

From Curiosity Generation to Satisfaction: Neurophysiological Mechanisms of the Curiosity Feedback Loop

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Abstract

Curiosity is the primary internal motivation driving information-seeking behavior. From the perception of information gaps that triggers curiosity, to the valuation of control that leads to information-seeking behavior, and subsequently to the acquisition of target information that satisfies curiosity, each stage is influenced by both current information input and feedback output from the preceding stage, thereby constituting a feedback loop. This loop is further embedded within the individual's lifelong developmental trajectory, continuously evolving with the accumulation of experience and brain maturation. The curiosity feedback loop model integrates the expected value model of control and the Bayesian reinforcement learning framework, synthesizing research evidence from multiple brain functional systems—including the monitoring system, reward system, and control system—thus offering novel perspectives for understanding the neurophysiological mechanisms underlying curiosity.

Full Text

From Induction to Relief: Neurophysiological Mechanisms Underlying the Curiosity Feedback Loop

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Abstract

Curiosity is the main intrinsic motivation driving information-seeking behavior. The curiosity feedback loop model decomposes a curious event into the following six processes: perceived information gap, curiosity generation, value assessment

of control, information seeking, curiosity satisfaction, and information integration. These processes create a positive feedback loop that contributes to sustainable knowledge acquisition. The model emphasizes the dynamic and changing nature of curiosity. In addition, this dynamic loop of curiosity is embedded in the lifelong development of the individual, changing as experience is accumulated and the brain develops. The model incorporates the expected value of control model and Bayesian reinforcement learning framework, and integrates research evidence from multiple functional brain systems such as the monitoring system, reward system, and control system. The model provides new ideas for understanding the neurophysiological mechanisms of curiosity.

Keywords: curiosity, intrinsic motivation, reinforcement learning, information seeking, curiosity relief

Curiosity, particularly epistemic curiosity, plays a crucial role in daily learning and life. Over the past several decades, substantial empirical research has confirmed that curiosity can enhance learning, improve cognition, stimulate creativity, and even alleviate anxiety (Baer et al., 2012; Hardy et al., 2017; Hagtvedt et al., 2019; Harrison & Dossinger, 2017; Gruber et al., 2019; Kashdan & Roberts, 2006). From theoretical discussions to questionnaire surveys, from behavioral experiments to neurophysiological studies, some researchers have focused on curiosity as a trait, while others have emphasized its state-like nature (Berlyne, 1954; Cervera et al., 2020; Kashdan & Ficham, 2004; Litman & Silvia, 2006; Loewenstein, 1994; Murayama et al., 2019). However, one frequently overlooked point is that curiosity evolves—it continuously changes and develops with accumulated experience and brain maturation. Therefore, this paper adopts a dynamic developmental perspective on curiosity, using a feedback loop model as a framework to explore the neurophysiological mechanisms from curiosity induction to curiosity satisfaction. We first clarify and define the concept of curiosity, then elaborate on each stage of the curiosity feedback loop model, summarize how curiosity changes and develops across the individual lifespan, and finally propose recommendations for future research based on this model.

1 Conceptualizing Curiosity

A primary challenge in constructing an integrated model of curiosity is the lack of conceptual clarity in existing literature. At the end of the nineteenth century, James (1891) proposed that curiosity is an instinct for actively exploring the environment that evolved for survival adaptation. More than half a century later, Berlyne (1954) used drive reduction theory to explain curiosity, viewing it as a thirst for information—much like hunger—that needs to be satisfied. Originally proposed by Hull (1943), drive reduction theory posits that drives are motivational structures that energize organisms to act to satisfy needs, thereby reducing the drive. Berlyne (1957) considered curiosity an aversive state, with novelty and uncertainty triggering curiosity, while information-seeking behavior

aims to resolve uncertainty and eliminate this aversive condition. Additionally, Berlyne (1954) distinguished between epistemic curiosity and perceptual curiosity. Epistemic curiosity represents a desire for knowledge information, primarily applicable to adult humans, whereas perceptual curiosity reflects a craving for novel sensory stimuli, observed not only in adult humans but also in animals and human infants. This very desire drives individuals' exploratory behaviors.

After proposing the drive reduction theory of curiosity, Berlyne (1970) further suggested that curiosity follows an optimal arousal principle: stimuli that are too novel induce anxiety, while those that are too familiar induce boredom, with curiosity peaking at moderate novelty levels along with maximum pleasure. This appears contradictory to his earlier description in two ways. First, according to drive reduction theory, drives should increase monotonically with stimulus novelty, thereby driving more information-seeking behavior. Second, if increased drives from novel stimuli correspond to aversive emotions, where does pleasure come from? Viewing curiosity as a dynamic process seems to resolve these contradictions. First, curiosity generation is conditional—when stimulus-induced arousal is too high or too low, what is triggered is not curiosity, or at least not curiosity alone, as other motivations emerge and weaken information-seeking behavior. Second, the aversive emotion from increased novelty and uncertainty and the pleasure from reduced novelty and uncertainty occur at different time points and do not conflict.

In 1994, Loewenstein proposed the information-gap theory, suggesting that information gaps trigger curiosity. Characteristics such as uncertainty, novelty, complexity, and surprise all relate to limitations in prior knowledge, creating information gaps for individuals. Loewenstein (1994) viewed curiosity as cognitive deprivation resulting from perceiving an information gap. Like drive theory, information-gap theory posits that curiosity motivates information seeking to eliminate the aversive state caused by information gaps. Loewenstein (1994) also noted that information itself has sufficient value to drive information-seeking behavior, even when such information serves no other immediate goals.

Building on this, Oudeyer et al. (2016) explicitly categorized curiosity within the conceptual framework of intrinsic motivation, defining it as an internal drive. Ryan and Deci (2000) defined intrinsic motivation as “the drive to act for the sake of enjoyment or challenge rather than external goods, pressures, or rewards. Individuals do something for its inherent satisfaction, enjoying the activity itself rather than its instrumental value.” Unlike intrinsic motivation, “extrinsically motivated activities have an obvious purpose, aiming for instrumental outcomes beyond the activity itself.” The key distinction lies in whether there is an instrumental purpose. Curiosity aligns with intrinsic motivation characteristics—the value of target information itself is sufficient to generate information-seeking without needing additional instrumental value (Bennett et al., 2016; Lau et al., 2020; Marvin & Shohamy, 2016; Oosterwijk et al., 2020).

The above definitions primarily treat curiosity as a temporary state—an instantaneous experience individuals express in response to environmental features,

possessing state-like qualities. Some researchers, however, view curiosity as a stable disposition that continuously generates desire for new knowledge or experiences, exhibiting trait-like characteristics (Kashdan & Ficham, 2004; Litman & Silvia, 2006). Based on this perspective, researchers have developed various curiosity measurement tools, including the Interest/Deprivation Type Epistemic Curiosity Scale (I/D type Epistemic Curiosity Scale; Litman, 2008), the Curiosity and Exploration Inventory-II (CEI-II; Kashdan et al., 2009), and the Five-Dimensional Curiosity Scale (5DC; Kashdan et al., 2018). These instruments typically address three aspects: the degree of desire for information (motivation), the intensity of information-seeking behavior (behavior), and the emotional state during information seeking (emotion).

These conceptualizations involve motivation, behavior, and emotion—such as the motivation to reduce uncertainty, information-seeking behavior, and aversion to information gaps or pleasure from novel stimuli—all seemingly reflecting curiosity. But what is the essence of curiosity? A clearer definition is necessary for in-depth exploration. Despite different expressions, most researchers agree that curiosity provides the impetus for information-seeking behavior (Berlyne, 1954; Loewenstein, 1994; Oudeyer et al., 2016). Thus, the essence of curiosity is motivation—specifically, intrinsic motivation aimed at obtaining information itself rather than other 附加价值. Integrating Loewenstein’s information-gap theory, this paper defines curiosity as the internal motivation generated after an individual perceives an information gap. Curiosity exists as one of the driving forces for information-seeking behavior. Emotions accompany curiosity generation and change with behavior and behavioral outcomes. Just as pulling a trigger to hitting a target is a process, behaviors (such as information seeking) and emotions (aversion, pleasure, boredom, etc.) represent a series of possible states and outcomes triggered by curiosity. In daily life, when expressing “I am curious,” what is often conveyed is a state of “I want to know,” which reflects motivation. Since motivation inevitably involves satisfaction or dissatisfaction, what process unfolds from curiosity induction to curiosity satisfaction? The next section elaborates on this journey.

2 Curiosity in Short-term Feedback Loops

Although curiosity is essentially motivational, curiosity motivation marks the beginning of a series of curiosity-related events that are influenced by subsequent outcomes. In other words, from curiosity induction to curiosity satisfaction constitutes a feedback loop. This feedback loop primarily includes six stages: “perceiving information gap, curiosity generation, value assessment of control, information seeking, curiosity satisfaction, and information integration.” This structure aligns substantially with Murayama et al.’s (2019) reward-learning framework of knowledge acquisition, which posits that sustainable knowledge acquisition begins with awareness of knowledge gaps, after which individuals initiate information-seeking behavior until acquiring knowledge generates a reward feeling that further reinforces information-seeking behavior, while knowl-

edge base expansion makes it easier to detect new knowledge gaps. Additionally, Gruber and Ranganath's (2019) prediction, appraisal, curiosity, and exploration (PACE) model suggests that curiosity begins with prediction error, followed by value assessment of future information indicated by this error, which then triggers curiosity and exploratory behavior and ultimately promotes learning and memory. The reward-learning framework focuses on the knowledge acquisition process, viewing "curiosity," "interest," and "surprise" as post-hoc explanations of experiences during knowledge acquisition. The PACE model considers curiosity a result of information value assessment, emphasizing curiosity's impact on memory. This paper argues that curiosity's essence is the primary driver of knowledge acquisition behavior, focusing on curiosity's dynamic nature.

Regardless of specific expressions, these models essentially derive from reinforcement learning (RL) models (Rescorla, 1972; Sutton & Barto, 1998). RL studies how natural and artificial systems learn to predict outcomes and optimize behavior in environments. The key to RL is changing behavior and motivation through reinforcers. Originating from psychology, this theory is now widely used in economics, machine learning, and other fields (Sutton & Barto, 2018). Compared to general RL, the most important characteristic of curiosity-induced information seeking is that the reinforcer is the information that satisfies curiosity itself.

This paper focuses on the neurophysiological mechanisms at each stage when elaborating the curiosity feedback loop model. The model positions curiosity as intrinsic motivation, treats information-seeking behavior as curiosity's induced outcome and emotion as its byproduct, and emphasizes curiosity's dynamic nature (see Figure 1a [Figure 1: see original paper]). According to Loewenstein's (1994) information-gap theory, perceiving an information gap creates a sense of deprivation and aversive emotion, generating a craving for information—namely, curiosity motivation. Based on current environment and past experience, individuals conduct value of control assessments according to expected outcomes of current activity states or potential behaviors (such as information seeking), evaluating how much control to exert and how to exert it to decide whether to initiate information seeking. Information seeking leads to different outcomes: successful information acquisition satisfies curiosity, while failure leaves curiosity unsatisfied. Various emotions also arise during this stage (Di Leo et al., 2019; Vogl et al., 2019). Due to new information input, the individual's state changes and becomes a cue for control value assessment, thereby influencing subsequent curiosity generation and information-seeking initiation. Curiosity satisfaction means obtaining information reward, which typically increases individuals' expectation value for new information and estimates of behavioral effectiveness, thereby reinforcing information-seeking behavior. Further information integration expands prior knowledge, making individuals more aware of new information gaps and triggering new information-seeking behavior. This process forms a positive feedback loop that contributes to sustainable knowledge acquisition. Conversely, information acquisition failure interrupts this positive feedback loop. It is important to note that we might simplistically understand

curiosity satisfaction as the presentation of target information in curiosity tasks. In reality, information-seeking processes and their outcomes are dynamic in authentic contexts—all information that narrows or widens information gaps changes individual states, leading to curiosity satisfaction or dissatisfaction.

The primary distinction between this paper and the reward-learning model (Murayama et al., 2019) is the integration of Shenhav et al.'s (2013, 2016) expected value of control (EVC) model. This integration is warranted because the transition from curiosity motivation generation to information-seeking behavior follows general behavioral decision-making principles, conforming to neuroeconomics principles (Rangel et al., 2008)—that is, information-seeking behavior initiation and strategy selection depend on a series of neurobiological value computations (Platt & Plassmann, 2014). The EVC model generalizes this motivation- and reward-based behavioral decision-making process (Figure 1b). It should be noted that control in the EVC model, also called cognitive control, refers to the ability to coordinate behavior to align with goals in non-automated tasks requiring time and effort. Actively initiated information seeking is precisely such a behavior requiring control. In the EVC model, the dorsal anterior cingulate cortex (dACC) connects state assessment and behavioral regulation. Specifically, the system transmits signals reflecting current activity states or potential behavioral outcomes to the dACC, which integrates expected reward and effort cost information to compute EVC, determines how to allocate control resources, and outputs the computation results to regulatory systems for control execution (Shenhav et al., 2013; Shenhav et al., 2016).

Additionally, the dopamine (DA) system plays a crucial role throughout the RL process. DA projecting to different brain regions may have different functions (Figure 1c). Dopaminergic neurons (DAN) primarily originating from the ventral tegmental area (VTA) and ventromedial substantia nigra (SN) and projecting to the nucleus accumbens (NAcc; located in the ventral striatum, VS) and anterior cingulate cortex (ACC) respond to reinforcer valence. In contrast, DAN mainly originating from dorsolateral and lateral SN and projecting to the prefrontal cortex (PFC) respond to reinforcer salience (Dayan & Niv, 2008; Matsumoto & Hikosaka, 2009; Ott & Nieder, 2019). Therefore, some researchers propose that valence-related DA updates value representations to implement RL, while salience-related DA signals the amount of attention stimuli require and participates in regulating cognitive control (Ott & Nieder, 2019; Sutton & Barto, 2018).

Curiosity's important function—promoting learning and memory (Gruber et al., 2014; Kang et al., 2009; Marvin & Shohamy, 2016)—is also closely related to the DA system. The hippocampus, a key brain region for learning and memory, has a functional circuit with midbrain VTA/SN DAN (Figure 1d; Lisman & Grace, 2005). DA release in the hippocampus enhances long-term potentiation (LTP), a critical step for memory consolidation (Lisman & Grace, 2005).

In summary, static observation of curiosity itself has limitations; only by connecting the series of events beginning with curiosity induction can we better

understand curiosity' s essence and function. The following sections elaborate on each stage of the model and their neurophysiological mechanisms.

Figure 1 Curiosity feedback loop model and its neurophysiological mechanisms. (a) The curiosity feedback loop process. Perceiving an information gap creates cognitive deprivation, triggering aversive emotion and generating craving for information—curiosity motivation. The system assesses the current state (including curiosity motivation) to obtain EVC, deciding whether information-seeking behavior is worth initiating. If the benefits of cognitive control outweigh the costs, control is initiated for information seeking. Successful information seeking satisfies curiosity. The experience of curiosity satisfaction becomes new input information, changing the current state and influencing subsequent curiosity generation and information-seeking initiation. Finally, acquired information integrates with prior knowledge, expanding the knowledge base and making individuals more likely to perceive new information gaps, triggering new information-seeking behavior. This process forms a positive feedback loop facilitating sustainable knowledge acquisition. (b) Motivation- and reward-based behavioral decision-making process, adapted from Shenhav et al.' s (2016) EVC model. Signals reflecting current activity states or potential behavioral outcomes are transmitted to the dACC, which computes EVC to determine control resource allocation and outputs results to regulatory systems for cognitive control execution. (c) Midbrain DA system. SN/VTA in the midbrain is the origin of DA release (Ballard et al., 2011; Cervera et al., 2020; Frankle et al., 2006). DA projections from midbrain to NAcc (part of VS), ACC, MFC, and other regions typically reflect the difference between received and expected rewards—reward prediction error (RPE). DAN activity relates to valence (reward increases DAN activity, punishment decreases it) and changes rapidly, enabling value representation updates for RL. In contrast, midbrain-to-PFC DA projections are valence-independent, transmitting stimulus salience signals that predict required attention and thus promote cognitive control. (d) Hippocampus-VTA/SN functional circuit. The hippocampus and midbrain VTA/SN DAN form a functional circuit. DA release in the hippocampus enhances LTP, facilitating memory consolidation.

Abbreviations: EVC—expected value of control; OFC—orbitofrontal cortex; dACC—dorsal anterior cingulate cortex; LPFC—lateral prefrontal cortex; MC—motor cortex; LC—locus coeruleus; DA—dopamine system; VTA—ventral tegmental area; SN—substantia nigra; NAcc—nucleus accumbens; VS—ventral striatum; MFC—medial prefrontal cortex; ACC—anterior cingulate cortex; PFC—prefrontal cortex; RPE—reward prediction error; RL—reinforcement learning

2.1 Curiosity Generation Stage

Loewenstein' s (1994) information-gap theory posits that curiosity functions like other drives—just as hunger prompts eating, curiosity prompts filling “information gaps.” Minimal or conflicting information can serve as a catalyst, driving information-seeking behavior. Typically, information gaps relate to individu-

als' prior knowledge, with the difference between current information and prior knowledge determining gap size. When detecting knowledge gaps, people actively initiate information-seeking behavior to acquire knowledge.

This raises the question: what size of information gap is optimal? Berlyne and Hebb (Berlyne, 1970; Hebb, 1955) identified an optimal level of information incongruity, termed the “optimal arousal” level. They argued that stimuli that are neither too familiar nor too novel evoke curiosity, while extreme incongruity triggers fear rather than exploration. Kidd et al. (2012) found that infants were most likely to look away from events with very low information content (highly predictable) or very high information content (highly surprising). Infants tend to maintain attention on events with moderate information levels. Kang et al. (2009) found similar results in adults: the relationship between curiosity for trivia question answers and confidence in those answers follows an inverted U-shaped curve—curiosity is weakest when participants know nothing or are extremely confident, and strongest when they are uncertain. Stronger curiosity motivation means more attentional resources are deployed. This strategy of generating maximum curiosity and attentional investment for moderate uncertainty effectively prevents wasting cognitive resources on overly predictable or overly complex events, thereby maximizing learning potential.

The primary brain regions involved in information gap detection are the hippocampus and ACC (Huang et al., 2021). The hippocampus participates in connecting new information during new memory formation and indexes stored information during long-term memory retrieval, with close ties to episodic memory establishment (Squire et al., 2007; Eichenbaum & Cohen, 2014). Consequently, the hippocampus is extremely sensitive to new or unexpected environmental information, which can activate the hippocampus to guide subsequent visual exploration (Liu et al., 2017; Voss et al., 2017). Beyond novel environments, cognitive conflict represents another important manifestation of information gaps. Monitoring cognitive conflict relates to the ACC, which some researchers propose houses a conflict monitoring system that tracks conflicts in information processing to calculate required control based on conflict magnitude and transmits this information to control centers (Botvinick et al., 2001; Shenhav et al., 2016). Studies have found that ACC activity indeed increases when presenting ambiguous images (curiosity-inducing materials) to participants (Jepma et al., 2012).

Moreover, as a motivation, curiosity has both approach and avoidance aspects—it approaches information (reward) while avoiding the negative emotions caused by information gaps. Berlyne (1957) noted that curiosity is an aversive state. Loewenstein (1994) believed that awareness of information gaps creates a sense of deprivation. Litman's (2008) deprivation-type curiosity suggests that curiosity may be an unsatisfied need state. Thus, curiosity and aversive emotions are intertwined. Recent empirical studies confirm this negative emotional component: van Lieshout, de Lange et al. (2021) used a lottery task to quantitatively manipulate information uncertainty, finding that stronger uncertainty generated

higher curiosity but lower pleasure. Jepma et al. (2012) used ambiguous images to induce curiosity and activated the anterior insular cortex (AIC), which is associated with negative arousal (such as pain and aversion; Shackman et al., 2011; Singer et al., 2009), indicating that curiosity generation involves an aversive emotional state.

2.2 Decision-Making Stage for Information-Seeking Behavior

First, it should be noted that information seeking is considered a typical curiosity-induced behavior. When people feel curious—that is, under curiosity motivation—they explore, ask questions, and manipulate interesting objects (Kidd & Hayden, 2015), all of which constitute information seeking. However, curiosity-induced behaviors are not limited to information seeking. For example, when someone avoids spoilers (Rosenbaum & Johnson, 2015), this information-avoidance behavior also partially originates from curiosity motivation. Furthermore, information seeking does not always involve overt behavior (Murayama et al., 2019). In classroom education, for instance, knowledge may be provided externally, with students as passive recipients. Even in such cases, however, students' understanding of information depends on their active processing of it. In other words, students still engage in mental information searching, a process requiring cognitive control.

(1) The Decision-Making Process of Information-Seeking Behavior

The transition from curiosity generation to information seeking shares characteristics and internal mechanisms with general behavioral decision-making (Figure 1b). Whether and how information-seeking behavior occurs results from a series of value computations (Platt & Plassmann, 2014; Rangel et al., 2008). Shenhav et al. (2013, 2016) describe this value as EVC. In tasks requiring cognitive control, EVC integrates expected benefits of control processes, the amount of control needed to achieve those benefits, and the costs of cognitive effort. Thus, EVC represents the net value of control, used to determine control allocation in subsequent behavior. EVC estimation occurs in the dACC, which receives input signals from the amygdala, AIC, OFC, midbrain, and other structures reflecting the organism's current state (such as current task demands, processing capacity, motivational state) and the value of potential behavioral outcomes (considering both outcome probability and expected value). The cognitive conflict mentioned above is just one of many signals processed by the dACC (Shenhav et al., 2016).

In curiosity-related research, the OFC appears to be a brain region that encodes information value. In a curiosity tradeoff task, researchers found that the OFC encoded both gambling stakes and the value of information satisfying curiosity, with these value signals transmitted to the midbrain DA system (Blanchard et al., 2015; Charpentier et al., 2018). However, researchers still disagree on whether information value encoding is consistent with natural reward encoding (Cervera et al., 2020). A study on object choice tasks effectively illustrates the difference between OFC and ACC in value encoding (Shenhav & Buckner, 2014).

When both objects had high value and participants had to choose one, anxiety levels were highest compared to choosing between two low-value objects or one high- and one low-value object. ACC activation aligned with anxiety levels—greater conflict produced stronger activation. In contrast, OFC activation only related to the value of the item about to be chosen—the higher the value, the stronger the activation. Thus, the OFC encodes expected reward or payoff, while the ACC reflects control demands of the task.

After the dACC computes control resource allocation schemes, results are output to regulatory systems for control execution. Brain regions primarily receiving output signals from the dACC include the LPFC, motor cortex, striatum, and LC (Shenhav et al., 2016).

Research shows that information gap activation of the ACC signals the LPFC, which decides whether to initiate exploratory behavior (Gruber & Ranganath, 2019; Gruber & Fandakova, 2021). A neuroimaging study using the trivia question paradigm found that high-curiosity trivia questions activated the LPFC more strongly than low-curiosity questions, possibly because high-curiosity questions have higher EVC (Kang et al., 2009; Gruber et al., 2014; Ligneul et al., 2018). Other curiosity studies also show stronger LPFC activity when facing high-uncertainty images (Jepma et al., 2012). The noradrenergic system, specifically the locus coeruleus (LC) where norepinephrine (NE) is synthesized, also participates in curiosity responses (Gompf et al., 2010). Pupil dilation in response to unpredictable, uncertain stimuli reflects LC activity (Joshi et al., 2016; Payzan-LeNestour et al., 2013).

Notably, information-seeking behavior typically begins with curiosity, but curiosity does not necessarily lead to information-seeking behavior—curiosity is only one motivation for information seeking. Sometimes “wanting to know” does not mean people will act to “find out.” The EVC model shows that emitting a behavior results from cost-benefit analyses. Given curiosity’s intrinsic motivational nature, information satisfying curiosity itself has reward properties that drive information seeking without needing additional instrumental value. Numerous studies support this view, showing that people are willing to pay costs (such as monetary costs, time costs, or electric shocks) to obtain curiosity-satisfying information (Bennett et al., 2016; Lau et al., 2020; Marvin & Shohamy, 2016). However, besides satisfying curiosity, information may have other additional values. For example, information may carry different emotional valences, and expectations of information’s emotional valence also affect information-seeking behavior (Hertwig & Engel, 2016). Charpentier et al. (2018) found that participants’ information-seeking behavior decreased when potentially obtained information was negative (involving monetary loss). However, other research indicates that even frightening pictures have reward properties that can elicit information-seeking behavior to satisfy curiosity (Oosterwijk et al., 2020).

Beyond information itself affecting value estimates of information-seeking behavior, the probability of obtaining information is also an important factor. Decisions to initiate information-seeking behavior depend not only on the value

information carries but also on the cost of obtaining it. As mentioned, people are willing to pay costs for curiosity-satisfying information, but when costs increase, the likelihood of information seeking decreases (Bennett et al., 2016). Research shows that assessing behavioral effectiveness importantly influences behavior selection and execution. When believing behavioral strategies are effective, individuals show more exploratory behavior to resolve uncertainty (Jaško et al., 2015; Sankaran et al., 2017). If a person does not believe they have sufficient ability to obtain information or if behavioral costs are too high, they will abandon information-seeking behavior (Noordewier & van Dijk, 2016; Silvia, 2005). If exploration fails to yield effective information satisfying curiosity motivation, the individual's belief in their ability to obtain target information decreases, ultimately eliminating motivation to initiate new information-seeking behavior (Tanaka & Murayama, 2014). Conversely, when effective information is obtained and transformed into knowledge, subjective ability and skills improve alongside knowledge acquisition. Therefore, knowledge and subjective ability develop together over time and may be indistinguishable in our learning system.

(2) The Role of Dopamine in Curiosity-Driven Reinforcement Learning

Beyond the ACC, the DA system is considered to play a key role in the interaction between motivation and cognitive control (Ballard et al., 2011; Berke, 2018; Bromberg-Martin et al., 2010). DAN from SN/VTA project to different brain regions with some functional differences (Figure 1c). DAN mainly from VTA and ventromedial SN projecting to NAcc and ACC respond to reinforcer valence, while DAN mainly from dorsolateral SN projecting to PFC respond to reinforcer salience (Dayan & Niv, 2008; Matsumoto & Hikosaka, 2009; Ott & Nieder, 2019). Thus, valence-related DA primarily updates value representations to implement RL, while salience-related DA signals required attention and participates in regulating cognitive control (Ott & Nieder, 2019; Sutton & Barto, 2018).

Schultz et al. (1997) first proposed DA's important role in RL, suggesting that DAN firing activity reflects the difference between actual and expected reward—reward prediction error (RPE)—rather than reward magnitude itself. Research shows that DAN responses change as learning progresses, with RPE changing rapidly, enabling RPE signals to update value representations of current states and potential behavioral outcomes in real time, thereby influencing subsequent behavioral decisions (Berke, 2018; Dayan & Niv, 2008; Hamid et al., 2016).

Numerous evidence shows that curiosity activates the midbrain DA system. Several fMRI studies report enhanced striatum activity during the anticipation phase after curiosity induction (the waiting period before curiosity-satisfying information presentation), with activation in these regions influenced by DA release from SN/VTA (Gruber et al., 2014; Kang et al., 2009; Lau et al., 2020; Oosterwijk et al., 2020). In trivia question tasks, high-curiosity questions elicit stronger midbrain DAN activity (Gruber et al., 2014; Kang et al., 2009). An-

other curiosity-related study showed that when potentially obtainable future information was more favorable, participants' craving for this information was stronger, with stronger SN/VTA and VS activation (Charpentier et al., 2018). Thus, although information is an indirect reward unlike primary rewards (such as water or food), DA responses to them are similar, suggesting that DA reflects something more abstract behind rewards, such as the value provided by reward objects (Berke, 2018; Matsumoto & Hikosaka, 2009).

Additionally, DA participates in another important process—cognitive control (Ott & Nieder, 2019; Sutton & Barto, 2018). Ott and Nieder (2019) summarized three main roles of DA in cognitive control: (1) controlling sensory input so stimuli relevant to potential behaviors are processed; (2) maintaining and manipulating working memory content; and (3) transmitting this information to premotor areas preparing behavioral responses. Some researchers propose that the interaction between motivation and cognitive control relates to DAN projections from VTA to LPFC. For example, LPFC DA levels relate to cognitive control and attention (Anderson, 2016; Durstewitz & Seamans, 2008). However, other evidence suggests that LPFC initiates motivated behavior by influencing VTA activity in response to expected reward (Ballard et al., 2011), implying that LPFC forms motivational cognitive control by influencing ACC and VTA. Hippmann et al.'s (2021) dynamic causal modeling analysis better supports the former view: when control demands are high, VTA exerts causal influence on PFC. More evidence is still needed to determine how DA participates in cognitive control. Moreover, although curiosity-driven information-seeking behavior also requires cognitive control and DA involvement, no curiosity-based research has directly addressed this.

(3) Curiosity's Enhancement of Learning and Memory

Beyond driving information seeking, curiosity's most important function is promoting individual learning and memory. Longitudinally, trait curiosity shows significant positive correlations with academic achievement across all stages from preschool to youth (Froiland et al., 2015; Shah et al., 2018; Tucker-Drob et al., 2016; Oudeyer et al., 2016). For state curiosity, information associated with high curiosity is better remembered even one day and at least two weeks after experiments (Gruber et al., 2014; Kang et al., 2009; Marvin & Shohamy, 2016). Thus, curiosity-induced memory enhancement does not fade quickly. This memory enhancement effect applies to children, adolescents, young adults, and older adults (Fastrich et al., 2018; McGillivray et al., 2015). Furthermore, curiosity states enhance memory not only for target information satisfying curiosity but also for other incidental information encountered in that state. Gruber et al. (2014) found that adults showed better memory for neutral faces inserted during the answer anticipation phase (especially early in this phase) following trivia questions. Children and adolescents also show enhanced memory for non-target information in curiosity states (Fandakova1 & Gruber, 2021).

Why does curiosity promote learning and memory? This may relate to enhanced hippocampal activity. Gruber and Ranganath's (2019) PACE model proposes

that curiosity stimulates DAN to enhance hippocampus-dependent memory encoding and consolidation. The hippocampus is a critical brain region for learning and memory, with LTP in the hippocampus being a key step in memory consolidation. Animal studies show that exposure to novel environments facilitates LTP enhancement, a process mediated by DA and NE systems (Li et al., 2003; Li et al., 2013). Additionally, NE (Straube et al., 2003) and DA activity (Moncada & Viola, 2007; Lisman et al., 2011) promote the transition from early LTP to lasting LTP.

This process is also confirmed in human studies. Literature on external motivation and memory shows that motivational states themselves can promote learning and memory (Shohamy & Adcock, 2010). The NAcc and SN/VTA complex form a functional circuit with the hippocampus (Lisman & Grace, 2005). Researchers have observed that when cues signaling high reward (external rewards like money) appear, activation in NAcc, SN/VTA, and hippocampus all increase, enhancing memory for related events (Lisman & Grace, 2005; Lisman et al., 2011; Shohamy & Adcock, 2010). Enhanced functional connectivity between SN/VTA and hippocampus under high reward conditions occurs not only during memory encoding (Murty & Adcock, 2014; Wolosin et al., 2012) but also during post-learning memory consolidation (Gruber et al., 2016). Gruber et al. (2016) found that during rest after learning, hippocampal representations from high-reward contexts were preferentially reactivated, meaning items learned in high-reward contexts were prioritized for consolidation.

The above describes external motivation's reinforcement learning mechanism. Curiosity as internal motivation operates similarly, except the reward becomes information itself. Research found that activation differences in the right hippocampus and bilateral NAcc when presenting high- versus low-curiosity questions predicted memory differences for high- versus low-curiosity answers (Gruber et al., 2014). However, activity in these regions during answer presentation could not predict memory for curiosity-related information. This suggests that DA released during anticipation of future information in high-curiosity states stimulates NAcc and hippocampus, thereby promoting learning of upcoming information. Studies also show that if learning is curiosity-driven, adding external motivation is unnecessary and ineffective, which is why other external rewards can sometimes reduce curiosity's facilitative effect (Murayama et al., 2010).

Beyond SN/VTA-hippocampus functional connectivity enhancing learning, curiosity also promotes learning by influencing attention during learning. Research shows that DA guides immediate attentional bias toward stimuli signaling past or future rewards (Anderson, 2016). An eye-tracking study found similar attentional bias in curiosity contexts: in high-curiosity states, participants directed more attention to locations where trivia answers would appear, showing anticipatory fixation (Baranes et al., 2015). High curiosity's alteration of attention relates to activation of attention networks, with curiosity or DAN activity changing activation states in frontal and parietal regions (related to attention) (Jepma et al., 2012).

Another system related to learning enhancement is the NE system. Pupil size changes reflect NE system activity, with pupil dilation to curiosity objects positively predicting learning efficiency (Nassar et al., 2012). Additionally, LC activity relates to emotional arousal states and also modulates hippocampal function to influence learning (Mather et al., 2016; Sakaki et al., 2014).

In summary, under curiosity states, increased hippocampal activity— Influenced by DA and NE systems—not only helps people remember what they are curious about but also helps them remember other information appearing in that state (after curiosity generation).

2.3 Curiosity Satisfaction Stage

In daily life, every action has potential outcomes, either positive or negative. These outcomes largely shape our future behavior and motivate decisions to obtain positive results. Curiosity-driven information-seeking behavior similarly requires a positive outcome—curiosity satisfaction—as feedback to consolidate these behaviors and motivations. Only curiosity satisfaction can complete the RL driven by curiosity motivation.

In the generalized RL model, an agent’s learning process heavily depends on its own experiences (Figure 2a [Figure 2: see original paper]). The agent emits an action that changes the environment, which simultaneously produces a reinforcement signal (reward or punishment) fed back to the agent. The agent then decides the next action’s emission strategy based on current environmental state and feedback reinforcement signal, following the principle of maximizing reward. The chosen action affects the next moment’s state and reinforcement signal, and this cycle repeats (Sutton & Barto, 2018). According to Gershman and Uchida’s (2019) interpretation, biological RL is Bayesian, involving three key components: state, value, and policy. First, state refers to the environmental state the organism currently occupies, such as time, location, and encountered objects. From a perceptual perspective, “the organism cannot obtain complete information about its current state but can only receive ambiguous information from sensory data.” What the organism actually obtains is a belief state based on Bayesian rules—using sensory data probability distribution ($P(x)$), prior probability of potential true states ($P(s)$), and likelihood estimates (conditional probability of obtaining current sensory data from true environmental states, $P(x|s)$) to compute posterior probability ($P(s|x)$), which is the optimal estimate of all past observation history. Second, value is the expected future reward calculated from the current state. In fact, belief state is the key independent variable for reward prediction, meaning value is a function of belief state. “Parameters of the value function for reward acquisition are gradually determined through experiences of rewards in different states” (Figure 2b). Third, policy is the decision about which action to take in the current state. “There exists a mapping from state to policy, which is modulated by learned values.” Since optimal policies are typically unknown, organisms must balance between “exploiting” behaviors with certain rewards and “exploring” behaviors that may yield better rewards.

Gershman and Uchida (2019) propose that “these three different forms of uncertainty (related to state, value, and policy) play central roles in DA modulation and being modulated.” In the Bayesian RL framework, “state uncertainty affects the DA system through belief state probability distribution,” with belief state computation possibly occurring in the medial prefrontal cortex (MPFC). “Value uncertainty affects the DA system through value function parameter probability distribution, and DA in turn drives value function parameter updates by reporting RPE.” The brain region mainly involved in value function formation is the striatum. A meta-analysis of RL studies also indicates that VS is a key subcortical structure participating in numerous RL processes (Garrison et al., 2013). Finally, “policy uncertainty affects the DA system through the probability distribution of organism behavior.” Single nucleotide polymorphism studies found that two proteins regulating DA levels—COMT and DARPP-32—are involved in directed and random exploration (Frank et al., 2009; Humphries et al., 2012). The Bayesian RL framework greatly enriches traditional RPE explanations of DA.

This model also applies to the RL process from curiosity induction to curiosity satisfaction. Taking distance from target information as an example, an individual’s perceived distance from target information—the belief state—is an estimate based on currently held information and past experience, not completely equivalent to the true distance between current environment and target information. This estimate determines the expected value of target information. The perceived distance from target information continuously changes as information seeking unfolds, and the expected value of target information changes dynamically accordingly. When the actual value of obtained information exceeds its expected value—when RPE is positive—it signals that the expected value of behavior can be increased, thereby enhancing the likelihood of subsequent curiosity generation and information seeking. Litman et al. (2005) found that the closer participants felt to knowing the answer, the more curious they became, with stronger VS activation.

Jepma et al.’s (2012) perceptual curiosity study and Ligneul et al.’s (2018) epistemic curiosity study both showed that during curiosity satisfaction stages (corresponding to image ambiguity resolution and trivia question answering, respectively), VS produced stronger neural activity. This contradicts Gruber et al.’s (2014) finding of striatal activation during answer anticipation rather than curiosity satisfaction. These discrepancies likely relate to task design differences across studies (Gruber et al., 2019). In Jepma et al. (2012) and Ligneul et al. (2018), curiosity-satisfying information did not always appear. Because satisfaction was often unattained, expected value estimates for target information decreased, and when target information was unexpectedly obtained, a clearly positive RPE emerged. In Gruber et al. (2014), trivia question answers always appeared, and the questions themselves were relatively dull, making both actual and expected values of answers relatively stable, so RPE during answer presentation did not change much, potentially weakening curiosity motivation.

Thus, for reinforcement of information-seeking behavior, simple curiosity satisfaction may be insufficient—information exceeding expected value is also important. Marvin and Shohamy (2016) used “information prediction errors” to represent the difference between actual and expected reward value of new information. If obtained information is unexpected and the information prediction error is positive, individuals will increase expected reward value for future new information. Research shows that when new knowledge is inconsistent with expectations, information-seeking behavior increases (Vogl et al., 2019). Conversely, if new information does not exceed expectations, people often feel disappointed, and information value is downgraded.

As mentioned earlier, some researchers believe information gaps induce aversive emotions—curiosity generation is accompanied by a negative emotion (Berlyne, 1957; Loewenstein, 1994). Others propose that curiosity may be accompanied by positive emotions (Grossnickle, 2016; Litman, 2008). These divergent understandings likely arise because researchers are not focusing on the same emotional process. When viewing curiosity’s development as a process, we find that emotions triggered at different stages continuously change. Emotions are generated during curiosity induction and also accompany curiosity satisfaction. During curiosity satisfaction, emotions such as pleasure (curiosity satisfaction), surprise (target information value exceeding expectations), disappointment (target information value failing to meet expectations), and helplessness (information-seeking failure) may arise (Di Leo et al., 2019; Vogl et al., 2019). Due to unclear curiosity definitions and inconsistent emotion assessment stages in research, disagreements about curiosity-related emotions have emerged.

2.4 Information Integration Stage

Thus far, the curiosity feedback loop has not truly ended. After obtaining target information, it requires further processing. If ultimately incorporated into existing knowledge structures, the prior knowledge base is updated. Information gaps directly arise from discrepancies between current information and prior knowledge. Updating the prior knowledge base makes new questions more likely to emerge, forming new information gaps that trigger new curiosity and initiate a new cycle.

Lydon-Staley et al. (2021) found that individuals high in deprivation-type curiosity build tighter knowledge networks and return to previously viewed thematic information more frequently during information seeking. Murayama (2019) summarized three pathways through which knowledge acquisition promotes further information seeking. First, as mentioned, knowledge acquisition makes individuals more aware of previously unrecognized “information gaps” because expanded knowledge networks reveal more space for knowledge expansion (Loewenstein, 1994). Awareness of knowledge gaps promotes curiosity generation and further guides knowledge acquisition behavior. Second, the rewarding feeling of obtaining information increases expected reward value for new information, and accumulated knowledge also makes individuals aware of relevant topics’ impor-

tance, both leading individuals to assign higher value to new information during assessment. Finally, besides increasing value of topic-related information, individuals' perceived ability to obtain information also improves, thereby increasing value estimates of information-seeking behavior.

However, after knowledge acquisition, both in experimental research and real learning situations, 钝化 perception of new information gaps may occur. Individuals fail to detect more information gaps or even terminate learning tasks because they subjectively believe they have fully understood the topic. This often occurs in experiments because induced materials (such as trivia) usually have little connection to prior knowledge and low practical utility, easily inducing satiation during answer acquisition (Marvin & Shohamy, 2016; Murayama et al., 2019). The problem in real learning environments is that students often mistakenly believe they have mastered learning content when they actually have not. As mentioned earlier, there is a gap between individuals' perceived states and true states (Gershman & Uchida, 2019). Related research shows that learners' judgments of their mastery of learning materials are often inaccurate and overly optimistic, frequently leading them to prematurely terminate their learning behavior (Murayama et al., 2016).

Overall, knowledge acquisition and integration enhance future curiosity motivation, drive more information-seeking behavior, and thereby make the knowledge acquisition process sustainable. Through the reward system's action, from curiosity induction to curiosity satisfaction to true information integration and back to new curiosity generation, a positive feedback loop is formed. Stable curiosity traits are precisely the result of repeated occurrence and eventual consolidation of these transient curiosity experiences (Fayn et al., 2019; Lydon-Staley et al., 2021).

3 Curiosity Across the Lifespan

The curiosity feedback loop model from induction to satisfaction demonstrates a small cycle of transient curiosity changes and development. In fact, curiosity's changes and development are embedded in a larger dynamic process—individuals' birth, growth, and aging.

3.1 Curiosity Development and Differentiation with Age

Numerous studies show that infants and young children systematically explore their environment to reduce uncertainty and fill information gaps, indicating no significant difference from adults in curiosity generation and expression (Begus et al., 2016; Leckey et al., 2020). However, stimuli that trigger curiosity and curiosity's effects change with age. What triggers curiosity differs across ages—infants prefer exploring visually novel objects, while young children prefer exploring objects with unclear functions (Kidd & Hayden, 2015; Schulz, 2012). In 2021, Fandakova and Gruber used the trivia paradigm to study how curiosity affects memory in 10-14-year-old participants, finding that the more curious

individuals were, the better their knowledge memory. Moreover, adolescents aged 12-14 showed better memory for trivia answers than children aged 10-12, largely related to adolescents' value expectations for target information—they found trivia questions more interesting than expected (Fandakova & Gruber, 2021). This may also be because adolescents have more prior knowledge, making it easier to establish connections with new information.

These age-related characteristics of curiosity may relate to brain development. The ACC, involved in conflict monitoring, plays an important role in curiosity generation and continues to mature from infancy through adolescence. Specifically, the error-related negativity (ERN), an ERP component related to cognitive conflict monitoring and processing, shows amplitude increasing with age throughout childhood. Fandakova et al. (2018) also found that 12-year-old children activated ACC and AIC when facing uncertain memory information, but only 10-12-year-olds activated LPFC when reporting uncertainty. Further analysis showed that children with stronger activation in conflict-related brain regions (especially AIC) at age 10 showed greater PFC activation in uncertainty assessment 1.5 years later. Based on this, Gruber and Fandakova (2021) hypothesized that with age, individuals continuously experience various cognitive conflicts causing information gaps, leading to improved conflict processing capacity based on ACC. Differences in ACC activation further lead to differential development of PFC-based assessment systems, ultimately causing children and adolescents to show differentiated curiosity and curiosity-driven exploratory behavior. Another longitudinal study also showed that structural changes in children's PFC from ages 7-15 relate to developmental changes in assessment processes (Fandakova et al., 2017). Fandakova et al. (2017, 2018, 2021) tend to understand LPFC as an assessment system, but in the EVC framework, LPFC more reflects control execution (Shenhav et al., 2016). For curiosity-related research, both perspectives seem able to explain existing findings, but which is more reasonable requires further investigation. Moreover, PFC is a relatively vague localization involving many subregions with functional differences (Reverberi, Lavaroni, et al., 2005), necessitating more detailed differentiation.

Overall, younger children rely more on ACC and AI functions, responding to simple information prediction errors and thus showing undifferentiated high curiosity. With maturation of the frontal system, LPFC begins comprehensive assessment of information prediction errors and other relevant factors (Fandakova et al., 2017, 2018; Fandakova & Gruber, 2021), or has stronger control capacity to focus attention on current tasks (Reverberi, Toraldo, et al., 2005; Shimamura, 2000). These may be reasons why younger children show broad interest across different domains while older children's interest domains begin to narrow and differentiate (Frenzel et al., 2012). Once curiosity is induced, LPFC also regulates hippocampus-dependent learning by stimulating the mesolimbic dopaminergic pathway (Gruber et al., 2014; Lau et al., 2020). It may be precisely this interaction between developed PFC and dopaminergic neuromodulation of hippocampus-dependent learning that explains the phenomenon mentioned earlier—curiosity induced by information prediction errors has stronger mem-

ory enhancement effects in adolescents than in children (Fandakova & Gruber, 2021).

3.2 Age-Related Decline in Curiosity

In addition to continuous differentiation with age, curiosity also declines with individual aging. Numerous survey studies find that from early to late adulthood, individuals' epistemic curiosity, interpersonal curiosity, and self-curiosity all decrease with age (Robinson et al., 2017). Openness to experience (Costa et al., 2000; Ziegler et al., 2015), sensation seeking (Giambra et al., 1992), and exploratory behaviors (Kashdan et al., 2009; Kashdan et al., 2004) related to curiosity also show corresponding declines.

Curiosity and related behavioral decline mainly relate to degeneration of two systems—the DA and NE systems. These systems are highly vulnerable to aging. Functional weakening and structural damage to brain regions crucial for curiosity in older adults may be important reasons for the aforementioned declines in subjective curiosity and related behaviors (Chowdhury et al., 2013; Eppinger et al., 2013; Sakaki et al., 2018).

However, precisely because curiosity can activate these two systems, it serves as a protective agent against aging. The hippocampus develops functional impairments with age (Mitchell et al., 2000; Raz et al., 2010), and curiosity can stimulate the hippocampus through DA and NE systems to slow memory function decline (Lisman & Grace, 2005). Transient curiosity induction or forming long-term curiosity traits has good anti-aging effects. A longitudinal study found that maintaining curiosity benefits individuals lifelong, particularly in hippocampal promotion of memory (Martin et al., 2007). Beyond memory protection, curiosity also improves other cognitive functions, possibly related to DA and NE system stimulation of PFC (Sakaki et al., 2018).

4 Summary and Outlook

In summary, the curiosity feedback loop model views curiosity' s development from a dynamic process perspective, decomposing a curiosity event into six processes: perceiving information gap, curiosity generation, value assessment of control, information seeking, curiosity satisfaction, and information integration. As a dynamic process, each stage is influenced by current information input and feedback output from previous stages. The model establishes curiosity' s intrinsic motivational nature, separates curiosity-induced emotions and behaviors, and specifically analyzes conditions, processes, and influences at each stage. Based on the RL model, the key difference is that in curiosity contexts, the most important reinforcer is the information satisfying curiosity itself, not other external rewards. Therefore, in the curiosity feedback loop, continuously inducing and satisfying curiosity and obtaining unexpected target information are keys to sustainable knowledge acquisition.

Moreover, this dynamic loop is embedded in individuals' lifelong development

processes. On one hand, it is influenced and constrained by various physiological changes during development; on the other hand, repeated consolidation of the curiosity loop also causes physiological changes that in turn affect our life course. Overall, the two curiosity-related systems—the DA and NE systems—promote short-term attention, memory, and information-seeking behavior, and also greatly benefit long-term cognitive function maintenance and improvement. However, despite curiosity’s significance for individual development from birth to old age, research on curiosity development characteristics and underlying neurophysiological mechanisms has just begun. More research data are needed to form a more complete understanding.

Curiosity research is becoming increasingly interdisciplinary and multi-domain, requiring a unified concept and framework as a basis for further scientific discussion. Future curiosity research should strengthen attention to the following aspects.

4.1 Strengthening Attention to Curiosity Satisfaction

Previous research has focused more on benefits brought by curiosity induction while neglecting that curiosity satisfaction is key to these benefits’ existence. In fact, unsatisfied curiosity is the norm in daily life and often brings a series of negative effects. For example, research finds that cognitive emptiness from unsatisfied epistemic curiosity leads to more irrational consumption, with individuals substituting material satisfaction for knowledge satisfaction (Wiggin et al., 2019). Therefore, future research should pay more attention to curiosity satisfaction.

4.2 Improving Existing Curiosity Research Paradigms

Curiosity research includes either survey studies treating curiosity as a stable trait or experimental studies addressing transient curiosity states. Common paradigms for transient curiosity states include the ambiguous picture paradigm for inducing perceptual curiosity (Jepma et al., 2012; Wiggin et al., 2019) and the trivia question paradigm for inducing epistemic curiosity (Kang et al., 2009; Ligneul et al., 2018; Marvin & Shohamy, 2016). Magic (Lau et al., 2020) or lottery task paradigms (Kobayashi & Hsu, 2019; van Lieshout, de Lange, et al., 2021; van Lieshout, Traast, et al., 2021) are also used to induce curiosity, though the type of curiosity induced is more ambiguous.

These curiosity research paradigms have limitations in addressing certain specific issues. For example: (1) Curiosity-satisfying information is either directly presented or obtained at a cost (waiting time, tokens, or experiencing aversive stimuli), failing to reflect participants’ active information-seeking behavior. (2) Paradigms basically present answers, creating stable expectations for curiosity satisfaction across trials; even when focusing on curiosity satisfaction, comparisons are made between trials (some satisfying curiosity, some not), making it impossible to know what effects sustained curiosity dissatisfaction has on par-

ticipants. (3) Curiosity-inducing materials lack ecological validity and practical value; trivia questions are often difficult to integrate due to their disconnected nature. Learning a brief, isolated trivia answer may be insufficient to stimulate further exploration interest in the topic. Thus, such paradigms make it difficult to detect how knowledge accumulation affects topic value perception. (4) Current paradigms focus more on how transient curiosity affects information seeking (with curiosity-satisfying information presented within seconds), which is beneficial for characterizing micro-mechanisms of information seeking but lacks holistic grasp of the entire knowledge acquisition process. Therefore, future research should enrich and improve curiosity paradigms to enable discussion of more realistic, specific curiosity questions.

4.3 Strengthening Comparisons Between Internal and External Reward Use

Curiosity-induced learning and externally rewarded learning are both reward-based learning. The difference is that curiosity is internal motivation, with information satisfying curiosity being internal reward. Many curiosity studies include both external and internal rewards, with confounding variables affecting understanding and interpretation of curiosity.

More importantly, there is a lack of comparative research on learning processes driven by internal versus external motivation. Since Festinger and Carlsmith (1959) proposed cognitive dissonance, researchers have recognized that when external rewards are insufficient, people generate their own rewards to rationalize behavior. Subsequently, researchers have found that external motivation can sometimes undermine internal motivation, reducing individuals' engagement in tasks (Deci et al., 1999; Eisenberger et al., 1999). This suggests educators must be very careful using external rewards to avoid counterproductive effects. Therefore, future research should explore the encoding processes, timing, and contexts of internal versus external reward use, striving to ensure learning is a self-driven, self-growing process.

4.4 Emphasizing Developmental Research on Curiosity

From state to trait, from animals to humans, from infants to the elderly, curiosity has important survival significance. However, most curiosity research focuses only on its cognitive benefits for adolescents and adults, ignoring its developmental patterns across the lifespan. For example, to date, almost no research has directly measured curiosity in children. How curiosity moves from small cycles into larger cycles and develops over longer time scales is a topic needing attention in future research.

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