The Development of Decision Making: The Role of Objective Uncertainty and Perceptual Novelty

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Abstract

Human decision-making is influenced by many factors, including uncertainty and novelty. Although widely studied, prior findings on these two secondary effects remain mixed, partly due to the confounding effect of reward value and the natural co-occurrence of uncertainty and novelty, which makes it challenging to disentangle them. To examine the unique contributions of uncertainty and novelty across age groups, we designed a two-armed bandit task that carefully controlled reward value and subjective uncertainty. On each trial, participants chose between two options varying systematically in perceptual novelty and objective uncertainty. Participants included 38 children (ages 4–6) and 37 undergraduates. By holding one factor constant while manipulating the other and applying a computational model to trial-by-trial choices, we found that children's decisions were primarily driven by perceptual novelty, while adults were guided by aversion to objective uncertainty. These findings highlight developmental changes in decision-making and offer directions for future research.

Keywords: Decision making; Reward Uncertainty; Perceptual Novelty; Reinforcement learning; Cognitive Development

Introduction

Decision-making is a fundamental cognitive process that underlies both human learning and daily cognitive activities (Fellows, 2004). Although a large body of research has emphasized the role of rewards in driving decision-making (Jarcho et al., 2012; Kray, Schmitt, Lorenz, & Ferdinand, 2018), there are both conceptual and practical reasons to explore factors beyond reward. First, situations where the reward differences between options are marginal are common in real life. For example, imagine two hotels with identical average ratings and prices, one offers consistently average reviews, while the other shows more polarized ratings. Which one does a traveler choose? In addition, reward does not appear to be the primary driver of decision-making across development (Blanco & Sloutsky, 2020, 2021). Finally, even in adults, real-world decision-making often involves more than simply maximizing rewards. Adults integrate multiple sources of information—such as sensory input, contextual cues, and long-term goals—and adapt their strategies depending on the situation (Fellows, 2004). Therefore, investigating non-reward influences on decision-making—which we will refer to as secondary effects—while controlling for reward value offers valuable insight into how humans make choices in complex environments.

Two secondary effects—novelty (Harris, 1965; Blanco & Sloutsky, 2020; Cockburn, Man, Cunningham, & O'Doherty, 2022) and uncertainty (Gottlieb, Oudeyer, Lopes, & Baranes, 2013; Wang, Yang, Macias, & Bonawitz, 2021; Nussenbaum et al., 2023)—have been central in the previous research. The following part will review the literature on them in both children and adults.

Uncertainty

Uncertainty critically shapes children's decisions. For example, Blanco and Sloutsky (2021) showed children frequently chose uncertain (hidden) options, regardless of reward values. While previous research largely focused on epistemic (subjective) uncertainty arising from children's limited knowledge (Frank, Doll, Oas-Terpstra, & Moreno, 2009; Gottlieb et al., 2013; Wang et al., 2021) or memory (Wan & Sloutsky, 2024), objective uncertainty—ineliminable environmental ambiguity (Payzan-LeNestour & Bossaerts, 2011)—remains understudied. Although some recent studies examined objective uncertainty, these manipulations were confounded by differences in total rewards (Nussenbaum et al., 2023). Thus, little is known about how children handle objective uncertainty independently from other factors.

Findings on uncertainty's role in adult decision-making are mixed. Some studies suggest uncertainty encourages exploration: adults tend to choose risky or unknown options (Gershman, 2019), engage in more exploration driven by expected information gain or when facing increased environmental noise (Wilson, Geana, White, Ludvig, & Cohen, 2014; Poli, Meyer, Mars, & Hunnius, 2022). However, other studies show that adults usually avoid ambiguity or high uncertainty of estimation, demonstrating aversion to uncertainty rather than perform exploration (Edwards, 1996; Payzan-LeNestour & Bossaerts, 2011; Cockburn et al., 2022; Nussenbaum et al., 2023).

Novelty

Novelty plays a central role in children's decision-making. Research has shown that children's systematic exploration is driven by graded novelty (Blanco & Sloutsky, 2020, 2021, 2024). Here, the exploration-exploitation dilemma is considered as a specific scenario of decision making, in which participants must decide whether to explore new options or exploit the familiar ones that might yield the highest reward. In the baseline condition, children completed a four-armed bandit with equally novel options offering fixed rewards and exhibited lag-based exploration: the options that had not been chosen for a relatively long time regained novelty and were more likely to be selected.

Furthermore, results of the congruent and competition conditions showed that highlighting one consistently novel option disrupted children's default exploration, reducing lag-based choices and option-switching (Blanco & Sloutsky, 2020). Supporting this, Nussenbaum et al. (2023) found that children favored the unfamiliar options, while Gao and Sloutsky (2025) showed perceptual novelty influenced children's decisions despite visible rewards and any sources of uncertainty. Thus, novelty consistently guides young children's decision-making.

In contrast, the role of novelty in adults' decisions is mixed. Cockburn et al. (2022) showed adults switched to novel options in high-uncertainty contexts, suggesting novelty may inflate reward expectations. However, other studies found that adults are less influenced by novelty than children, especially when all rewards value were fixed (Blanco & Sloutsky, 2020) or when novel options did not have the highest reward values (Gao & Sloutsky, 2025).

Current Study

Conceptual Framework

We identified three main reasons for the mixed findings. First, prior studies often used broad or inconsistent definitions of novelty and uncertainty, causing conceptual confusion. Second, novelty and uncertainty frequently overlap in real-world situations, making them difficult to disentangle experimentally. Third, many studies confound novelty and uncertainty effects with reward, making it hard to isolate their independent roles. Therefore, we proposed a new conceptual framework, which highlights both shared and distinct components of novelty and uncertainty:

- **Uncertainty** divides into *subjective uncertainty* and *objective uncertainty*. Objective uncertainty reflects environmental unpredictability that cannot be eliminated by learning (e.g., lottery outcomes).

- **Novelty** divides into *perceptual novelty* (changes in appearance, e.g., new packaging for familiar chips) and *epistemic novelty*.

- The intersection of novelty and uncertainty is epistemic novelty (also called *subjective uncertainty*), which arises from lack of knowledge and can be eliminated through learning (e.g., not knowing the contents of a wrapped gift).

To examine the unique contributions of uncertainty and novelty and help account for inconsistencies in previous findings, the current study focuses on objective uncertainty and perceptual novelty.

Study Design

The current study aims to (1) control for the confounding effects of reward value and (2) disentangle the unique contributions of perceptual novelty and objective uncertainty, addressing the part of the mixed findings discussed in the literature review. Participants completed a two-armed bandit task, where four options varied systematically along high or low levels of perceptual novelty and objective uncertainty. Notably, the average rewards across options were kept equal, ensuring that participants could not optimize choices based on reward alone, and feedback on rewards was provided for both options, regardless of the participant's choice. Therefore, proportional selection should be at chance level if that participant is driven purely by reward or general information gain.

Considering immature cognitive control early in development (Plude, Enns, & Brodeur, 1994; Hanania & Smith, 2010; Deng & Sloutsky, 2016), we expect children to be more influenced by perceptual novelty, showing attention-driven patterns (Blanco & Sloutsky, 2020). In contrast, given the control of the information-seeking mechanism, adults are expected to avoid the uncertain option and not be influenced by perceptual novelty (Payzan-LeNestour & Bossaerts, 2011).

Methods

Participants

Forty-five typically developing children aged 4 to 6 years were recruited for this study. Five children were excluded from the final analysis due to failure to complete the experiment, and two additional children were excluded for not answering any comprehension questions correctly (see Results). These exclusions did not alter the overall pattern of results. The final sample included 38 children (18 girls, M_{age} = 4.68 years, SD = 0.57 years, range: 4-6 years). The adult sample comprised 37 undergraduate students (29 females, M_{age} = 18.43 years, SD = 0.69 years, range: 18-20 years). Children were recruited from local preschools and childcare centers in Columbus, with written informed consent obtained from their parents or legal guardians. Each participating family was reimbursed according to the standard rate. Adult participants were undergraduate students at The Ohio State University, participating for course credit.

Stimuli

There were four types of options, each represented by an animal in the game: (1) LU-LN option (Low-Uncertainty-Low-Novelty option), (2) HU-LN option (High-Uncertainty-Low-Novelty option), (3) LU-HN option (Low-Uncertainty-High-Novelty option), (4) HU-HN option (High-Uncertainty-High-Novelty option). Each option had three dimensions: reward uncertainty, perceptual novelty, and reward value (see Table 1).

For the LU-LN option and LU-HN option options, their reward values were constant (= 7) throughout the game and across participants. For the HU-LN option and HU-HN options, their reward values were randomly drawn from a normal distribution ($\mu = 7$, $\sigma = 2$), and these values were predetermined before the task, making them the same for all partic-

Table 1: Stimuli Structure.

Option Type	Label	Uncertainty	Novelty	Reward Value
LU-LN	Turtle	Low	Low	7
HU-LN	Cat	High	Low	$N(7,2)$
LU-HN	Elephant	Low	High	7
HU-HN	Sheep	High	High	$N(7,2)$

ipants. Therefore, on average the reward value of each option was the same, while the reward uncertainty was not: the LU-LN option and LU-HN option were of low reward uncertainty, whereas the HU-LN option and HU-HN option were of high reward uncertainty.

The perceptual novelty was manipulated by how each option was presented. On each trail, each option was presented as a cartoon picture. To control the perceptual novelty, the LU-LN option and HU-LN option only had one picture, respectively, throughout the game. In contrast, the LU-HN and HU-HN options each had a pool of 30 unique pictures, with each picture presented only once during the task, ensuring that these two option types were always perceptually novel to the participants. Furthermore, only the LU-LN and HU-LN options were presented in the training session to familiarize participants and control the perceptual novelty of these two options.

To help participants understand and recognize the option, each option had a background of fixed color. These four options were further combined into six pairs. Only the pair of LU-LN option and HU-LN option was presented in training. In testing, all combinations were presented. Each condition has 10 trials, resulting in a total of 60 trials, presented in random order in the testing phase.

Procedure

The experiment consisted of instructions, comprehension questions, training, testing, and a memory test. The procedure for adults and children was the same, except that adults responded using a mouse and keyboard, while children responded using a touchscreen, with an experimenter recording their verbal responses.

Instruction Instruction was one source of controlling the reward uncertainty of the options. Participants were told that their task was to collect as many logs as possible to build a big log house. Particularly, they were explicitly told that the turtle (LU-LN) and elephants (LU-HN) would always give them the same fixed number of logs in every trial. In other words, not only the reward value of the turtle (LU-LN) and elephants (LU-HN) would be fixed, but also the reward value of these two animals would be the same. Participants were also explicitly told that the cat (HU-LN) and sheep (HU-HN) would give them a different number of logs in each trial. In this way, participants were explicitly informed of the reward uncertainty.

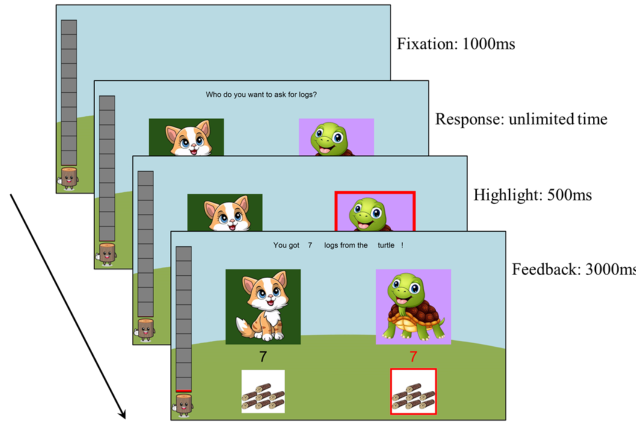

Figure 1: Trial Structure.

Comprehension questions The goal of the comprehension questions was to investigate if children understand the relationship between the two options of low uncertainty. There were 3 comprehension questions trials, asking about the relationship between the turtle and elephant options. Specifically, participants were asked: ”The turtle and elephants give you the same number of logs. If the turtle gives you [number] logs, how many logs does an elephant give you?” The question frame remained the same and the numbers were selected from 3, 9, and 15 in a random order. The feedback was given after each of their responses.

Training The primary goal of the training phase was to control the perceptual novelty of the LU-LN and HU-LN options by familiarizing participants with these two choices. The trial structure is shown in Figure 1. The training phase consisted of 15 trials. Each trial began with a 1000 ms fixation, followed by the presentation of two options with the question, 'Who do you want to ask for logs?' There was no time limit for the decision-making phase. After participants made their choice, the selected option was highlighted for 500 ms. Finally, feedback was presented for 1000 ms. Importantly, the reward value of both the chosen and unchosen options was provided to participants, reducing cognitive load on working memory and ensuring that the primary source of uncertainty came from reward uncertainty. Only the LU-LN and HU-LN options were presented during the training phase. Immediately following the training, participants were reminded of the rules outlined in the instructions, after which the testing phase began.

Testing The testing phase consisted of 60 trials, divided into three blocks, with a self-paced break between blocks. Maintaining the same trial structure as the training phase, the testing phase included all options. The order of different pairs of options was pseudo-randomly determined to ensure that no specific types of pair clustered within a block. The probability of each option appearing at the left or right position was equal.

Memory test At the end of the experiment, participants had a surprise memory test. Specifically, for each animal, they were asked: (1) "Did this animal always give you the same or different number of logs?" and (2) "How many logs do you think you can get from this animal by asking them?"

Results

Comprehension Question

To assess participants' understanding of the instructions, we evaluated the accuracy of comprehension questions across the two age groups. Two children were excluded from the analysis due to failure to answer any comprehension questions correctly (i.e., mean accuracy rate of 0), indicating at least a lack of understanding of the equivalence of the rewards of the LU-LN and LU-HN options. After exclusion, the results showed that all adults answered the comprehension questions correctly (100%), while children had an accuracy of 88.6% (SD = 0.21). Only 10 children didn't reach perfect accuracy, but all children answered at least one question correctly.

Choice proportions

To assess the independent effect of a single factor, another factor needs to be held constant. Specifically, to compare the high and low perceptual novelty, we combined the responses in the pair of LU-LN versus LU-HN with the responses in the pair of HU-LN versus HU-HN. To compare the high and low objective uncertainty, we combined the responses in the pair of LU-LN versus HU-LN with the responses in the pair of LU-HN versus HU-HN. Since the sum of the proportional selections of the two options in each condition equals 1, and we used a two-armed bandit task, only the proportional selections of the "high-level" options were included in the analysis. Results are shown in the Figure 2.

A 2×2 mixed-design ANOVA was conducted to examine the effects of age group (between-subject factor) and factor types (within-subject factor) on the proportional selection of high-level options. The analysis revealed a significant main effect of age group, $F(1,146) = 8.04$, $p = .005$, $\eta_p^2 = 0.05$, and a marginally significant main effect of factor types, $F(1,146) = 2.85$, $p = .093$. There was no significant interaction between age group and factor types, $F(1,146) = 0.0059$, $p = .939$. The post-hoc t-tests revealed that children selected more high-level options than adults at both novelty, $t(64.34) = 3.37$, $p = .001$, and uncertainty, $t(65.49) = 2.38$, $p = .020$.

To further investigate the independent effects of perceptual novelty and objective uncertainty on decision-making, one-sample t-tests were conducted to compare the mean proportional selection of high-level options to the chance level of 0.5 for each age group. When novelty was held constant, adults showed a significant avoidance of the high-uncertainty option ($M = 0.40$, $SD = 0.24$), $t(36) = -2.47$, $p = .019$, Cohen's $d = 0.41$, while children's responses did not significantly differ from chance ($M = 0.52$, $SD = 0.18$), $t(37) = 0.64$, $p = .523$. Conversely, when uncertainty was held constant,

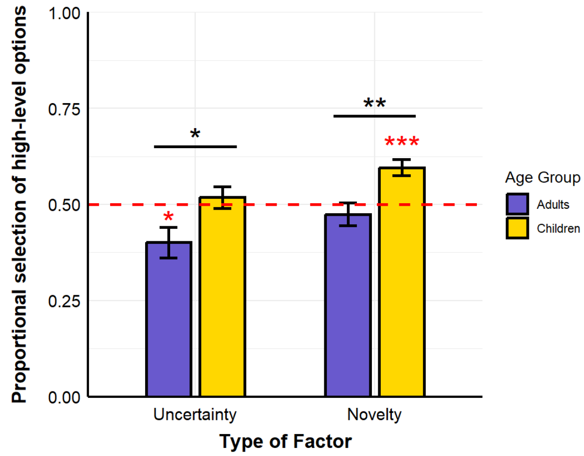

Figure 2: Proportional selection of high-level options. The proportion of trials on which the high-level option of a certain factor was chosen while holding another factor constant in the testing phase. Error bars reflect standard errors of the mean.

children selected the high-novelty option significantly above chance ($M = 0.60$, $SD = 0.13$), $t(37) = 4.68$, $p < .001$, Cohen's $d = 0.76$, whereas adults' selection did not differ from chance ($M = 0.47$, $SD = 0.18$), $t(36) = -0.87$, $p = .393$.

Memory test

To assess participants' memory representations of the options, we examined there responses to the first question, where responses of "same" were coded as 1, and "different" as 0. The distributions of responses to the second question are addressed in the Discussion section.

Among children, the mean proportion of "same" responses was 76.3% ($SD = 0.43$) for the LU-LN options, 76.3% ($SD = 0.43$) for the LU-HN options, 15.8% ($SD = 0.37$) for the HU-LN options, and 23.7% ($SD = 0.43$) for the HU-HN options. All proportions significantly differed from the chance level of 50% ($ps < .001$), indicating that children were able to distinguish between certain and uncertain options.

Adults demonstrated an even clearer pattern. The mean proportion of "same" responses was 94.6% ($SD = 0.23$) for the LU-LN options and 91.9% ($SD = 0.28$) for the LU-HN options. No participants reported "same" for the HU-LN options ($M = 0$, $SD = 0$), and only 2.7% ($SD = 0.16$) did so for the HU-HN options. Again, all proportions significantly differed from the 50% chance level ($ps < .001$), suggesting that adults had a correct representation of reward variability associated with each option.

Computational modeling

To further differentiate the role of uncertainty and novelty in driving participants' choices across the conditions, we adopted a computational model developed by a previously related study (Blanco & Sloutsky, 2020) which assumed that participants' choices probabilities are calculated by the following function:

$$P_{i,t} = \frac{e^{\gamma \cdot V_{i,t}}}{\sum_{j=1}^{n} e^{\gamma \cdot V_{j,t}}} \tag{1}$$

where $P_{i,t}$ is the probability of choosing option i on trial t. γ is the inverse temperature parameter that controls random exploration. It is a free parameter ranging from 0 to positive infinity. At $\gamma = 0$ choice probabilities become completely random (i.e., equal between two options), while γ approaches positive infinity the model chooses the most favorable option (i.e., the option with the highest weighted combination of uncertainty and novelty) on every trial. $V_{i,t}$ is the value of each option. It is determined by perceived uncertainty $U_{i,t}$, and novelty $N_{i,t}$ according to the following function:

$$V_{i,t} = (w_1 \cdot U_{i,t} + w_2 \cdot N_{i,t}) \tag{2}$$

where the w_1 and w_2 are the free parameters weighting the uncertainty and novelty for each participant in decision-making. $U_{i,t}$ represents the uncertainty of the option i on trial t and $N_{i,t}$ represents the novelty of the option i on trial t. $N_{i,t}$ of the option was encoded in a binary way (1 = novel, 0 = familiar). Specifically, the novelty of the LU-LN option and HU-LN option were encoded as 0, while the novelty of the LU-HN option and HU-HN option were encoded as 1. $U_{i,t}$ was considered to be represented by the perceived variability of rewards. Based on the previous literature (Dearden, Friedman, & Russell, 1998), the perceived variability of rewards (here is the $U_{i,t}$) is updated using the following function:

$$U_{i,t} = \frac{\beta_{i,t-1}}{\lambda_{i,t-1} \cdot (\alpha_{i,t-1} - 1)} \tag{3}$$

where $\alpha_{i,t-1}$, $\beta_{i,t-1}$, and $\lambda_{i,t-1}$ are the parameters that define the reward variability (i.e., uncertainty $U_{i,t}$) of option i on trial t. They are updated using the following functions (Dearden et al., 1998):

$$\alpha_{i,t} = \alpha_{i,t-1} + \frac{1}{2} \tag{4}$$

$$\beta_{i,t} = \beta_{i,t-1} + \frac{\lambda_{i,t-1} \cdot (M_{i,t-1} - \mu_{i,t-1})^2}{2 \cdot (\lambda_{i,t-1} + 1)} \tag{5}$$

$$\lambda_{i,t} = \lambda_{i,t-1} + 1 \tag{6}$$

where $M_{i,t-1}$ is the objective reward value of option i on trial t in the task. $\mu_{i,t}$ is the perceived reward value of option i on trial t that is updated using the following function (Dearden et al., 1998):

$$\mu_{i,t} = \frac{\lambda_{i,t-1} \cdot \mu_{i,t-1} + M_{i,t-1}}{\lambda_{i,t-1} + 1} \tag{7}$$

Given that the goal of the current study was not to examine the effect of reward values and that in our paradigm, the reward value of each option on average was the same, the reward value was not included in the equation.

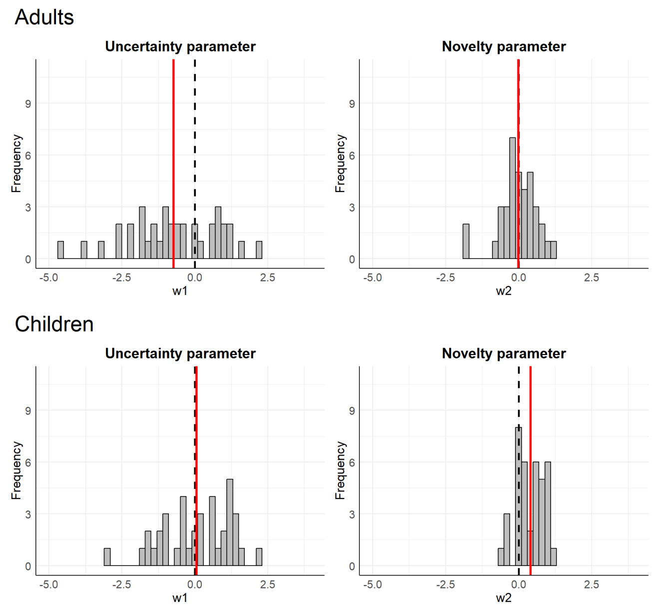

Figure 3: Best-fitting uncertainty (w_1) and novelty (w_2) parameters. Histograms of the best-fitting w_1 and w_2 parameters for both adults and children are presented. Red solid lines indicate the means of the parameter distributions, and dashed lines indicate the reference value of 0.

To avoid weights being biased toward components with extreme variance, the reward value, uncertainty value, and novelty value were normalized using Max-Min normalization. Each participant completed 20 runs, and we selected the parameters corresponding to the smallest negative log-likelihood for that participant as their best-fitting parameters.

The results are presented in the Figure 3. To reveal the effect of novelty and uncertainty, the parameter values of w_1 and w_2 were compared with 0 for each age group. For adults, the mean value of uncertainty parameter w_1 is significantly lower than 0 ($M = -0.72, SD = 1.56$), $t(36) = -2.83, p = .008$, indicating that most adults demonstrated uncertainty-aversion in when making choices, while the mean value of the novelty parameter w_2 is centered around 0, ($M = -.01, SD = 0.64$), $t(36) = -.01, p = .897$, indicating that perceptual novelty doesn't have a significant influence on adults' decision-making. For children, the mean value of uncertainty parameter w_1 is not significantly different from 0, ($M = 0.06, SD = 1.15$), $t(37) = 0.35, p = .732$. Given the spread distribution, the result suggests that uncertainty may have a complex effect on children's decision-making, instead of mere uncertainty aversion like adults. In comparison, children's mean value of the novelty parameter w_2 is significantly higher than 0, ($M = 0.41, SD = 0.49$), $t(37) = 5.16, p < .001$, indicating that children's decision-making can be novelty-driven.

A repeated-measures ANOVA (Type III) was performed to compare the best-fitting parameter values between age groups and parameter types. There was a significant main effect of age group, $F(1,73) = 11.88, p < .001, \eta_p^2 = 0.14$ and a significant main effect of parameter type, $F(1,73) = 10.12, p = .002, \eta_p^2 = 0.12$. There was no significant interaction, $F(1,73) = 1.20, p = .276$. We then further compare the mean differences in the w_1 and w_2 parameters between two age groups. The results showed children's mean value of uncertainty parameter w_1 (M = 0.06) is significantly higher than that of adults (M = -0.72), $t(66.30) = 2.49, p = .015$, indicating that children didn't show as much uncertainty-aversion as adults. The results also showed that the mean value of the novelty parameter value w_2 (M = 0.41) is significantly higher than the average value of adults (M = -0.01), $t(67.64) = 3.23, p = .002$, indicating that, children weighed perceptual novelty much more than adults in decision making.

Overall, our computational modeling results are consistent with our behavioral pattern findings, that children's decision-making is driven by novelty-seeking, while adults are driven by uncertainty aversion.

Discussion

The current study examined how perceptual novelty and objective uncertainty influence decision-making in children and adults under conditions where reward value and subjective uncertainty were carefully controlled. Both the behavioral results and computational results indicate that children preferred options with higher perceptual novelty adults avoided objective uncertainty.

Because the current findings depend on the assumption that reward value is on average the same across options, one concern is whether perceived reward differences influenced uncertainty effects. In other words, adults' uncertainty aversion and children's reduced sensitivity to uncertainty could result from viewing uncertain options as less rewarding. To test this, an individual-level analysis correlated participants' reward estimations (i.e., responses to the second question in the surprise memory test) with their selection of uncertain options. If reward perception influenced decisions, a significant positive correlation would be expected. However, no significant correlations were found for children or adults ($ps > .05$). Thus, perceived reward did not systematically drive choices, confirming effective reward control and supporting the independent effects of perceptual novelty and objective uncertainty.

Indifference to uncertainty

Unsurprisingly, when uncertain options no longer offers informational value, it becomes less appealing to children. Interestingly, in a high-entropy environment lacking immediate rewards or information, children neither actively approach nor avoid uncertainty. One possible explanation—that children are insensitive to uncertainty—is ruled out by existing evidence (Lyons & Ghetti, 2011; Blanco & Sloutsky, 2021) and by the current findings showing greater variance in their reward estimates for uncertain options (Levene's test: $F(3,131) = 3.73$, $p = .013$, with both variance of HU-LN and HU-HN larger than LU-HN, $ps < .05$, and variance of HU-HN marginally larger than LU-LN, $p < .10$). In other words, children did encode uncertainty.

Since children's indifference cannot be explained by insensitivity, two interpretations remain. First, just like children's well-documented overconfidence (O'Leary & Sloutsky, 2019; Shin, Bjorklund, & Beck, 2007), this indifference to uncertainty may protect them from negative emotions associated with uncertainty, thereby promoting persistent exploration and learning in complex environments.

Alternatively, children's indifference to risk may reflect a fundamentally different learning context: exploration in childhood is largely cost-free. Early in development, caregivers buffer children from the consequences of poor decisions, reducing the perceived costs of uncertainty and encouraging a trial-and-error approach to learning.

Prospect Theory

The ambiguity aversion observed in adults is consistent with prospect theory, which posits that people avoid risk when facing potential gains but may seek risk when facing losses (Kahneman & Tversky, 2013). In the gain context of the current study—where rewards were always guaranteed—adults avoided objective uncertainty, aligning with the theory. In contrast, children did not exhibit such aversion, suggesting their decisions may not conform to the predictions of prospect theory. These findings point out a potential developmental boundary in the theory's applicability across age groups.

Attentional Mechanism

The current findings highlight the critical role of bottom-up attention in guiding children's decision-making. A strength of the current study is that we exclude the alternative explanations, such as novelty inflates the reward expectations (Cockburn et al., 2022) or novelty provides epistemic value (Blanco & Sloutsky, 2021). The current finding that perceptual saliency alone—without instrumental or informational benefit—can strongly influence young children's decisions aligns with previous research on distributed attention and immature cognitive control in early childhood (Plude et al., 1994; Hanania & Smith, 2010; Deng & Sloutsky, 2016; Blanco & Sloutsky, 2020; Gao & Sloutsky, 2025).

Future Direction

Despite supporting the role of attentional mechanism, the current study does not rule out the possibility of information-seeking mechanism in development (Gottlieb et al., 2013; Wang et al., 2021). Given the gradual maturation of executive functions, it is likely that bottom-up attention emerges earlier and potentially scaffolds the development of more strategic top-down control (Blanco & Sloutsky, 2020; Gao & Sloutsky, 2025). Future research could further investigate how these two mechanisms interact across development.

Acknowledgments

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