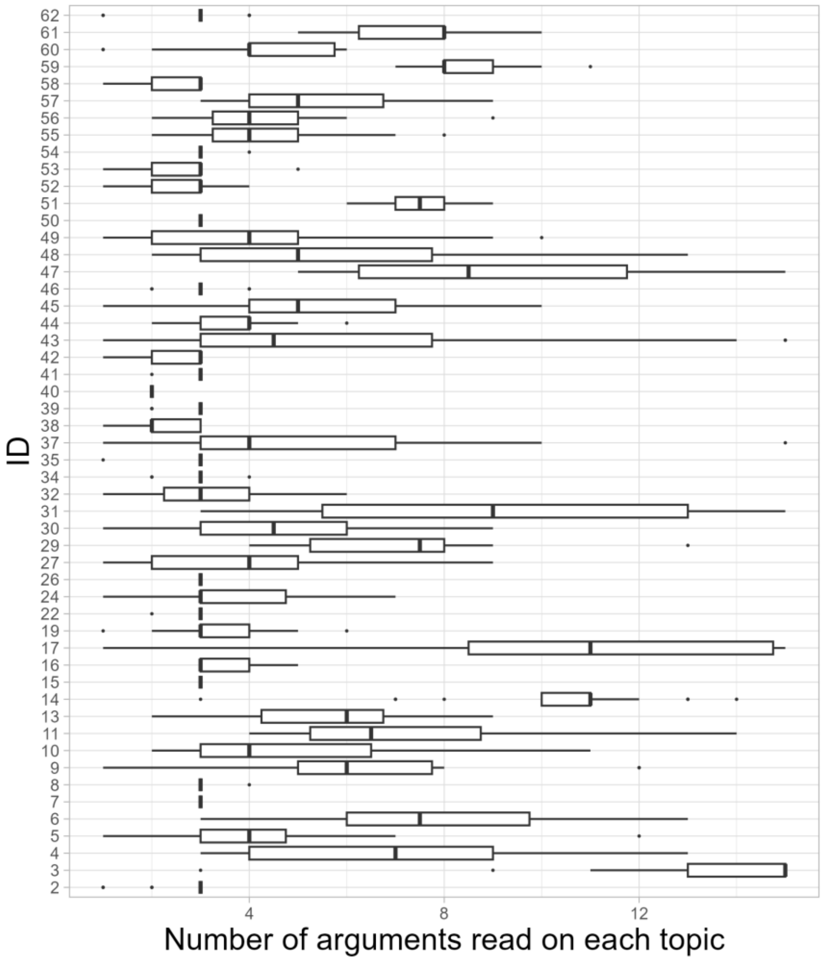

Figure 3. Boxplot reflecting the number of arguments read on each topic for all participants. (n=52). The boxes represent the value from the lower quartile to the upper quartile; the whiskers indicate the minimum value to the maximum.

The generalized linear mixed model showed a marginal positive effect of overt social curiosity on the number of arguments read per topic, b = .11, 95% confidence interval (CI) = [-.01, .24], SE = .06, z = 1.77 (Figure 4A). Similarly, the Spearman's correlation results (see Figure 8) indicated a significant correlation between overt social curiosity and average number of arguments read ($r = 0.30$, $p < 0.05$). In other words, participants who scored higher on overt social curiosity tended to read more arguments in this experiment.

In addition, the results indicated that the higher familiarity ratings were marginally related to the lower number of arguments read, b = -.04, 95% CI = [-.08, .01], SE = .02, z = -1.68 (Figure 4B).

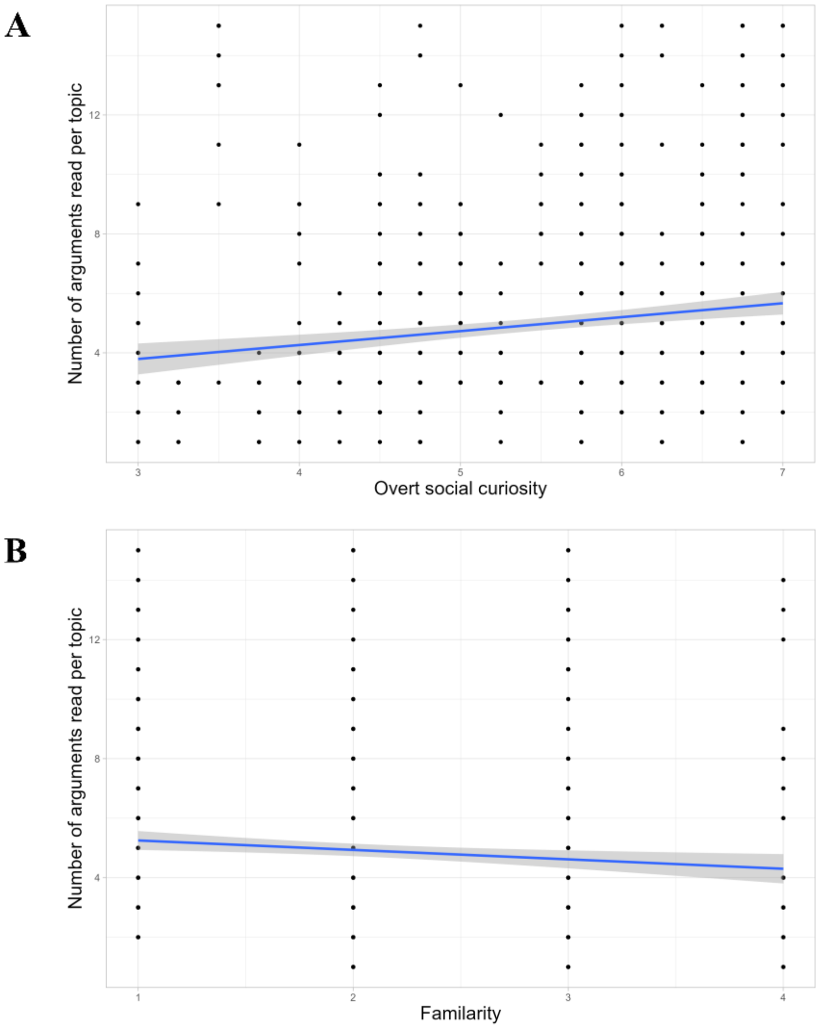

Figure 4. **A.** scatter plot showing the relationship between overt social curiosity and number of arguments read; **B.** scatter plot showing the relationship between familiarity and number of arguments read. The line is the linear regression line fitted to the data points. Shaded areas represent 95% confidence intervals.

No effect of state curiosity rating and other dimensions of trait curiosity was found, indicating that these factors do not exert influence on the number of arguments read by participants.

6.1.2 Proportion of arguments read

First, the predictive effect of argument type on the proportion of arguments read was analysed (Figure 5). When familiarity rating was controlled, the proportion of SR arguments read (mean = 0.38, SD = 0.24) is significantly higher than SI (mean = 0.30, SD = 0.17), b = 0.08, 95% CI = [.04, .12], SE = .02, t = 4.17, and NR (mean = 0.28, SD = 0.15) categories, b=0.10, 95% CI = [.06, .14], SE = .02, t = 5.14. The difference between the SI and NR categories was not significant.

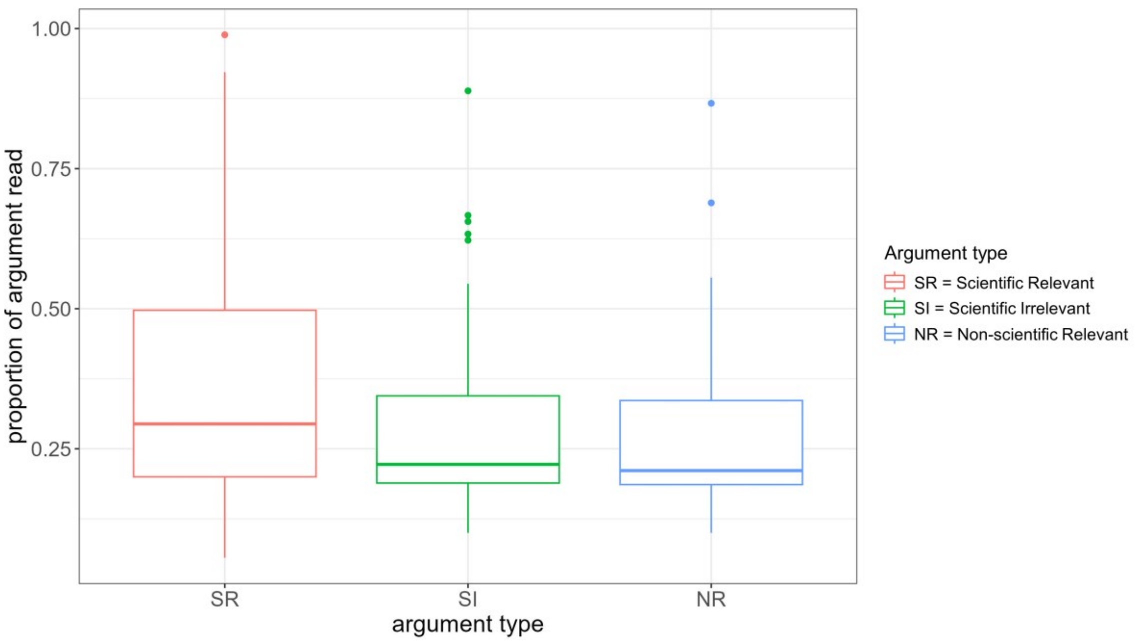

Figure 5. The proportion of three categories of arguments read by all participants. The boxes represent the value from the lower quartile to the upper quartile; the line inside the box represents the median value; the whiskers indicate the minimum value to the maximum.

Second, state curiosity as well as other argument-related ratings were added in the linear mixed model as new predictors. Results showed that state curiosity rating is marginally associated with the proportion of argument read, b = 0.05, 95% CI = [-.00, .11], SE = .03, t = 1.88, as shown in Figure 6. The proportion of SR arguments read is still higher than SI, b = 0.05, 95% CI = [.00, .10], SE = .02, t = 2.11, but the proportion of arguments read did not differ between SR and NR, and SI and NR categories.

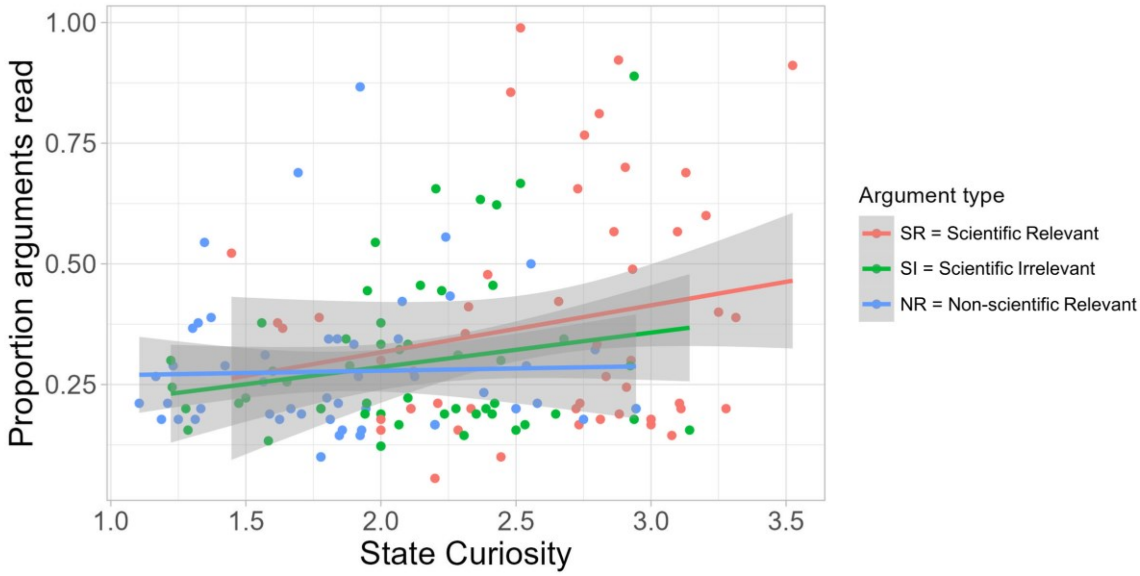

Figure 6. State curiosity as a predictor for proportion of arguments read among three categories. Shaded areas represent 95% confidence intervals.

In the third model, all dimensions of trait curiosity were added as new fixed effects. Interestingly, when trait curiosity was controlled for, the predictive effect of state curiosity no longer approached significance, which indicated that the variance in state curiosity was explained by individual traits. The effects of argument type on the proportion are still strong. The SR arguments were read more frequently than SI, b = 0.06, 95% CI = [.01, .11], SE = .03, t = 2.25. No significant difference between SR and NR, and SI and NR.

These three models were compared through the Maximum Likelihood (ML) ratio test. The chi-square indicated no significant difference among their fitting. Adding state and trait curiosity into the model seems to have little impact on improving the model fit. In other words, argument type predicted the proportion of argument read above the effect of curiosity.

6.1.3 Switching probability

In the context of information seeking, the switch decision indicates exploration strategy – trying to explore other information sources, whereas staying in the same information source reflects exploitation behaviour – exploiting the current information source. In the current study, 69.86% of arguments were read after switching the argument category, involving exploration, while exploitation constitutes 30.14%.

The generalized linear mixed-effects model indicated a main effect of argument type on participants' switch behaviour. Specifically, when compared to the SR argument (mean = 0.62, SD = 0.49), a higher probability of switch decisions was observed from SI type argument (mean = 0.74, SD = 0.44), b = .67, 95%CI = [.46, .89], SE = 0.11, z = 6.26, as can be seen from the model plot Figure 7. Moreover, the decision to switch also occurred more frequently while reading NR arguments (mean = 0.77, SD = 0.42) compared to SR ones, b = .85, 95%CI = [.61, 1.08], SE = 0.12, z = 7.11. In other words, exploration behaviour is more common when exposed to irrelevant arguments compared to relevant ones, and also more common from non-scientific than scientific arguments.

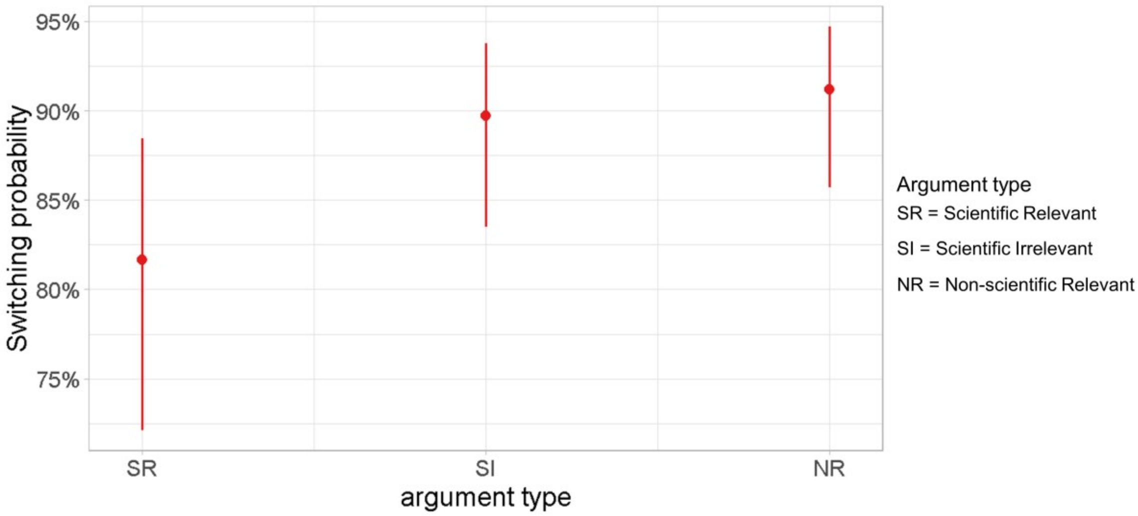

Figure 7. Model estimates for the probability of switches among different argument types. The dots represent the median value; the whiskers indicate the minimum value to the maximum.

In addition, the model also showed that participants' overt social curiosity level is negatively associated with switch decisions, b = -.66, 95%CI = [-1.17, -.15], SE = 0.26, z = -2.55. This suggests that individuals with higher overt social curiosity were more likely to engage in exploitation behaviour.

6.1.4 Relationship between trait and state curiosity

In the current study, the mean of participants' state curiosity is 2.28 (SD = 0.97). Research question 2 concerned the influence of trait curiosity on state curiosity during argument reading. Figure 8 shows the Spearman's correlation matrix, with darker colours representing stronger correlations. Among all dimensions of trait curiosity, only scores on thrill seeking correlated negatively with the state curiosity rating ($r = -0.41$, $p < 0.01$). This indicates that participants with a higher tendency to seek thrill show lower state curiosity in this experiment, which makes sense considering the science-related nature of arguments. No correlation was found between state curiosity and other dimensions of trait curiosity.

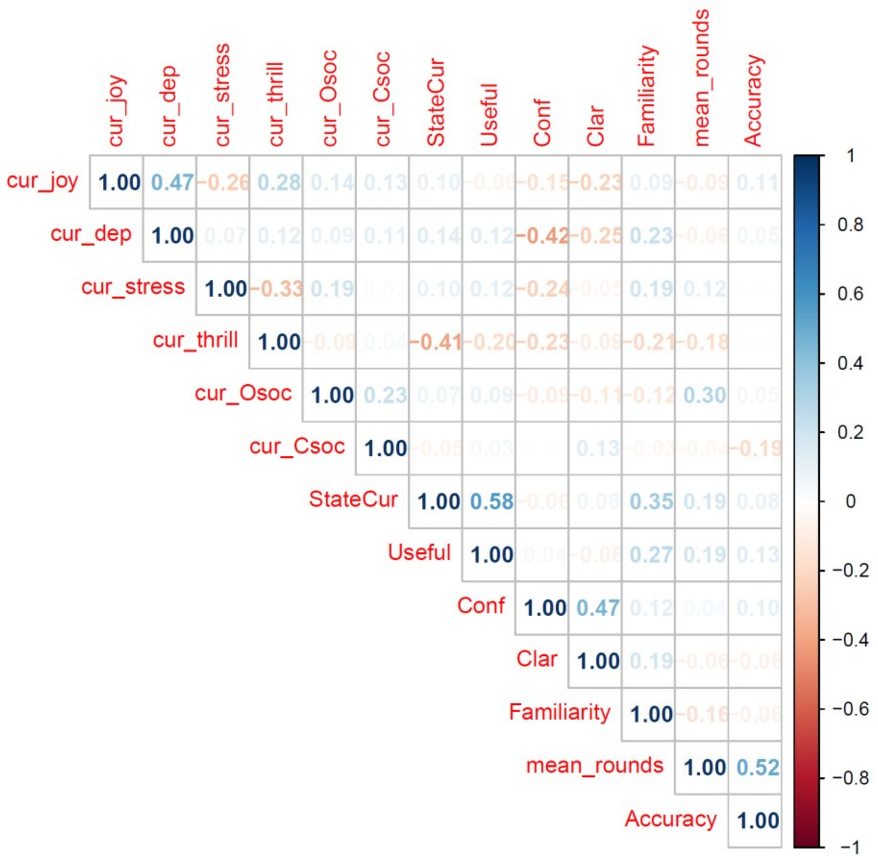

Figure 8. Spearman's correlation matrix on trait curiosity, subjective ratings, and behavioural variables. Darker colours represent stronger correlations.

The results from the linear mixed-effect model further support the relationship observed in the correlation analysis. These results indicated a significant predictive influence of the thrill-seeking dimension of trait curiosity on state curiosity, b = -.15, 95% CI = [-0.24, -0.06], SE = 0.05, t = -3.20, in the expected negative direction (as illustrated in Figure 9A). The other dimensions of trait curiosity had no influence on state curiosity.

The model also showed a main effect of argument type (Figure 9B). Participants showed greater state curiosity for SR type arguments (mean = 2.67, SD = 0.89) than SI (mean = 2.18, SD = 0.95), b = 0.52, 95% CI = [.42, .62], SE = .05, t = 10.21, and NR (mean = 1.85, SD = 0.89), b = 0.86, 95% CI = [0.76, 0.96], SE = .05, t = 16.70. State curiosity rating for SI was also higher than for NR arguments, b = 0.34, 95% CI = [0.24, 0.44], SE = .05, t = 6.46.

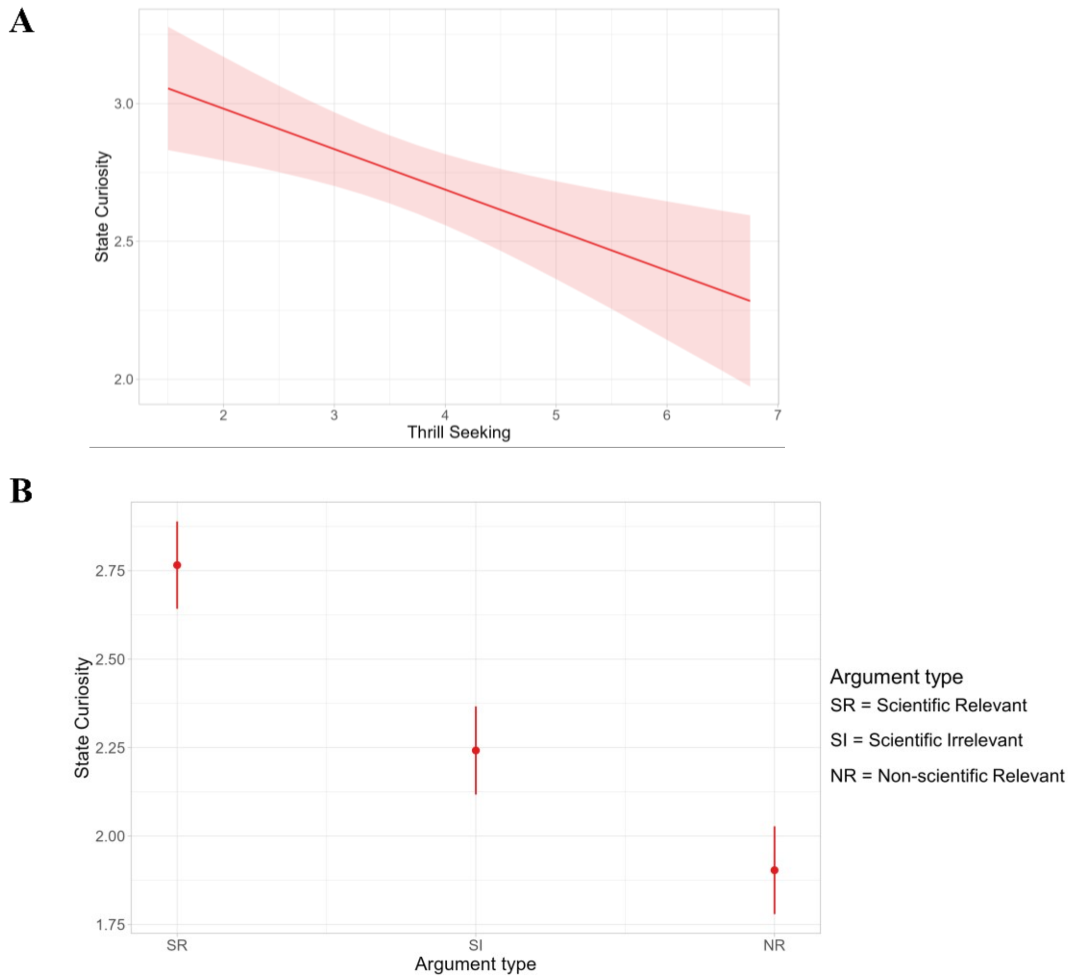

Figure 9. A. Model estimates for state curiosity, with thrill seeking as predictor. Shaded areas represent 95% confidence intervals. **B.** Model estimates for state curiosity among three argument categories.

In addition, the correlation matrix also showed the relationship between curiosity and other subjective ratings. For example, a significant positive correlation was observed between state curiosity rating and usefulness rating ($r = 0.58$, $p < 0.001$). This suggests that people tend to get curious about the arguments that are considered useful. Besides, it is interesting to note that state curiosity is also positively correlated with familiarity rating ($r = 0.35$, $p < 0.05$), suggesting that individuals tend to exhibit greater state curiosity on topics that they are more familiar with.

The model further revealed the positive effects of familiarity on state curiosity, b = 0.04, 95% CI = [.00, .07], SE = .02, t = 2.14. Besides, participants also feel more curious about arguments with greater clarity, b = 0.13, 95% CI = [.09, .17], SE = .02, t = 6.65. Whilst their confidence in usefulness ratings has negative effects on state curiosity, b = -0.12, 95% CI = [-.15, -.09], SE = .02, t = -6.96.

6.2 Eye movement analyses results

6.2.1 First fixation duration

According to the LMM model, state curiosity alone had no effect on the first fixation duration. However, when state curiosity is controlled, the first fixation duration varies among different argument types. Specifically, the duration for NR type argument is shorter compared to both SR type, b = -0.02, 95% CI = [-.03, -.00], SE = .01, t = -2.37, and SI type arguments, b = -0.02, 95% CI = [-.04, -.01], SE = -.01, t = -2.94.

The result also showed effects of two dimensions of trait curiosity on first fixation duration. Participants exhibiting higher levels of overt social curiosity had longer first fixation duration, b = 0.04, 95% CI = [.00, .08], SE = .02, t = 2.17 (Figure 10A), while those with higher stress tolerance exhibit shorter first fixation duration, b = -0.03, 95% CI = [-.07, -.00], SE = .02, t = -2.09 (Figure 10B).

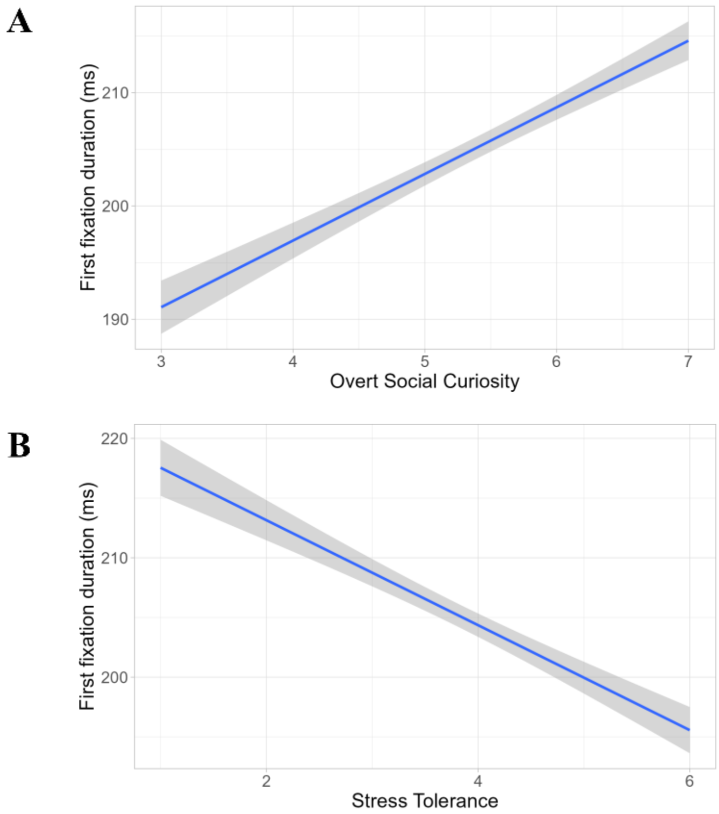

Figure 10. A. Plot for the relationship between overt social curiosity and first fixation duration (ms); **B.** Plot for the relationship between stress tolerance and first fixation duration (ms).

Note: The line represents the linear regression line fitted to the data points. Shaded areas represent 95% confidence intervals. This also applies for Figure 11 and Figure 12.

In addition, both word length and word frequency affected first fixation durations. Participants have longer first fixation duration for longer words, b = 0.02, 95% CI = [.01, .03], SE = .01, t = 3.71, and shorter first fixation duration for high-frequency words, b = -0.01, 95% CI = [-.02, -.00], SE = .01, t = -2.40.

6.2.2 Gaze duration

Similar to the results of first fixation duration, participants with higher levels of overt social curiosity had longer gaze duration, b = 0.05, 95% CI = [.00, .09], SE = .02, t = 2.00 (Figure 11A), while those with higher stress tolerance exhibited shorter gaze duration, b = -0.04, 95% CI = [-.08, -.00], SE = .02, t = -2.19 (Figure 11B).

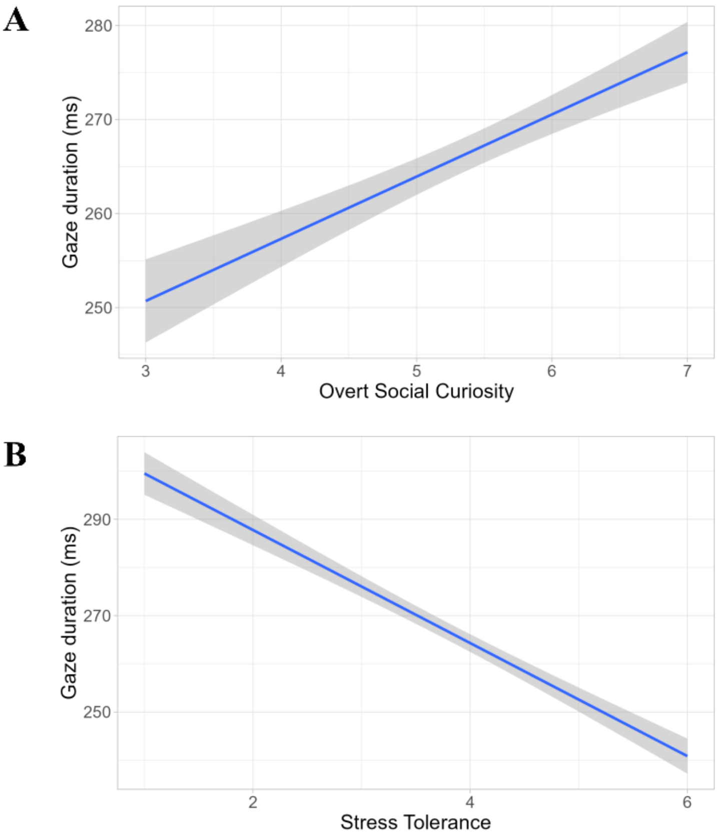

Figure 11. A. Plot for the relationship between overt social curiosity and gaze duration (ms); **B.** Plot for the relationship between stress tolerance and gaze duration (ms).

Gaze duration was also affected by word length and word frequency. Participants had longer gaze duration for longer words, b = 0.15, 95% CI = [.13, .16], SE = .01, t = 22.36, and shorter gaze duration for high-frequency words, b = -0.05, 95% CI = [-.06, -.03], SE = .01, t = -6.92.

However, neither state curiosity nor argument type was found to have an impact on gaze duration.

6.2.3 Regression path duration

The model indicated the effects of overt social curiosity and thrill seeking on regression path duration. Participants with higher levels of overt social curiosity had longer regression path duration, b = 0.06, 95% CI = [.01, .12], SE = .03, t = 2.25 (Figure 12A). Participants who exhibited a greater thrill seeking tendency also tend to spend more time rereading the previous text, b = 0.08, 95% CI = [.03, .12], SE = .02, t = 3.23 (Figure 12B).

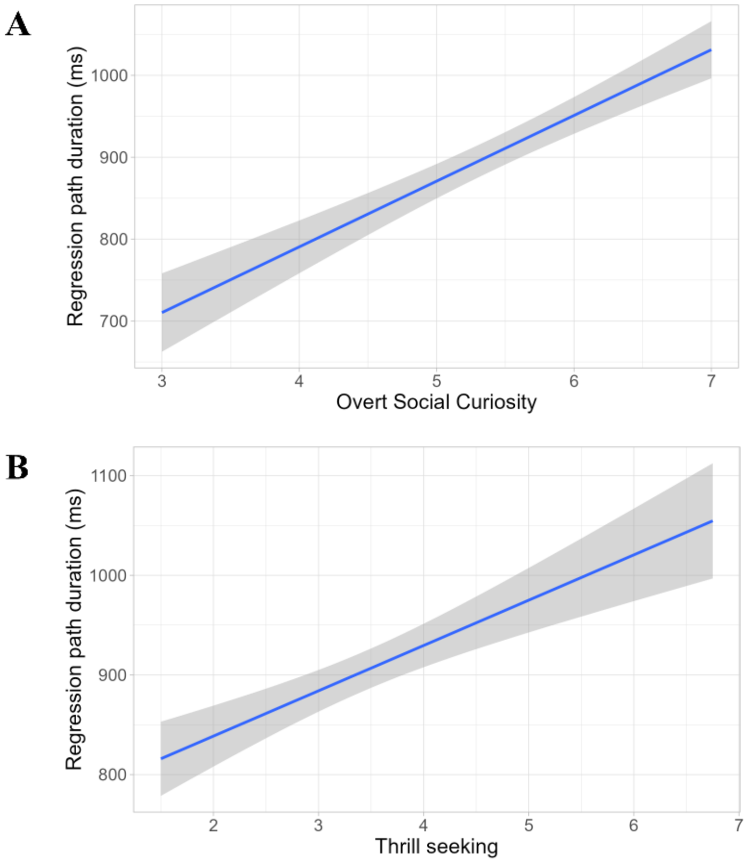

Figure 12. A. Plot for the relationship between overt social curiosity and regression path duration (ms); **B.** Plot for the relationship between thrill seeking and regression path (ms).

In addition, word length predicted regression path duration, with longer regression path duration for longer word, b = 0.35, 95% CI = [.29, .40], SE = .03, t = 12.69.

However, neither state curiosity nor argument type was found to have an impact on regression path duration.

6.2.4 Total fixation duration

Results showed a main effect of state curiosity on the total fixation duration. Increased state curiosity was associated with longer total fixation duration, b =

0.03, 95% CI = [.02, .05], SE = .01, t = 4.21, meaning that people spend more time reading arguments they were more curious about.

However, the model revealed an interaction between state curiosity and argument type. As can be seen in Figure 13, the impact of state curiosity on total reading time differs across argument types. The post-hoc analysis for interactions showed that for NR type arguments, the impact of state curiosity on the total reading time is significantly stronger compared to SR type ($b=.05$, $SE=.01$, $p < 0.001$), and marginally stronger than SI type ($b=.03$, $SE=.01$, $p = 0.06$).

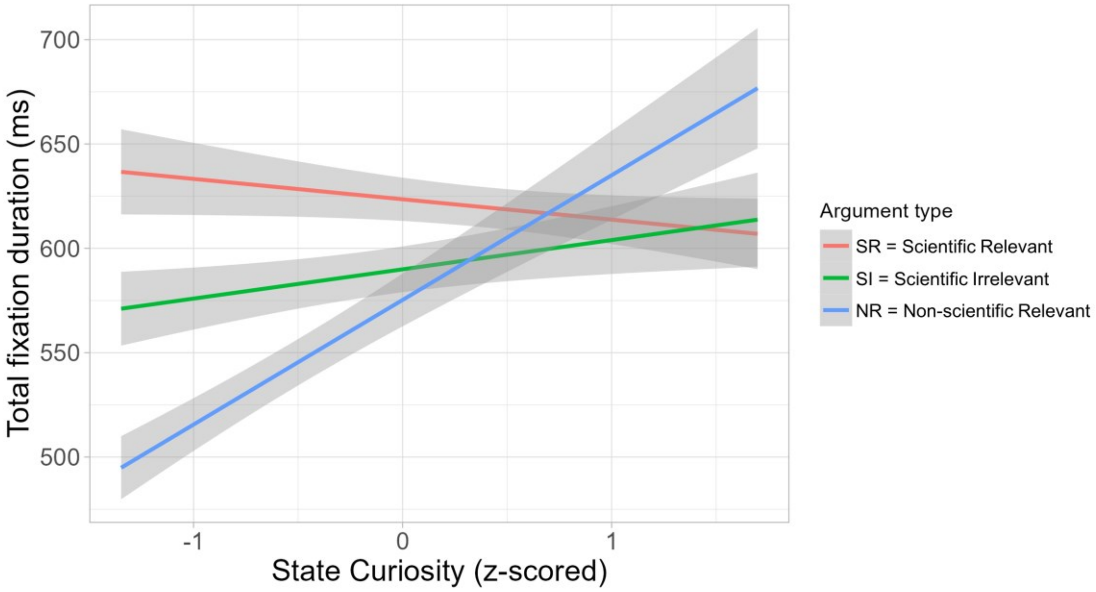

Figure 13. The effects of the interaction between state curiosity and argument type on total fixation duration.

Trait curiosity was not associated with the total fixation duration, while word length and word frequency predicted the total fixation duration. Participants had longer total fixation duration on longer words, b = 0.22, 95% CI = [-.20, .24], SE = .01, t =21.35, and shorter total fixation duration on high-frequency words, b = -0.10, 95% CI = [-.12, -.08], SE = .01, t = -8.98.

6.2.5 Skipping probability

After thorough data quality checks, the first run skip rate was 42.63%. A generalized linear mixed effect model was performed for skipping probability. According to the results, both state curiosity and trait curiosity had no effects on skips. However, the argument type was found to have an impact on skipping probability (Figure 14). Specifically, words were skipped more frequently in SR type argument (Mean = 0.44, SD = 0.50) than SI type (Mean = 0.43, SD = 0.49), b = .14, 95% CI = [.01, .28], SE = .07, z = 2.04, and marginally more frequently than NR type (Mean = 0.40, SD = 0.49), b =.13, 95% CI = [-.01, .27], SE = .07, z = 1.88.

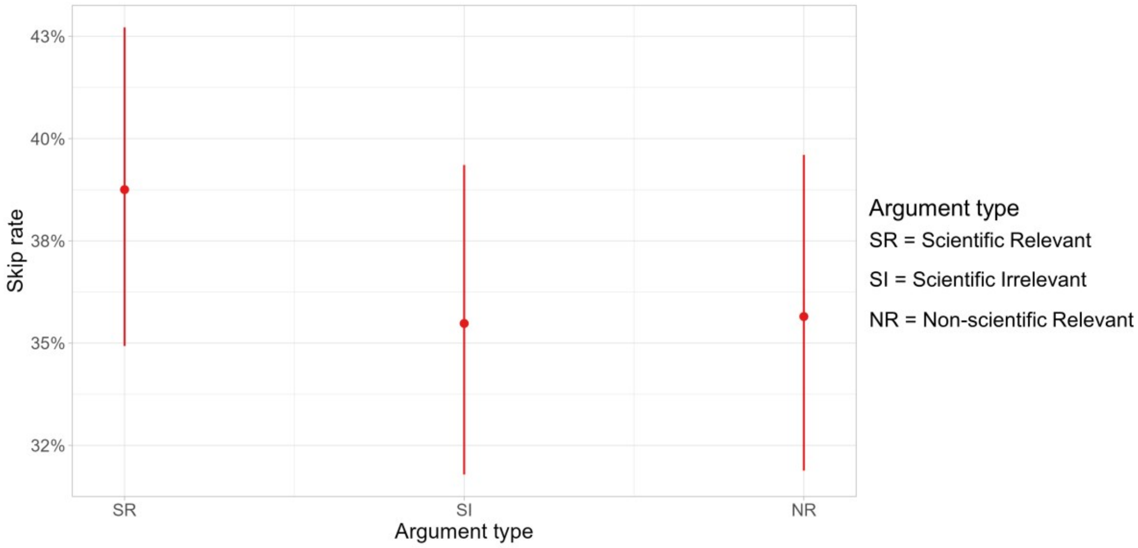

Figure 14. Model estimates for skipping probability among three argument categories.

Besides, results also revealed that longer words were skipped less, b = -.53, 95% CI = [-.60, -.46], SE = .04, z = -14.74. No effect of word frequency was found.

7 Discussion

The main goals of the present study were to investigate the effect of both state and trait curiosity on reading behaviours, including task performance and eye movement measures, and to examine the relationship between state and trait curiosity in the information-seeking process. This section will briefly highlight the main findings, provide interpretations based on previous studies, and acknowledge the limitations while suggesting potential avenues for future studies.

7.1 The effect of state curiosity and information quality

Different from the conventional experimental paradigm that triggers curiosity through trivia questions (Kang et al., 2009; Gruber et al., 2014; Baranes et al., 2015) or blurred images (Jepma et al., 2012), the current study was designed as a bandit task which incorporated information with various qualities. It mirrored the real-world information-seeking context in which people need to evaluate information with varying qualities. In this way, the study not only examined the effect of curiosity but also provided insights into the role of argument quality in the decision-making process.

7.1.1 The effect of state curiosity on task performance

Contrary to predictions, no effect of state curiosity was found on participants' task performance, that is, the number of arguments read, and the switching probability. Although the results (Figure 6) indicated a marginally positive effect of state curiosity on the proportion of arguments read, this influence was no longer present when trait curiosity was included in the full model. Thus, the results were not in agreement with H1.1 which was that stronger state curiosity would be associated with more active task performance.

Then the question arises: why state curiosity, as the intrinsic motivation to acquire new information, was not related to reading performance? A possible explanation can be the presence of extrinsic rewards in the current experiment. Different from the self-initiated information-seeking process, in laboratory settings, participants were aware of the task requirements and compensatory rewards (a movie ticket in the current case). Thus, information-seeking in such as situation can be both intrinsically (curiosity-driven) and extrinsically (task-driven) motivated. Previous theories emphasize the similarities between information-seeking behaviour driven by curiosity and extrinsic rewards; especially the reward-learning perspective highlights a common mechanism underlying different reward types (Murayama, 2022). However, extrinsic rewards have been demonstrated to undermine intrinsic motivation (Deci et al., 1999). The present results give some hints about how curiosity works in the presence of extrinsic rewards. Future research can delve deeper into the influence of extrinsic rewards on the motivational power of curiosity.

Familiarity is another factor that might account for the lack of effect of state curiosity on reading performance. In the current analyses, stronger state curiosity was linked to higher familiarity ratings, that were correlated with a lower number of arguments read. Different from Berlyne’s novelty-driven theory of curiosity, which considers novelty as one essential force for triggering curiosity (Berlyne, 1950; Dubey & Griffiths, 2020), the current analyses posit that familiarity can make participants more curious when dealing with science-related issues. As the opposite side of novelty, familiarity means more background knowledge of the target topic, which reflects a narrower information gap (Lowenstein, 1994). In this sense, the present results support the idea that curiosity could be related to a reduced information gap, rather than a wider one, aligning with the findings proposed by Litman et al. (2005). However, in the task-driven information-seeking process, a smaller information gap also means that fewer arguments are needed. This is why familiarity can have a negative impact on the number of arguments read. Once participants have gathered enough information to answer the question, the information gap is resolved, and there is no longer a necessity to continue searching. This finding corresponds with Berlyne's study, where rats spent less time exploring stimuli they were already familiar with (Berlyne, 1950).

7.1.2 The effect of state curiosity on fixation duration

State curiosity was found to have a positive effect on participants' total fixation duration. This means participants would spend more time and get more engaged in reading information that they are more curious about. The results thus supported Hypothesis 3.1 which was that state curiosity affects fixation patterns. Previous studies have demonstrated the influence of lexical and linguistic variables on fixation duration, including word frequency, and word length (Rayner, 2009; Conklin et al., 2018). Therefore, in the current study, these factors were controlled for. Fixation is the period when humans acquire and process new information. In addition to the linguistic factors, cognition also has a strong influence on fixation duration (Rayner, 2009). The present study found that curiosity, as a cognitive state, is associated with a longer reading duration during the processing of scientific information, which may be due to more allocation of attention. Thus, curiosity does not only influence the fixation location - where to move the eyes, as demonstrated by Baranes et al. (2015), but it also affects the fixation duration - when to move the eyes. In addition, as curiosity is also an epistemic emotion, the results also indicate the effect of emotion on fixation duration. Similarly, Gere et al. (2017) showed that positive mood is related to longer fixation and dwell time on food pictures. Future studies could explore the underlying mechanism behind the effect of state curiosity on fixation duration.

Interestingly, in the current study, the effect of state curiosity on total fixation duration interacted with argument types (Figure 13). The results indicated that the total fixation duration for non-scientific arguments was highly influenced by state curiosity. As curiosity can arise from uncertainty and ambiguity (Lamnina & Chase, 2019), the conflicting information in lower-quality arguments could explain the longer total fixation durations in association with increased curiosity while reading the non-scientific arguments. These arguments may also require careful reading to evaluate the reliability and usefulness of information towards the task. Compared with non-scientific arguments, the time participants spend reading scientific relevant information is barely influenced by state curiosity. In other words, regardless of participants' level of curiosity, high-quality information was processed meticulously, maybe due to its utility for the task demands and inherently rewarding nature.

7.1.3 The influence of argument quality in information-seeking process

The results indicate that participants are able to detect good-quality information sources. First, participants were more curious about scientific relevant arguments than non-scientific or irrelevant ones. According to the reward-learning framework, information serves as a reward (Murayama et al., 2019; Murayama, 2022). Good quality arguments are more helpful for resolving the information gap. Therefore, they provide more rewarding value, and thus are easier to trigger state curiosity. This may suggest that in addition to the commonly mentioned collative variables like novelty, uncertainty, and complexity (Berlyne, 1960), the practical utility of information in bridging knowledge gaps could also play a significant role in piquing curiosity.

Moreover, the rewarding experience of acquiring reliable knowledge would foster the expected rewarding value of new information, thereby motivating next-round information-seeking behaviour (Murayama, 2022). This may also explain why the switching probability for SR-type arguments was the lowest. Participants exploited the good quality arguments, which were reliable and useful for the task demands. In addition, the proportion of arguments read was the highest for scientific relevant arguments, indicating that participants engaged with good-quality information more frequently. The proportion variable reflects the extent to which an individual relies on different sources of information to make decisions. These results indicate that participants can distinguish information with different qualities and are able to use reliable information to make health-related decisions.

7.2 The effect of trait curiosity

Overall, partial support was found for both Hypothesis 1.2, linking trait curiosity to different task performance, and Hypothesis 3.2, indicating the association between trait curiosity and fixation patterns. Among the five dimensions of trait curiosity, Overt Social Curiosity and Stress Tolerance were associated with participants' task performance and eye movements during reading; Thrill Seeking was positively related to regression path duration; whereas no effect was found from Joyous Exploration and Deprivation Sensitivity.

According to Kashdan et al. (2020), Joyous Exploration and Deprivation Sensitivity represent distinct emotional aspects of curiosity, drawing from Litman's (2008) distinction between interest- and deprivation-type of curiosity. A recent study found that interest-type curiosity predicts feelings of interest and pleasure during information seeking; while deprivation-type curiosity is associated with feelings of frustration (Ryakhovskaya et al., 2022). However, in the current science-related decision-making task, these emotional facets of curiosity did not significantly impact participants' reading performance. The following discussion will focus on the other two dimensions that played a crucial role: overt social curiosity and stress tolerance.

7.2.1 The effect of Overt Social Curiosity

Although the current experiment did not involve social interaction, the results showed various effects of Overt Social Curiosity on both participants' reading performance and eye movements. It seems that people scoring high on Overt Social Curiosity differ from others in the current decision-making task. Specifically, people with higher overt social curiosity tend to 1) read more arguments (see Figure 4A); 2) make fewer switches between argument categories, i.e., they tended to exploit more information from the same source; 3) have longer first fixation duration (Figure 10A); 4) longer gaze duration (Figure 11A); and 5) longer regression path duration (Figure 12A).

In contrast to Covert Social Curiosity, i.e., surreptitious strategy such as prying and gossiping, Overt Social Curiosity is the motivation to know others' behaviour, thoughts, and feelings, through overt means such as directly talking (Kashdan et al., 2020). The items on this dimension describe social interaction behaviour, with an emphasis on an "overt" approach. The example items are: "I ask a lot of questions to figure out what interests other people"; "I like finding out why people behave the way they do." (Kashdan et al., 2020).

Thus, overt social curiosity reflects a tendency to ask questions and understand why people act the way they do; it is an urge to delve deep and uncover the reasons and motivations behind human behaviour. The present results indicate that this resilient motivation in understanding social behaviour is also associated with a more persistent and determined style in information seeking. For example, participants with higher overt social curiosity acquired more arguments on each topic before feeling satiated. They made fewer switch decisions, which means that those who scored high on overt social curiosity were more likely to exploit one source of information once they found it reliable. The longer regression path duration suggests they spent more time rereading the texts. Together with the longer first fixation duration and longer gaze duration, this indicates a more conscientious and careful reading style. The current analyses provide an initial indication of the surprising effect of social curiosity on health-related science information consuming style. Further studies are needed to assess the reliability, and explore the psychological underpinnings, of this effect.

7.2.2 The effect of Stress Tolerance

In addition to Overt Social Curiosity, Stress Tolerance was also found to affect participants' reading eye movement, specifically, first-pass fixation duration. People with higher stress tolerance exhibited shorter first fixation duration and gaze duration. In other words, they stayed shorter on words during the first pass.

Stress Tolerance evaluates one key cognitive dimension of trait curiosity. The initiation of curiosity requires not only exposure to novel stimuli, but also individual’s confidence in coping with the stress when confronting uncertainty and ambiguity (Silvia, 2008). Stress Tolerance reflects people’s perceived ability to handle the stress that arises from exploring new, complex, and uncertain situations (Kashdan et al., 2018). The inherent stress and anxiety can cause a motivational conflict of whether to approach or avoid (Berlyne, 1960; Kashdan et al., 2008). People who score high on Stress Tolerance tend to be more willing to embrace the stress induced by engaging with novel and uncertain circumstances (Kashdan et al., 2020). The present results indicate that this trait also enables them to engage more swiftly in reading arguments, with potentially less doubt and hesitation when encountering new information of uncertain quality. In essence, individuals with higher stress tolerance tend to be quicker and more decisive readers during the information-seeking process.

7.3 The relationship between trait curiosity and state curiosity

Research question 2 concerned the influence of trait curiosity on state curiosity. Within 5 dimensions of trait curiosity, Thrill Seeking was found to be negatively correlated with participants' state curiosity during reading. The linear mixed-effects model further confirmed the effect, whereby the higher participants scored on Thrill Seeking dimension, the less they felt curious while reading health-related arguments.

Thrill Seeking reflects a personality tendency to be adventurous, and ready to take risks. People with high score on thrill seeking are eager to acquire novel, complex, and pleasurable experiences, even though it may risk physical, social, or financial safety (Kashdan et al., 2018; Kashdan et al., 2020). Compared with adventurous and exciting experiences, reading science-related arguments piece by piece may sound less curious for thrill-seekers. Especially considering the content of arguments is health-related. Previous studies have revealed a link between Thrill Seeking and health-related impulsive problems, such as alcohol abuse and unsafe sexual behaviours (Hittner & Swickert, 2006; Donohew et al., 2000). People scoring high on Thrill Seeking tend to prioritize an adventurous and hedonistic lifestyle over one focused on health. This may also explain the negative association between thrill seeking and state curiosity in the current experiment.

No significant correlation or effect was found between state curiosity and other dimensions of trait curiosity. This may be due to the limited sample size. In addition, in the current study, the evaluation for state curiosity is tailored to each argument read, and thus is highly influenced by the content quality. This may also make the observed relationship between state and trait curiosity appear somewhat ambiguous.

Nonetheless, the present results offer new insights into the relationship between state and trait curiosity from a cognitive perspective. Previous research has predominantly explored the correlation through an emotional lens, for example, examining the role of curiosity in developing interpersonal closeness (Kashdan & Roberts, 2004), or its effect on life well-being (Kashdan & Steger, 2007), usually intertwined with other positive or negative affects. In contrast, the current results investigate the influence of trait curiosity on state curiosity within information-seeking context, evolving science-related knowledge searching and decision-making, which emphasises curiosity as a cognitive condition. Future research could enrich this understanding by considering the specific role of science curiosity in the information-seeking process.

7.4 Limitations and future directions

There are several limitations of the current study that should be acknowledged. First, the sample size was limited (N=52 for behavioural analysis; N=49 for eye-tracking analysis), and the sample was highly skewed towards women. Additionally, data were collected using non-probability sampling methods, which may result in sampling bias. These aspects may make it challenging to generalize the results to different populations.

Secondly, the 5DCR questionnaire was used in the current study to measure participants' trait curiosity. As a self-report questionnaire (indicate the degree to which the statements describe you: "I find it fascinating to learn new information"; "The smallest doubt can stop me from seeking out new experiences" etc.; Kashdan et al., 2020), the 5DCR cannot avoid the potential risk of social desirability bias. Although the survey was conducted online, without researchers present, it remains challenging to completely avoid the tendency to answer questions in a manner that is more favoured by society. Besides, the Finnish translational version of 5DCR was used in the current study for the first time. While the internal consistency of the Finnish version scale was satisfactory, further validation regarding translation and cultural adaptation would be beneficial.

A third limitation of the current study is the absence of a specific examination of science curiosity. Science curiosity, as a component of trait curiosity, is defined as “a general disposition, variable in intensity across persons, that reflects the motivation to seek out and consume science information for personal pleasure” (Kahan et al., 2017, p.180). It signifies individual differences in cognition associated with understanding science-related materials (Kahan et al., 2017). Studies have indicated the profound positive influence of science curiosity on people’s engagement with science information, and science-related decision making (Motta et al., 2021). For example, research by Kahan et al. (2017) showed that individuals who are more curious about science tend to hold less polarized political viewpoints.

As a tool to evaluate people’s disposition of science curiosity, the Science Curiosity Scale (SCS) was invented, encompassing both self-report and behavioural measurement (Kahan et al., 2017). However, due to the intensive time required for implementing the SCS, this aspect of trait curiosity was not included in the current study. Nonetheless, recent research has proposed reduced forms of SCS, which are shorter but still maintain good reliability and validity (Motta et al., 2021). With the help of the applicable scale, future studies could further explore the role of science curiosity in the information-seeking process, particularly its impact on facilitating evidence-based decision-making.

Furthermore, the current analyses did not include model diagnostic procedures for LMMs and GLMMs. That is because, theoretically, there are some assumptions underlying mixed-effects models, such as the normal distribution of both random effects and residual errors, as well as the assessment of the influence individual observations have on the model fit (Gałecki & Burzykowski, 2013). However, unlike the well-established diagnostics method for standard linear regression, the model diagnostics procedure for LMM and GLMM is more complex and presents challenges in interpretation (West et al., 2022). Due to the intricate nature of diagnostic approaches for LMMs and GLMMs, this process was not presented in the current study. However, to meet the model assumptions, skewed measures were log-transformed before the analyses.

The results and limitations of the current study also suggest possible avenues for future research. For example, this study used health-related topics to create a decision-making context; it would be interesting to examine curiosity within other decision-making contexts such as finances and politics. Secondly, information-seeking is often supported by a blend of intrinsic motivation and extrinsic rewards (Murayama, 2022); investigating the impact of extrinsic rewards on the motivational power of curiosity could yield valuable insights. Thirdly, the eye movement measures in the current study mainly focus on fixation durations; other measures such as pupil size and blinking rate could also be considered to enrich the understanding of the cognitive process underlying the curiosity state. In addition, as mentioned earlier, science curiosity should be investigated in the science-based decision-making contexts; related research would be thought-provoking for cultivating students’ curiosity in science learning within the educational context. Finally, a quantitative approach was used in this study to investigate the effect of curiosity in information-seeking tasks, while it would benefit from a mixed research method. For example, in future studies, a qualitative approach may provide a more concrete understanding of how curiosity affects people’s daily decision-making.

7.5 Conclusion

This study provides new insights into the role of curiosity in the information-seeking process. Firstly, it highlights that stronger state curiosity is related to longer reading and more careful information processing, with the effects being interacted with information quality. Secondly, it underscores how trait curiosity profile shapes one's approach to seeking information. Notably, overt social curiosity is associated with a more persistent and determined information-seeking style, while stress tolerance indicates a quicker and more decisive reader. In addition, it examines the effect of trait curiosity on state curiosity during health-related decision-making, and reveals the negative effect of thrill-seeking tendency on processing scientific information.

The strengths of this study are that it investigates curiosity in a real-life information-seeking context, with the help of a multi-armed bandit task. Eye movement analyses provide immediate and objective insights into information processing strategies (Tsai et al., 2022). Furthermore, the thesis provides practical implications for science communication and public decision-making. Firstly, this study indicates that public has ability to distinguish and utilize information with varying quality. Secondly, evoking curiosity is a key operator in supporting individuals in processing information thoroughly and making sound decisions based on scientific evidence, and should be emphasized in future science communication and science education. Disseminating science information that, with improved utility and familiarity, can be beneficial for cultivating curiosity.

References

Andrews, T. J., & Coppola, D. M. (1999). Idiosyncratic characteristics of saccadic eye movements when viewing different visual environments. *Vision research*, *39*(17), 2947-2953.

Apps, M. A. J., Rushworth, M. F. S., & Chang, S. W. C. (2016). The Anterior Cingulate Gyrus and Social Cognition: Tracking the Motivation of Others. In *Neuron* (Vol. 90, Issue 4, pp. 692–707). Cell Press. https://doi.org/10.1016/j.neuron.2016.04.018

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. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Bavoľár, J., & Miháľ, Š. (2019). Decision-making styles and information search-the relationships with need for cognition and curiosity. *Psychology & Its Contexts/Psychologie a Její Kontexty*, *9*(2).

Bergemann, D., & Valimaki, J. (2006). Bandit problems. *SSRN.*

Berlyne DE: Novelty and curiosity as determinants of exploratory behaviour. *Br J Psychol Gen Sect* 1950, 41:68-80.

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

Berlyne, D. E. (1960). Conflict, arousal, and curiosity. New York: McGraw-Hill.

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

Berridge, K. C. (2004). Motivation concepts in behavioral neuroscience. *Physiology and Behavior*, *81*(2), 179–209. https://doi.org/10.1016/j.physbeh.2004.02.004

Berridge, K. C. (2009). Wanting and liking: Observations from the neuroscience and psychology laboratory. *Inquiry*, *52*(4), 378–398. https://doi.org/10.1080/00201740903087359

Bowler, L. (2010). The self - regulation of curiosity and interest during the information search process of adolescent students. *Journal of the American Society for Information Science and Technology*, *61*(7), 1332-1344.

Cardoso-Leite, P., & Bavelier, D. (2014). Video game play, attention, and learning: How to shape the development of attention and influence learning? In *Current Opinion in Neurology* (Vol. 27, Issue 2, pp. 185–191). Lippincott Williams and Wilkins. https://doi.org/10.1097/WCO.0000000000000077

Castelhano, M. S., & Henderson, J. M. (2008). Stable individual differences across images in human saccadic eye movements. *Canadian Journal of Experimental Psychology*, *62*(1), 1–14. https://doi.org/10.1037/1196-1961.62.1.1

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

Chua, H. F., Boland, J. E., & Nisbett, R. E. (2005). Cultural variation in eye movements during scene perception. In *PNAS August* (Vol. 30). www.pnas.orgcgidoi10.1073pnas.0506162102

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.

Collins, R. P., Litman, J. A., & Spielberger, C. D. (2004). The measurement of perceptual curiosity. *Personality and individual differences*, *36*(5), 1127-1141.

Conklin, K., Pellicer-Sánchez, A., & Carrol, G. (2018). Researching Reading. In *Eye-Tracking: A Guide for Applied Linguistics Research* (pp. 80–111). chapter, Cambridge: Cambridge University Press.

Conklin, K., Pellicer-Sánchez, A., & Carrol, G. (2019a). Introduction to Eye-Tracking. In *Eye-Tracking* (pp. 1–13). Cambridge University Press. https://doi.org/10.1017/9781108233279.002

Conklin, K., Pellicer-Sánchez, A., & Carrol, G. (2019b). Researching Reading. In *Eye-Tracking* (pp. 80–111). Cambridge University Press. https://doi.org/10.1017/9781108233279.005

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature reviews neuroscience*, *3*(3), 201-215.

Deci, E. L., Koestner, R., & Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological bulletin*, *125*(6), 627.

Delgado, M. R., Locke, H. M., Stenger, V. A., & Fiez, J. A. (2003). Dorsal striatum responses to reward and punishment: effects of valence and magnitude manipulations. *Cognitive, Affective, & Behavioral Neuroscience*, *3*, 27-38.

Donohew, L., Zimmerman, R., Cupp, P. S., Novak, S., Colon, S., & Abell, R. (2000).

Dubey, R., & Griffiths, T. L. (2020). Understanding exploration in humans and machines by formalizing the function of curiosity. *Current Opinion in Behavioral Sciences*, *35*, 118-124.

Edwards, W. (1954). The theory of decision making. *Psychological bulletin*, *51*(4), 380.

EyeLink Data Viewer 4.3.1 [Computer software]. (2022). Oakville, Ontario, Canada: SR Research Ltd.

Facione, P. A. (1990). *Critical thinking: A statement of expert consensus for purposes of educational assessment and instruction.* Millibrae, CA: The California Academic Press.

Facione, P. A., Facione, N. C., & Giancarlo, C. A. (2001). *California critical thinking disposition inventory: CCTDI inventory manual*. Millbrae, CA: California Academic Press.

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

Fröber, K., Stürmer, B., Frömer, R., and Dreisbach, G. (2017). The role of affective evaluation in conflict adaptation: an LRP study. Brain Cogn. 116, 9–16. doi: 10.1016/j.bandc.2017.05.003

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.

Gałecki, A., & Burzykowski, T. (2013). *Linear mixed-effects model using R: a step-by-step approach*. Springer New York.
Gere, A., Kókai, Z., & Sipos, L. (2017). Influence of mood on gazing behavior: Preliminary evidences from an eye-tracking study. *Food Quality and Preference*, *61*, 1-5.
Ginter, F., & Laippala, V. (2017). Finnish Internet Parsebank.
Gomes, D. G. (2022). Should I use fixed effects or random effects when I have fewer than five levels of a grouping factor in a mixed-effects model? *PeerJ*, *10*, e12794.
Gottlieb, J., Oudeyer, P. Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. In *Trends in Cognitive Sciences* (Vol. 17, Issue 11, pp. 585–593). https://doi.org/10.1016/j.tics.2013.09.001
Grossnickle, E. M. (2016). Disentangling Curiosity: Dimensionality, Definitions, and Distinctions from Interest in Educational Contexts. In *Educational Psychology Review* (Vol. 28, Issue 1, pp. 23–60). Springer New York LLC. https://doi.org/10.1007/s10648-014-9294-y
Gruber, M. J., & Ranganath, C. (2019). How Curiosity Enhances Hippocampus-Dependent Memory: The Prediction, Appraisal, Curiosity, and Exploration (PACE) Framework. In *Trends in Cognitive Sciences* (Vol. 23, Issue 12, pp. 1014–1025). Elsevier Ltd. https://doi.org/10.1016/j.tics.2019.10.003
Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of Curiosity Modulate Hippocampus-Dependent Learning via the Dopaminergic Circuit. *Neuron*, *84*(2), 486–496. https://doi.org/10.1016/j.neuron.2014.08.060
Gruber, M. J., Valji, A., & Ranganath, C. (2019). Curiosity and learning: a neuroscientific perspective. In *The Cambridge Handbook of Motivation and Learning* (pp.397-417). Cambridge University Press. https://doi.org/10.1017/9781316823279.020
Grüning, D. J., & Lechner, C. M. (2023). Measuring six facets of curiosity in Germany and the UK: A German-language adaptation of the 5DCR and its comparability with the English-language source version. *Journal of Personality Assessment*, *105*(2), 283-295.
Hare, T. A., O'Doherty, J., Camerer, C. F., Schultz, W., & Rangel, A. (2008). Dissociating the role of the orbitofrontal cortex and the striatum in the computation of goal values and prediction errors. *Journal of Neuroscience*, *28*(22), 5623–5630. https://doi.org/10.1523/JNEUROSCI.1309-08.2008
Hauke, J., & Kossowski, T. (2011). Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data. *Quaestiones geographicae*, *30*(2), 87-93.
Hayhoe, M. (2000). Vision using routines: A functional account of vision. *Visual Cognition*, *7*(1-3), 43-64.
Hills, T. T., Todd, P. M., Lazer, D., Redish, A. D., & Couzin, I. D. (2015). Exploration versus exploitation in space, mind, and society. *Trends in cognitive sciences*, *19*(1), 46-54.
Hittner, J. B., & Swickert, R. (2006). Sensation seeking and alcohol use: A meta-analytic review. Addictive Behaviors, 31, 1383–1401.
Hoeken, H., Timmers, R., & Schellens, P. J. (2012). Arguing about desirable consequences: What constitutes a convincing argument? *Thinking & reasoning*, *18*(3), 394-416.
Hoffman, J. E. (2016). Visual attention and eye movements. *Attention*, 119-153.

Hoffman, J. E., & Subramaniam, B. (1995). The role of visual attention in saccadic eye movements. In *Perception & Psychophysics* (Vol. 57, Issue 6).

Hong, J. C., Hwang, M. Y., Szeto, E., Tai, K. H., & Tsai, C. R. (2021). Undergraduate Science Students' Scientist–Practitioner Gap: the Role of Epistemic Curiosity and Cognitive Flexibility. *International Journal of Science and Mathematics Education*, *19*, 899-913.

Irwin, D. E., & Gordon, R. D. (1998). Eye movements, attention and trans-saccadic memory. *Visual Cognition*, *5*(1–2), 127–155. https://doi.org/10.1080/713756783

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

Jurafsky, D., Bell, A., & Girand, C. (2002). The role of the lemma in form variation. *Laboratory phonology*, *7*, 3-34.

Just, M. A., & Carpenter, P. A. (2018). Using eye fixations to study reading comprehension. In *New methods in reading comprehension research* (pp. 151-182). Routledge.

Kahan, D. M., Landrum, A., Carpenter, K., Helft, L., & Hall Jamieson, K. (2017). Science curiosity and political information processing. *Political Psychology*, *38*, 179-199.

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.

Kashdan, T. B., & Roberts, J. E. (2004). Trait and state curiosity in the genesis of intimacy: differentiation from related constructs. J*ournal of Social and Clinical Psychology, 32*,792–816. doi:10.1521/jscp.23.6.792.54800.

Kashdan, T. B., & Steger, M. F. (2007). Curiosity and pathways to well-being and meaning in life: Traits, states, and everyday behaviors. *Motivation and Emotion*, *31*, 159-173.

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.

Kashdan, T. B., Rose, P., & Fincham, F. D. (2004). Curiosity and exploration: Facilitating positive subjective experiences and personal growth opportunities. In *Journal of Personality Assessment* (Vol. 82, Issue 3, pp. 291–305). Lawrence Erlbaum Associates Inc. https://doi.org/10.1207/s15327752jpa8203_05

Kashdan, T. B., Rose, P., & Fincham, F. D. (2004). Curiosity and exploration: Facilitating positive subjective experiences and personal growth opportunities. *Journal of personality assessment*, *82*(3), 291-305.

Kashdan, T. B., Stiksma, M. C., Disabato, D. J., McKnight, P. E., Bekier, J., Kaji, J., & Lazarus, R. (2018). The five-dimensional curiosity scale: Capturing the bandwidth of curiosity and identifying four unique subgroups of curious people. *Journal of Research in Personality*, *73*, 130-149.

Keith Rayner (2009) Eye movements and attention in reading, scene perception, and visual search, *The Quarterly Journal of Experimental Psychology*, *62*(8), 1457-1506.

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

Kliegl, R., Wei, P., Dambacher, M., Yan, M., & Zhou, X. (2011). Experimental effects and individual differences in linear mixed models: Estimating the relationship between spatial, object, and attraction effects in visual attention. *Frontiers in psychology*, *1*, 238.

Knuuti, J. (2020). Kauppatavarana terveys–selviydy terveysväitteiden viidakossa. *Helsinki: Minerva Kustannus Oy*.

Lai, M. L., Tsai, M. J., Yang, F. Y., Hsu, C. Y., Liu, T. C., Lee, S. W. Y., ... & Tsai, C. C. (2013). A review of using eye-tracking technology in exploring learning from 2000 to 2012. *Educational research review*, *10*, 90-115.

Lamnina, M., & Chase, C. C. (2019). Developing a thirst for knowledge: How uncertainty in the classroom influences curiosity, affect, learning, and transfer. *Contemporary Educational Psychology*, *59*, 101785.

Li, S., Ren, X., Schweizer, K., Brinthaupt, T. M., & Wang, T. (2021). Executive functions as predictors of critical thinking: Behavioral and neural evidence. *Learning and Instruction*, *71*, 101376.

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

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. (2019). Curiosity: Nature, dimensionality, and determinants. In *The Cambridge Handbook of Motivation and Learning* (pp. 418-442). Cambridge University Press. https://doi.org/10.1017/9781316823279.020

Litman, J. A., & Jimerson, T. L. (2004). The Measurement of Curiosity As a Feeling of Deprivation. *Journal of Personality Assessment*, *82*(2), 147–157. https://doi.org/10.1207/s15327752jpa8202_3

Litman, J. A., & Spielberger, C. D. (2003). Measuring epistemic curiosity and its diversive and specific components. *Journal of personality assessment*, *80*(1), 75-86.

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

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

Lu, Y., & Scott, M. (2023). Generalized linear mixture model. https://bookdown.org/ks6017/GLM_bookdown3/

March, J. G. (1991). Exploration and exploitation in organizational learning. Organization science, 2(1), 71-87.

Minitab. (2023). *What is a link function?* (C) Minitab, LLC. All Rights Reserved. 2023. Retrieved March 5, 2024, from https://support.minitab.com/en-us/minitab/21/help-and-how-to/statistical-modeling/regression/supporting-topics/logistic-regression/link-function/

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.

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.

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

Naylor, F. D. (1981). A State‐Trait Curiosity Inventory. *Australian Psychologist*, *16*(2), 172–183. https://doi.org/10.1080/00050068108255893

Olson, K., Camp, C., & Fuller, D. (1984). Curiosity and need for cognition. *Psychological reports*, *54*(1), 71-74.

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*(1), 190–206. https://doi.org/10.1016/j.actpsy.2013.06.003

Pinheiro, J., and Bates, D. M. (2000). Mixed Effects Models in S and S-PLUS. New York, NY: Springer. doi: 10.1007/978-1-4419-0318-1

Pinto, Y., van der Leij, A. R., Sligte, I. G., Lamme, V. A., & Scholte, H. S. (2013). Bottom-up and top-down attention are independent. *Journal of vision*, *13*(3), 16-16.

R Core Team (2023). *The R project for statistical computing*. Available online at https://www.R-project.org/

Rajaretnam, T. (2015). *Statistics for social sciences*. SAGE.

Rayner, K. (2009). Eye movements in reading: Models and data. *Journal of eye movement research*, *2*(5), 1.

Rayner, K. (1998). Eye Movements in Reading and Information Processing: 20 Years of Research. *Psychological Bulletin, 124* (3), 372-422.

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.

Reichle, E. D., Pollatsek, A., Fisher, D. L., & Rayner, K. (1998). *Psychological Review Toward a Model of Eye Movement Control in Reading* (Vol. 105, Issue 1). Psychological Association, Inc.

Reio, T. G., & Callahan, J. L. (2004). Affect, curiosity, and socialization-related learning: A path analysis of antecedents to job performance. *Journal of Business and Psychology*, *19*, 3-22.

Reio, T. G., Jr., & Callahan, J. L. (2004). Affect, curiosity, and socialization-related learning: a path analysis of antecedents to job performance. *Journal of Business and Psychology,* *19*,3–22. doi:10.1023/B:JOBU.0000040269.72795.ce.

Reis, H. T., Collins, W. A., & Berscheid, E. (2000). The relationship context of human behavior and development. Psychological Bulletin, 126, 844–872.

Renninger, K. A., & Hidi, S. (2015). *The power of interest for motivation and engagement*. Routledge.

Riby, D. M., & Hancock, P. J. (2008). Viewing it differently: Social scene perception in Williams syndrome and autism. *Neuropsychologia*, *46*(11), 2855-2860.

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

Robbins, H. (1952). Some aspects of the sequential design of experiments. *Bulletin of the American Mathematical Society*, 55, 527-535.

Rotgans, J. I., & Schmidt, H. G. (2014). Situational interest and learning: Thirst for knowledge. *Learning and Instruction*, *32*, 37-50.

Ryakhovskaya, Y., Jach, H. K., & Smillie, L. D. (2022). Curiosity as feelings of interest versus deprivation: Relations between curiosity traits and affective states when anticipating information. *Journal of Research in Personality*, *96*, 104164.

Schulz, E., Konstantinidis, E., & Speekenbrink, M. (2015). Learning and decisions in contextual multi-armed bandit tasks. In *37th Annual Meeting of the Cognitive Science Society (CogSci 2015)* (pp. 2122-2127).

Schwarz, N. (2000). Emotion, cognition, and decision making. *Cognition & emotion*, *14*(4), 433-440.

Scott, S. G., & Bruce, R. A. (1995). Decision-making style: The development and assessment of a new measure. *Educational and psychological measurement*, *55*(5), 818-831.

Sensation seeking, impulsive decision-making, and risky sex: Implications for risk-taking and design of interventions. Personality and Individual Differences, 28, 1079–1091.

Shin, D. J. D., Lee, H. J., Lee, G., & Kim, S. Il. (2019). The role of curiosity and interest in learning and motivation. In *The Cambridge Handbook of Motivation and Learning* (pp. 443–464). Cambridge University Press. https://doi.org/10.1017/9781316823279.020

Silvia, P. J. (2008). Appraisal components and emotion traits: Examining the appraisal basis of trait curiosity. *Cognition and Emotion*, *22*(1), 94-113.

Spielberger, C. D. (1972). Anxiety as an emotional state. In C.D. Spielberger (Ed.), *Anxiety: Current trends in theory and research* (pp. 23±49). New York: Academic Press

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.

Van Dijk, E., & Zeelenberg, M. (2007). When curiosity killed regret: Avoiding or seeking the unknown in decision-making under uncertainty. *Journal of Experimental Social Psychology*, *43*(4), 656-662.

Van Eemeren, F. H., Garssen, B., & Meuffels, B. (2009). *Fallacies and judgments of reasonableness: Empirical research concerning the pragma-dialectical discussion rules* (Vol. 16). Springer Science & Business Media.

West, B. T., Welch, K. B., & Galecki, A. T. (2022). *Linear mixed models: a practical guide using statistical software*. Second Edition, CRC Press.

Appendices

Appendix 1

Five-Dimensional Curiosity Scale Revised (5DCR), in original English and translated Finnish version.

Below are statements people often use to describe themselves. Please use the scale below to indicate the degree to which these statements accurately describe you. There are no right or wrong answers. / Ihmiset käyttävät usein alla olevia väitteitä kuvailemaan itseään. Käytä alla olevaa asteikkoa kuvaamaan kuinka hyvin väittämät kuvaavat sinua. Väittämiin ei ole oikeita tai vääriä vastauksia.

1 – Does not describe me at all / Ei kuvaa minua ollenkaan
2 – Barely describes me / Ei kuvaa minua juurikaan
3 – Somewhat describes me / Kuvaa minua jonkin verran
4 – Neutral / Neutraali
5 – Generally describes me / Kuvaa minua
6 – Mostly describes me / Kuvaa minua
7 – Completely describes me / Kuvaa minua täysin

Joyous Exploration:
1 I view challenging situations as an opportunity to grow and learn. / Näen haastavat tilanteet mahdollisuutena kasvaa ja oppia.
2 I seek out situations where it is likely that I will have to think in depth about something. / Hakeudun tilanteisiin, joissa on todennäköistä, että minun tarvitsee ajatella jotakin syvällisesti.
3 I enjoy learning about subjects that are unfamiliar to me. / Nautin uusien asioiden opettelusta.
4 I find it fascinating to learn new information. / Minusta on kiehtovaa oppia uusia asioita.

Deprivation Sensitivity:

1 Thinking about solutions to difficult conceptual problems can keep me awake at night. / Saatan valvoa koko yön ratkaisten vaikeita käsitteellisiä pulmia.

2 I can spend hours on a single problem because I just can't rest without knowing the answer. / Saatan viettää tunteja yksittäisen ongelman parissa, sillä en voi levätä ennen kuin tiedän vastauksen.

3 I feel frustrated if I can't figure out the solution to a problem, so I work even harder to solve it. / Turhaudun, kun en löydä ratkaisua pulmaan, joten työskentelen entistä kovemmin ratkaistakseni sen.

4 I work relentlessly at problems that I feel must be solved. / Teen paljon töitä sellaisten ongelmien eteen, jotka tarvitsevat mielestäni ratkaisun.

Stress Tolerance: (entire subscale reverse-scored)

1 The smallest doubt can stop me from seeking out new experiences. / Pieninkin epäilys voi estää minua etsimästä uusia kokemuksia.

2 I cannot handle the stress that comes from entering uncertain situations. / En siedä epävarmoista tilanteista aiheutuvaa stressiä.

3 I find it hard to explore new places when I lack confidence in my abilities. / Minun on hankala tutustua uusiin paikkoihin, kun tunnen epävarmuutta kyvyistäni.

4 It is difficult to concentrate when there is a possibility that I will be taken by surprise. / Minun on hankala keskittyä, jos tilanteessa on yllätetyksi tulemisen mahdollisuus.

Thrill Seeking:

1 Risk-taking is exciting to me. / Riskien ottaminen innostaa minua.

2 When I have free time, I want to do things that are a little scary. / Haluan tehdä vapaa-aikanani asioita, jotka ovat hiukan pelottavia.

3 Creating an adventure as I go is much more appealing than a planned adventure. / Tilanteessa luotu seikkailu on paljon houkuttelevampi kuin suunniteltu seikkailtu.

4 I prefer friends who are excitingly unpredictable. / Suosin ystäviä, jotka ovat jännittävän arvaamattomia.

Social Curiosity:

Overt Social Curiosity

1 I ask a lot of questions to figure out what interests other people. / Kyselen paljon kysymyksiä selvittääkseni toisten mielenkiinnonkohteita.

2 When talking to someone who is excited, I am curious to find out why. / Kun keskustelen innostuneen henkilön kanssa, minua kiinnostaa tietää innostuksen syy.

3 When talking to someone, I try to discover interesting details about them. / Keskustellessani jonkun kanssa, yritän saada heistä selville mielenkiintoisia yksityiskohtia.

4 I like finding out why people behave the way they do. / Minusta on mukavaa selvittää miksi ihmiset käyttäytyvät omalla tavallaan.

Covert Social Curiosity

1 When other people are having a conversation, I like to find out what it's about. / Kun muut keskustelevat, haluan tietää mitä keskustelu koskee.

2 When around other people, I like listening to their conversations. / Kun olen muiden ympäröimänä, kuuntelen mielelläni heidän keskustelujaan.

3 When people quarrel, I like to know what's going on. / Kun toiset riitelevät, haluan tietää mistä on kyse.

4 I seek out information about the private lives of people in my life. / Etsin tietoa elämässäni olevien ihmisten yksityiselämästä.

Appendix 2

Linear and generalized linear mixed-effects models for behavioural and eye movement analyses.

Table 2. Generalized linear mixed-effects model for the number of arguments read. *(Number ~ StateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + Familiarity + (1 | Topic) + (1 | ID))*

Predictors	Number of arguments read			
	b	SE	z-value	p-value
(intercept)	1.67	0.67	2.50	**0.012**
state curiosity	-0.05	0.03	-1.45	0.147
joyous exploration	0.02	0.09	0.26	0.795
deprivation sensitivity	-0.03	0.07	-0.38	0.704
stress tolerance	0.004	0.06	0.07	0.943
thrill seeking	-0.08	0.06	-1.40	0.161
overt social curiosity	0.11	0.06	1.77	0.077
covert social curiosity	-0.07	0.07	-1.06	0.287
Familiarity	-0.04	0.02	-1.68	0.094
Random Effects				
σ^2	0.21			
τ00 ID	0.18			
τ00 Topic	0.01			
ICC	0.48			
N Topic	18			
N ID	52			
Observations	909			
Marginal R^2 / Conditional R^2	0.066 / 0.515			

Table 3. Linear and generalized linear mixed-effects model for the proportion of arguments read, and switching probability. *(Proportion / Switches ~ StateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + argument type + Confidence + Clarity + Familiarity + (1 | Argument) + (1 | ID))*

Predictors	**Proportion of arguments read**				**Switching probability**			
	b	**SE**	**t-value**	**p-value**	**b**	**SE**	**z-value**	**p-value**
(intercept)	0.44	0.36	1.21	0.230	2.69	2.69	0.10	0.318
arg type [SI]	-0.06	0.03	-2.25	**0.026**	0.67	0.11	6.25	**<0.001**
arg type [NR]	-0.06	0.03	-1.87	0.064	0.85	0.12	7.11	**<0.001**
state curiosity	0.04	0.03	1.55	0.123	0.05	0.05	1.05	0.296
joyous exploration	0.005	0.04	0.13	0.899	0.37	0.39	0.95	0.340
deprivation sensitivity	-0.00	0.03	-0.17	0.864	0.17	0.28	0.62	0.535
stress tolerance	0.01	0.02	0.49	0.623	0.27	0.23	1.19	0.235
thrill seeking	-0.03	0.02	-1.16	0.250	0.04	0.22	0.18	0.859
overt social curiosity	0.02	0.03	0.90	0.372	-0.66	0.26	-2.54	**0.011**
covert social curiosity	-0.02	0.03	-0.65	0.516	-0.27	0.28	-0.94	0.348
Confidence	0.04	0.04	1.07	0.289	-0.01	0.06	-0.09	0.929
Clarity	-0.07	0.05	-1.44	0.153	-0.07	0.07	-0.95	0.340
Familiarity	-0.03	0.05	-0.61	0.542	0.02	0.05	0.36	0.723
Random Effects								
σ^2	0.01				3.29			
τ00 Argument					0.00			
τ00 ID	0.03				2.82			
ICC	0.75							
N Argument					270			
N ID	52				52			
Observations	156				3534			
Marginal R^2 / Conditional R^2	0.133 / 0.781				0.201 / NA			

Note: arg type [SI] = scientific irrelevant arguments; arg type [NR] = non-scientific relevant arguments.

Table 4. Linear mixed-effects model for state curiosity. *(StateCur ~ cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + argument type + Confidence + Clarity + Familiarity + (1 | Argument) + (1 | ID))*

Predictors	**State curiosity**			
	b	**SE**	**t-value**	**p-value**
(intercept)	2.50	0.55	4.52	**<0.001**
arg type [SI]	-0.52	0.05	-10.21	**<0.001**
arg type [NR]	-0.86	0.05	-16.70	**<0.001**
joyous exploration	0.10	0.08	1.30	0.193
deprivation sensitivity	0.02	0.06	0.34	0.733
stress tolerance	-0.01	0.05	-0.22	0.825
thrill seeking	-0.15	0.05	-3.20	**0.001**
overt social curiosity	0.004	0.05	0.07	0.944
covert social curiosity	-0.01	0.06	-0.24	0.810
Confidence	-0.12	0.02	-6.96	**<0.001**
Clarity	0.13	0.02	6.65	**<0.001**
Familiarity	0.04	0.02	2.14	**0.033**
Random Effects				
σ^2	0.60			
τ_{00} Argument	0.08			
τ_{00} ID	0.13			
ICC	0.26			
N Argument	270			
N ID	52			
Observations	4437			
Marginal R^2 / Conditional R^2	0.176 / 0.388			

Note: arg type [SI] = scientific irrelevant arguments; arg type [NR] = non-scientific relevant arguments.

Table 5. Linear mixed-effects models for first fixation duration and gaze duration. *(DV ~ argument type*zStateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + zLength + zlogFrequency + (1 | word) + (1 | Argument) + (1 | ID))*

Predictors	First fixation duration				Gaze duration			
	b	SE	t-value	p-value	b	SE	t-value	p-value
(intercept)	5.27	0.20	26.03	**<0.001**	5.47	0.24	22.69	**<0.001**
arg type [SI]	0.01	0.01	0.71	0.478	-0.00	0.01	-0.18	0.859
arg type [NR]	-0.02	0.01	-2.37	**0.018**	-0.01	0.01	-0.66	0.511
state curiosity	0.00	0.00	1.02	0.309	-0.00	0.01	-0.84	0.404
joyous exploration	-0.03	0.03	-1.26	0.207	-0.03	0.03	-1.02	0.306
deprivation sensitivity	0.03	0.02	1.26	0.207	0.03	0.02	1.18	0.238
stress tolerance	-0.03	0.02	-2.09	**0.037**	-0.04	0.02	-2.19	**0.028**
thrill seeking	0.01	0.02	0.84	0.400	0.03	0.02	1.35	0.178
overt social curiosity	0.04	0.02	2.17	**0.030**	0.05	0.02	2.00	**0.045**
covert social curiosity	-0.02	0.02	-0.68	0.494	-0.03	0.03	-1.28	0.202
word length	0.02	0.01	3.71	**<0.001**	0.15	0.01	22.36	**<0.001**
word frequency	-0.01	0.01	-2.40	**0.017**	-0.05	0.01	-6.92	**<0.001**
arg type [SI] × state curiosity	-0.003	0.01	-0.50	0.618	0.01	0.01	1.13	0.260
arg type [NR] × state curiosity	-0.01	0.01	-0.93	0.354	0.01	0.01	1.04	0.297
Random Effects								
σ^2	0.14				0.20			
τ_{00} word	0.01				0.01			
τ_{00} Argument	0.00				0.00			
τ_{00} ID	0.02				0.02			
ICC	0.14				0.15			
N word	1585				1585			
N Argument	270				270			
N ID	49				49			
Observations	25603				25603			
Marginal R^2 / Conditional R^2	0.027 / 0.164				0.132 / 0.261			

Note: arg type [SI] = scientific irrelevant arguments; arg type [NR] = non-scientific relevant arguments. State curiosity and word length have been z-scored; word frequency has been log-transformed and then z-scored.

Table 6. Linear and generalized linear mixed models for regression path duration and skipping probability. *(DV ~ argument type*zStateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + zLength + zlogFrequency + (1 | word) + (1 | Argument) + (1 | ID))*

Predictors	Regression path duration				Skipping probability			
	b	**SE**	**t-value**	**p-value**	**b**	**SE**	**z-value**	**p-value**
(intercept)	5.73	0.30	19.36	**<0.001**	-0.72	0.70	-1.03	0.301
arg type [SI]	-0.03	0.03	-1.07	0.284	-0.14	0.07	-2.04	**0.041**
arg type [NR]	0.03	0.03	1.03	0.306	-0.13	0.07	-1.88	0.060
state curiosity	0.02	0.01	1.66	0.098	-0.00	0.02	-0.04	0.968
joyous exploration	-0.03	0.04	-0.84	0.401	-0.09	0.10	-0.89	0.375
deprivation sensitivity	0.01	0.03	0.47	0.635	-0.04	0.07	-0.56	0.574
stress tolerance	-0.04	0.02	-1.61	0.107	0.02	0.06	0.40	0.691
thrill seeking	0.08	0.02	3.23	**0.001**	0.08	0.06	1.33	0.185
overt social curiosity	0.06	0.03	2.25	**0.025**	0.03	0.07	0.41	0.685
covert social curiosity	0.00	0.03	0.04	0.972	0.08	0.08	1.01	0.313
word length	0.35	0.03	12.69	**<0.001**	-0.53	0.04	-14.74	**<0.001**
word frequency	0.04	0.03	1.28	0.202	0.03	0.04	0.76	0.448
arg type [SI] × state curiosity	0.01	0.01	1.04	0.298	-0.02	0.03	-0.58	0.563
arg type [NR] × state curiosity	0.02	0.01	1.43	0.153	0.03	0.03	0.99	0.324
Random Effects								
σ^2	0.62				3.29			
τ_{00} word	0.41				0.44			
τ_{00} Argument	0.01				0.16			
τ_{00} ID	0.03				0.21			
ICC	0.42				0.20			
N word	1585				1588			
N Argument	270				270			
N ID	49				49			
Observations	25603				45673			
Marginal R^2 / Conditional R^2	0.090 / 0.473				0.073/0.256			

Note: arg type [SI] = scientific irrelevant arguments; arg type [NR] = non-scientific relevant arguments. State curiosity and word length have been z-scored; word frequency has been log-transformed and then z-scored.

Table 7. Linear mixed-effects model for total fixation duration. *(DV ~ argument type*zStateCur + cur_joy + cur_dep + cur_stress + cur_thrill + cur_Osoc + cur_Csoc + zLength + zlogFrequency + (1 | word) + (1 | Argument) + (1 | ID))*

Predictors	**Total fixation duration**			
	b	**SE**	**t-value**	**p-value**
(intercept)	5.66	0.37	15.42	**<0.001**
arg type [SI]	0.00	0.02	0.05	0.959
arg type [NR]	-0.07	0.02	-2.71	**0.007**
state curiosity	0.03	0.01	4.21	**<0.001**
joyous exploration	0.02	0.05	0.38	0.702
deprivation sensitivity	0.00	0.04	0.05	0.958
stress tolerance	-0.03	0.03	-0.89	0.376
thrill seeking	0.04	0.03	1.48	0.138
overt social curiosity	0.05	0.03	1.44	0.151
covert social curiosity	-0.01	0.04	-0.17	0.865
word length	0.22	0.01	21.35	**<0.001**
word frequency	-0.10	0.01	-8.98	**<0.001**
arg type [SI] × state curiosity	0.02	0.01	1.56	0.119
arg type [NR] × state curiosity	0.04	0.01	3.71	**<0.001**
Random Effects				
σ^2	0.39			
τ_{00} word	0.03			
τ_{00} Argument	0.02			
τ_{00} ID	0.06			
ICC	0.21			
N word	1585			
N Argument	270			
N ID	49			
Observations	25603			
Marginal R^2 / Conditional R^2	0.157 / 0.336			

Note: arg type [SI] = scientific irrelevant arguments; arg type [NR] = non-scientific relevant arguments. State curiosity and word length have been z-scored; word frequency has been log-transformed and then z-scored.