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BRIEF REPORT

Adolescents Sample More Information Prior to Decisions Than Adults When Effort Costs Increase

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Making better decisions typically requires obtaining information relevant to that decision. Adolescence is marked by increasing agency in decision-making and an accompanying increase in impulsive decisions, suggesting that one characteristic of adolescent decision-making is a tendency to make less-informed decisions. Adolescents could also be especially averse to the effort associated with acquiring relevant information to make decisions. To investigate this possibility, we recruited adolescents (M_age = 15.02 years) in upper-secondary schools and young adults (M_age = 20.53 years) attending university in the Netherlands to complete an effort-based information sampling task, in which participants could sample information until obtaining sufficient evidence to make a decision. Effort costs for sampling were systematically varied. Surprisingly, adolescents sampled more evidence than adults before making decisions when sampling effort costs were low. Further, adolescents obtained stronger evidence prior to their decisions than adults as effort costs increased, exhibiting less aversion to effort costs associated with information sampling. Exploratory computational models supported these findings. Both adolescents and adults used simple heuristics in deciding whether to sample additional information or make a final decision, and adolescents sought a higher evidence threshold before deciding compared with adults. These results suggest that adolescents may require more certainty to make decisions compared with adults and be less averse to effort costs when gathering information to aid decisions.

Keywords: adolescent, information sampling, effort costs, heuristics, effort-based decision-making

Supplemental materials: https://doi.org/10.1037/dev0001397.supp

Adolescence is marked by increased independence for self-directed decision-making and an accompanying increase in impulsive decision-making (Crone & Dahl, 2012; Defoe et al., 2015; Kann et al., 2018; Romer et al., 2017; Somerville et al., 2010; Steinberg, 2007). Many experimental studies have attempted to capture this pattern (for review, see Rosenbaum et al., 2018), focusing on developmental differences in reward sensitivity, peer influence, risk tolerance, and preferences for immediate or future...
outcomes (Albert et al., 2013; Blankenstein et al., 2016; Braams et al., 2015; Figner et al., 2009; Lejeune et al., 2003; Mitchell et al., 2008; van den Bos et al., 2015). In these laboratory tasks, adolescents are typically presented with full information about the consequences of their choices. However, for many decisions associated with impulsivity, such as drug use and sexual activity, and for many decisions not stereotypically associated with risk or impulsivity, such as deciding whether or where to attend college or on a future occupation, full information is not directly available. Instead, individuals often need to gather information from peers, observation, or other sources prior to making decisions. How, and how much, information is gathered impacts final choices (Rosenbaum et al., 2018; Wulff et al., 2018). However, evidence on developmental differences in information gathering is comparatively scarce.

Some evidence suggests that adolescents gather more information than adults, reflecting a general pattern of decreased exploration from childhood through adulthood (Gopnik et al., 2017; Nussenbaum & Hartley, 2019). For example, adolescents explore more information than adults when potential choices lead to immediate reward (e.g., Jepma et al., 2020; Kwak et al., 2015). However, this greater exploratory behavior may not generalize to contexts in which reward after information gathering is delayed. When selecting between options offering high reward or high informational value, adolescents were more likely to favor the high reward option than adults (Somerville et al., 2017). Adolescents also sampled less information than older children and adults when drawing from two lotteries before picking which lottery to play for a reward, making decisions with comparatively less information (van den Bos & Hertwig, 2017). The delay in reward incurred by additional information sampling may discourage adolescents from more sampling (Christakou et al., 2011; de Water et al., 2014; Galván, 2010; van den Bos et al., 2015). Adolescents may also be more confident that the available information is sufficient to make good decisions; even when selecting less-rewarding options than adults, adolescents expressed similar levels of confidence in their decisions (Jepma et al., 2020).

Another underexplored possibility is that adolescents are more averse to the effort costs required to obtain information. Although some evidence suggests that adolescents are less sensitive to effort costs than adults when exerting effort for reward (Rodman et al., 2021; Sullivan-Toole et al., 2019), effort in these paradigms also led to immediate reward. Thus, adolescents may be more averse than adults to effort costs when not directly associated with immediate reward. Exerting effort to accumulate information for decisions without immediate payoffs may be particularly aversive for adolescents.

We investigated whether adolescents sample less information than adults prior to decisions and whether adolescents are more sensitive than adults to sampling effort costs. To this end, we developed an effort-based information sampling task (adapted from Clark et al., 2006, 2009; originally designed to capture reflection impulsivity). Sampling effort costs were manipulated by varying the number of mouse clicks to sample information. In this task, participants see 25 gray squares that can be clicked to reveal one of two colors underneath. Participants are instructed to select which color is the underlying majority and can decide which color is the majority at any point during the trial. Several task features mitigate confounding factors on effort-based sampling decisions. First, the effort required to sample information was made explicit, preventing differences in individuals’ ability to learn about implicit effort costs from influencing decisions; second, no feedback was provided to avoid strategy formation and prevent reward and punishment sensitivities from affecting subsequent decisions; third, sampled information was always available, reducing working memory demands, which influence information sampling (Hertwig et al., 2004); and last, certainty could always be achieved if desired by sampling until a majority is flipped (e.g., 13 squares of one color).

Given prior evidence of adolescents’ limited information sampling prior to decisions and decreased preference for information over reward compared with adults, we predicted less information sampling in adolescents than adults. Consequently, we also predicted that age-related differences in sampling would become more pronounced as the effort costs to sample information increased such that adolescents would decrease sampling more than adults if effort costs for sampling increased. Additionally, Bayesian models from prior research and novel heuristic models were fit to better determine the mechanisms underlying differences in information sampling behavior (Hauser et al., 2017; Ma, Sanfey, & Ma, 2020).

Method

Transparency and Openness

This study was preregistered and was performed according to the preregistration except where explicitly indicated otherwise. All data, materials, and analysis code, including the preregistration, are publicly available on the project’s repository on the Open Science Framework (osf.io/qydfc; Foster & Deardorff, 2017). All analyses were conducted in R Studio, Version 1.2.5042 (R Core Team, 2020). Mixed models were run using the lmerTest package (Kuznetsova et al., 2017), built upon the lmer4 package (Bates et al., 2015). The snowfall package was used for conducting computational models (Knaus et al., 2009). Data were visualized using the ggplot2 and ggrepur packages (Kassambara & Kassambara, 2020; Wickham, 2011). All study procedures were approved by the Ethics Review Board at the University of Amsterdam (protocols: 2019-DP-9963, “Cognitive Effort and Individual Differences,” and 2019-DP-10361, “Age-Related Differences in Information Sampling Effort”).

Participant Sample

Adults (N = 359; $M_{\text{age}} = 20.53$ years, $SD_{\text{age}} = 2.34$; range = 17.83–47.00; 247 female, two nonbinary, 11 unreported) were recruited from the local university participant pool and completed the protocol for partial course credit. Adolescents (N = 95; $M_{\text{age}} = 15.02$ years, $SD_{\text{age}} = 0.52$; range = 13.59–17.00; 48 female, one unreported) were recruited from secondary schools in the Netherlands. We only included adolescents attending upper-level secondary school students because only these students typically continue to university, increasing the validity of age comparisons with our university sample by sampling from similar adolescent populations in terms of cognitive ability and other factors. Participating adolescents provided informed consent and parental passive or active consent, depending on school preference. Deviating from the preregistration, we decided prior to analyses to eliminate participants who failed to sample any square on all medium- or high-effort trials, reasoning that these participants did not experience
these sampling effort costs. This criterion excluded a similar percentage of participants across groups: 28 adults (6.1%) and six adolescents (5.9%). Highly convergent results were obtained with the full sample (online supplemental materials). In another deviation, we included all participants in age group analyses, even if age was unknown, because adolescents and adults were recruited separately, ensuring that adults and adolescents with unknown age could be assigned to the correct age group.

Procedure

The study took place over one session in which the effort-based information sampling task was completed among other cognitive assessments and questionnaires. The full protocol typically ranged from 50 to 80 min. Adolescents completed the session in groups of 15–28 participants. Adults completed the session in two groups of approximately 190 participants in a large study hall. The information sampling task was administered using NeuroTask (scripting.neurotask.com; Murre, 2016), an online task environment. As part of the larger protocol, participants also completed the Intolerance of Uncertainty Scale (Carleton et al., 2007), administered via Qualtrics (Provo, UT), within the same session. Preregistered analyses of these data are in the online supplemental materials.

Effort-Based Information Sampling Task

The effort-based information sampling task was adapted from Clark and colleagues (2009), with several alterations (see Figure 1). On each trial, participants saw a $5 \times 5$ array of gray squares that could be flipped via clicking to reveal one of two colors underneath, yellow or blue. Participants were instructed to decide which color was the underlying majority color. Participants selected the majority color by clicking one of two buttons beneath the array at any point during the trial. Sampled squares remained flipped for the entire trial. To manipulate sampling effort costs, participants were instructed that the number of clicks needed to flip a square would vary across trials (one, four, or 12 clicks), similar to other effort-based decision-making tasks (Sullivan-Toole et al., 2019; Treadway et al., 2009). A small square in the upper right corner indicated how many clicks were needed to sample a square. To discourage participants from sampling less only to proceed through the task more quickly, the instructions indicated that participants would play for 15 min, thereby mitigating potential confounding opportunity costs. Instructions emphasized that participants could sample as many squares as desired until feeling certain enough to make a decision. Participants completed 10 trials at each effort level, resulting in 30 trials, and trial order was randomized within participants. The same 10 screen arrangements of blue and yellow squares were used at each effort level. The majority color on each screen ranged from 17 to 20 out of the 25 squares. A 2-s interval was used between trials, and no feedback was provided. If participants had played for more than 15 min, the task ended after the current trial. Participants finishing earlier progressed in the study protocol or were dismissed (if no task followed the current one). Instead of the preregistered procedure of rewarding participants on two randomly selected trials per effort level, every participant was compensated €1.00 after the full protocol due to practical concerns in compensating participants different amounts while testing in groups. We completed a second preregistration prior to data collection noting this change in compensation procedure. Participants were informed of the €1.00 compensation prior to beginning.
the task. Adolescent instructions were translated into Dutch and reviewed by three native speakers (online supplemental materials).

Analyses

We observed a strong bimodal distribution for participant age (online Supplemental Figure 2); thus, we focus on our preregistered analyses testing age group differences, rather than using age as a continuous variable across the entire sample. Preregistered analyses with age as a continuous variable are included in the online supplemental materials. Two primary outcome variables were calculated for each trial and then averaged over trials at each difficulty level within participants: total squares sampled (Clark et al., 2009) and $p(\text{correct})$, that is, the probability that the color chosen is the majority color, which was formalized as a Bayesian inference problem using an uninformative prior updated with the sampled information at the time of decision, as follows (as in Bennett et al., 2017):

$$p(\text{correct}) = Pr(\text{correct}) = \sum_{M=13}^{25} Pr(\hat{e} = M | n_1, n_2)$$

where $n_1$ is the number of squares flipped of the selected majority color, $n_2$ is the number of squares flipped of the color not selected, and $Pr(n_1, n_2 | \hat{e} = 13)$ is the likelihood of the sampled squares if the true number of squares of the chosen color ($\hat{e}$) were the majority ($M$, with a total number of squares of 25 and majority of 13). $p(\text{correct})$ provides complementary information to the number of squares sampled as participants could see different strengths of evidence while sampling the same number of squares (e.g., 12 blue and four yellow squares provide stronger evidence for blue [$> 99\%$] than eight blue and eight yellow squares [$50\%$]). More information on this calculation is included in the online supplemental materials. Analysis of discrimination errors, in which participants do not select the shown majority color (Clark et al., 2009), is included in the online supplemental materials. Mixed-model linear regressions were conducted with random slopes (effect of effort cost) and intercepts for participants, including covariation between random slopes and intercepts. Low-effort trials were coded as 0 to directly compare group differences with minimal effort costs, medium-effort trials as 1, and high-effort trials as 2. We adopted this linear code based on pilot data with adults showing a linear decline at the one-, four-, and 12-click effort levels on average. Exploratory analyses treating effort level as an ordinal variable and examining potential quadratic effects are included in the online supplemental materials. Adolescents were coded as $-0.5$, and adults as $0.5$. Thus, main effects indicate age differences on low-effort trials, and interactions indicate whether adolescents and adults differ in the effect of effort costs.

Computational Modeling

To better understand the mechanisms underlying information sampling, we fit several exploratory computational models. We fit two families of models: regular Bayesian (Hauser et al., 2017; Ma, Sanfey, & Ma, 2020; Ma, Westhoff, & van Duijvenvoorde, 2020) and new heuristic models. We describe the motivation for these models below, and full mathematical descriptions of the models are included in the online supplemental materials. The Bayesian models consist of prior beliefs over the distribution of yellow and blue squares and an evolving posterior distribution. Given that participants initially have no information about the distribution, the prior is an uninformative beta distribution, and the posterior is updated with each sample.

The first Bayesian model (Bayesian optimal) computes the value of both sampling more and the value of stopping at each possible state that a person can be in (combination of blue and yellow squares flipped). When 13 squares of one color are flipped, the majority color is known with full certainty. Thus, these states (13 blue or yellow) are considered end states, in which sampling more has no value (i.e., 0) and the expected value of stopping is the reward for being correct (1). By starting with the final state, we can retrogress in sampling time to obtain the expected value of sampling or stopping for every possible state. The value of stopping is the product of the probability that a color is the majority and a 1-point reward for accuracy. The value of sampling is the product of the probability of the next state (i.e., a state with one more yellow or one more blue square) and the expected value of that next state. The probability of the next state is determined by the current state. For example, if the current sample consists of many more blue than yellow squares, it is also more likely that the next square will be blue. The value of the next state is again the expected value of stopping and value of sampling more. This process proceeds until one of the end states is met, and therefore these end states can be used to calculate the expected value of each state by recursively taking steps back in time (i.e., dynamic programming). Note that in principle, more information will always yield better predictions of the majority, and the optimal solution is to sample until 13 squares of one color are revealed. However, these Bayesian models can be adapted to accommodate that sampling itself is costly. In our models, the sampling cost is a free parameter that reflects subjective sampling cost. In sum, this model calculates the expected value of sampling for more information by calculating how much further sampling would improve a future decision minus the cost of search (online supplemental materials).

The second Bayesian model (Bayesian uncertainty) also assumes that agents use Bayesian updating of the beta distribution and that search is costly, but now, sampling stops when a subjective certainty criterion is met. The uncertainty of a state at a given time is determined by the standard deviation of the beta distribution, and the model stops sampling when the standard deviation is below a threshold, with some decision noise. In this model, both the threshold and cost of search are free parameters.

Finally, we also added versions of the Bayesian models in which the cost of sampling within a trial increases over time (urgency), indicating increasing impatience to make a decision regardless of the available evidence with each box opened. Following Hauser et al. (2017), the urgency parameter was fixed over participants within effort conditions and resulted in a trial-by-trial increase in the subjective search cost.

The heuristic models are based on simple count data from the total squares sampled. The absolute difference model (absolute difference) assumes that agents only attend to the absolute difference between yellow and blue squares and stop sampling when a threshold of minimum difference is met. Another heuristic model (total
squares) assumes that agents stop sampling after a threshold of a certain number of sampled squares is met. Finally, we implemented a heuristic model that uses the combination of absolute difference and total squares sampled (two-rule). This model continues to sample until a threshold of a certain number of sampled squares is met or until a difference threshold is hit, with no priority over each rule. For all heuristic models, the threshold value(s) were free parameters estimated for each participant within each effort condition.

Model Fitting

The free parameters of the models were estimated by fitting the model predictions to participants’ decisions for each participant for each effort level. For model selection purposes, we computed and then summed the Bayesian information criterion (BIC) across all subjects for all models, in which lower BIC values indicate better fit. All model parameters were estimated using the L-BFGS-B method in the optim toolbox in R (Byrd et al., 1995; Nash & Varadhan, 2011). This algorithm allows box constraints in which each parameter can be given a lower and/or upper bound (online supplemental materials). To prevent local minima, we generated 20 sets of randomly generated starting values for the parameter values from a uniform distribution within the bounds. Models were fit to each effort level separately to determine how effort impacted sampling strategies. Parameters of the best-fitting model were used to study developmental differences in sampling strategies.

Results

Sampling Effort Is Higher in Adolescents Than Adults

Descriptive statistics for outcome variables are included in Table 1. The number of squares flipped decreased with increasing effort costs, $\beta = -2.83$, $t(451.98) = -23.90$, $p < .001$. In contrast to our hypotheses, adolescents sampled more squares on low-effort trials than adults, $\beta = -1.37$, $t(451.98) = -2.35$, $p = .019$, and no significant interaction between age group and effort level was observed, $\beta = -0.32$, $t(451.98) = -1.36$, $p = .176$. Follow-up t tests showed that adolescents sampled more squares than adults at all effort levels (all $ps < .05$; see Figure 2). $p$(correct) decreased with increasing effort, $\beta = -.04$, $t(452.00) = -14.31$, $p < .001$. Age groups did not significantly differ on low-effort trials, $\beta = .01$, $t(452.00) = 1.34$, $p = .183$; however, a significant group by effort level interaction was observed, $\beta = -.02$, $t(452.00) = -3.53$, $p < .001$, showing that adults decreased more in $p$(correct) than adolescents as effort costs increased (see Figure 2). Follow-up t tests indicated that adults and adolescents did not significantly differ in $p$(correct) on the low- and medium-effort levels ($ps > .3$) but that $p$(correct) was significantly higher in adolescents than adults on high-effort trials, $t(153.44) = 3.05$, $p = .019$. These results indicate that adolescents and adults had similar probability of responding correctly on low-effort trials, but adolescents had a higher probability of responding correctly on high-effort trials. Preregistered models using age as a continuous variable across the entire sample

Table 1

Descriptive Statistics for Each Age Group at Each Effort Level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Adolescents</th>
<th></th>
<th>Adults</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low Medium</td>
<td>High</td>
<td>Low Medium</td>
<td>High</td>
</tr>
<tr>
<td>Squares flipped</td>
<td>13.54 (6.09)</td>
<td>10.08 (5.06)</td>
<td>8.19 (4.64)</td>
<td>12.15 (4.88)</td>
</tr>
<tr>
<td>$p$(correct)</td>
<td>0.94 (0.09)</td>
<td>0.91 (0.10)</td>
<td>0.88 (0.10)</td>
<td>0.95 (0.07)</td>
</tr>
<tr>
<td>No-sample trials</td>
<td>3.49 (10.56)</td>
<td>4.70 (14.35)</td>
<td>6.35 (16.21)</td>
<td>1.34 (7.9)</td>
</tr>
</tbody>
</table>

Note: Data are presented as means and standard deviations.

Figure 2

Sampling Behavior of Adolescents and Adults for Each Effort Level

Note. Left panel: Mean number of squares sampled per trial. Middle panel: Mean probability of responding correctly per trial. Right panel: Overall percentage of trials without any sampling. Bars represent the group means, and error bars indicate standard error of the mean. Overall, sampling decreased as effort costs increased, with adults sampling fewer squares on each trial and achieving an increasing smaller probability of responding correctly as effort costs increased. See the online article for the color version of this figure.
and exploratory models with age within groups found similar overall patterns of decreased sampling effort with age (online supplemental materials).

Trials Without Information Sampling Indicate Effort Avoidance

During data collection, we discovered that participants completed some trials without any sampling. We subsequently explored whether no-sample trials differed by age and by effort level using the full data sample. No-sample trials increased with effort level, $\beta = 2.43, t(452.00) = 4.83, p < .001$, and were less frequent in adults than adolescents on low-effort trials, $\beta = -2.33, t(452.00) = -2.16, p = .031$. A significant group by effort level interaction was observed, $\beta = 1.99, t(452.00) = 1.98, p = .048$, indicating that adults selectively avoided high-effort trials more than adolescents.

Decision Accuracy Is Similar Across Groups

We explored decision accuracy to examine whether the additional sampling by adolescents led to better task performance. Accuracy was high in both groups at all effort levels (adults: 97%, 95%, and 90%; adolescents: 96%, 93%, and 93%, for low-, medium-, and high-effort trials, respectively). Accuracy decreased with higher effort costs, $\beta = -0.03, t(451.96) = -7.29, p < .001$, and was higher in adults than adolescents on low-effort trials, $\beta = 0.02, t(451.77) = 2.49, p = .013$. A group by effort level interaction was observed, $\beta = -0.02, t(451.96) = -2.58, p = .010$, indicating that adults had higher accuracy on low-effort trials but that accuracy decreased more as effort costs increased compared with adolescents. When excluding no-sample trials, accuracy decreased with increased effort levels, $\beta = -0.02, t(491.16) = -5.42, p < .001$, but no significant effect of age group, $\beta = .01, t(849.18) = 1.36, p = .174$, or interaction was observed, $\beta = -0.01, t(491.16) = -1.57, p = .118$, suggesting that adolescents’ additional sampling effort did not greatly improve decision accuracy.

Sampling Effort Decreases With Task Progression and Especially in Adolescents

We ran two exploratory models to determine whether the number of squares sampled changed across the task, with trial number (Trial 1 coded as 0), age group, and effort level and all interactions included as predictors, and random intercepts and slopes for participants. We observed significant main effects of trial number
Superior models do not guarantee that the best model captures participant behavior. We examined the posterior predictions from the two-rule model across effort levels. The total squares flipped threshold ($k_{total} = 14.29, SE = .046$) was observed, $b = -3.24, (452.00) = 2.48$, suggesting that participants maintained a higher threshold for evidence than adults across effort levels.

Finally, in the two-rule model, we tested for developmental differences in the two thresholds using mixed-model across effort levels with random intercepts and slopes for participants across effort levels. The total squares flipped threshold ($k_{total} = 14.29, SE = .046$) was observed, $b = -3.24, (452.00) = 2.48$, suggesting that participants maintained a higher threshold for evidence than adults across effort levels.

### Table 2

<table>
<thead>
<tr>
<th>Bayesian Information Criterion (BIC) for Each Model per Age Group, as Well as for Each Effort Level Across Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
</tr>
<tr>
<td>------------------</td>
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</table>

**Note:** Numbers in brackets represent 95% confidence intervals of summed BIC for each model at each effort level from 5,000 bootstrapped iterations. The two-rule model fit best for both age groups at all effort levels.
First, we generated random sequences of sampling blue and yellow squares for all possible trials within the information sampling task (mimicking the random sampling by participants). Then, based on the parameter estimates, we calculated the probability of stopping or sampling further at all possible combinations of squares opened and effort level. The probability on each trial in the simulation to stop or sample was based on a draw of a uniform distribution between 0 and 1. If the drawn number was higher than the probability to stop, the simulation sampled an additional square. We ran one simulation for each participant for 30 trials, as in the actual task. Simulated sampling behavior based on the two-rule heuristic model showed similar behavior to both the adolescent and adult participants at all effort levels (see Figure 6).

**Discussion**

Before making important choices, we often can search for information. This information can be used to improve the outcomes of our decisions but requires some effort to obtain. Given prior evidence of adolescents’ increased impulsivity and decreased preference for information over reward compared with adults, we predicted less information sampling in adolescents than adults. Consequently, we also predicted that age-related differences in sampling would become more pronounced with increased effort costs such that adolescents would decrease sampling more than adults if effort costs for sampling information increased.

Adolescents and adults were sensitive to sampling effort costs. Both groups decreased information sampling and obtained weaker evidence for decisions as effort costs increased. Surprisingly, however, adolescents sampled more information than adults prior to making decisions and were more willing than adults to expend effort to sample information as effort costs increased. We applied computational modeling to further investigate the possible mechanism underlying these developmental effects. These analyses revealed that a heuristic two-threshold model, which combined a minimum evidence threshold for deciding and an absolute sampling threshold, outperformed the more sophisticated Bayesian models in predicting adolescent and adult sampling behavior (Hauser et al., 2017; Ma, Sanfey, & Ma, 2020; Ma, Westhoff, & van Duijvenvoorde, 2020). These analyses indicate that participants relied on a simple strategy when sampling information to make decisions and that sampling strategies did not qualitatively shift with age. Differences between age groups in the heuristic model were largely driven by adolescents exhibiting higher evidence thresholds for making decisions. Evidence thresholds decreased linearly with increasing effort costs in adults, whereas sampling thresholds were more similar on medium- and high-effort trials in adolescents.
been shown to delay responding to gather more perceptual information for their decisions. Adolescents have shown that adolescents may be more willing to expend extra effort to sample information than adults at higher effort costs, indicating this age when immediate reward is available.

2014). These results are also in line with recent evidence showing that adolescents were less averse to higher effort costs to obtain reward and persisted in exerting effort longer than adults even after earning reward (Rodman et al., 2021; Sullivan-Toole et al., 2019). Similar to this prior work, in which adolescents’ extra sampling effort did not yield higher reward than adults, greater sampling within increasing effort costs here did not result in appreciably higher task accuracy compared with adults. With maturation, adolescents may better learn what and how much information is sufficient to make sufficiently accurate decisions. For example, to better calibrate the amount of information needed for subsequent decisions, adolescents may exhibit the type of over-sampling compared with adults observed here to better approximate ideal information gathering with more experience and maturation. Adolescents may also put obtained information to less efficient use when making decisions, leading to potentially less accurate decisions, despite obtaining more information. Collectively, these results suggest that adults better conserve and calibrate their effort by not sampling more information than needed to maintain good performance.

Our study has several limitations that potentially constrain its generalizability. Sampling behavior may change outside of the classroom or testing environment. Further, although both adolescents and adults completed the study protocol in classrooms, differences in testing environments and group testing sizes may have played a role in the group differences in sampling behavior. Being informed that the task would take 15 min may have diminished the ecological validity of our task as decision horizons are not always fully known in the real world. Further, our task reduced working memory demands, which may be required in different decision-making contexts and has been shown to influence information sampling (Rakow & Rahim, 2010; van den Bos & Hertwig, 2017). Our compensation for task completion was relatively small, and different reward structures may motivate sampling effort differently across adolescents. We observed significant decreases in overall sampling effort across the task, and adolescents decreased sampling effort more overall across trials than adults. Reward structure and task length thus both also likely contribute to the overall results reported here, and future work should examine the explanatory power of these metatask trends. Moreover, our sample was restricted to likely university-bound and university-attending individuals in the Netherlands, which increased the validity of our age comparisons but reduces generalizability to other populations that may exhibit more risky and impulsive decision-making (Delker et al., 2018; Defoe et al., 2015). Whether these age differences in response to information search costs are consistent in other populations should be examined.

The two-rule heuristic model was identified as the best-fitting model. However, model recovery analyses indicated that data generated by the total squares heuristic model were frequently classified as being generated by the two-rule heuristic model, suggesting that there is some uncertainty between the two-rule and total squares heuristic models as the true underlying model for participants’ sampling behavior. Further, we assume that clicking was equally costly across individuals, and cost was not well defined within our computational models. Clicking, though a relatively simple action, may be differentially fatiguing between individuals and populations. Indeed, we observed a greater decrease in overall search behavior across the task in adolescents compared with adults. Future studies could examine differences in fatigue due to persistent clicking or recovery between clicks between individuals.
and different age groups. Computational modeling could further isolate the role of fatigue in information search behavior (Niyogi et al., 2014).

Conclusions

The present study introduces an effort-based information sampling task that enables explicit manipulation of sampling effort costs and assessments for how much evidence individuals acquire prior to making decisions. Effort-based decision-making remains relatively underexplored across development. Unexpectedly, adolescents sampled more information than adults, requiring a higher threshold of evidence, prior to making decisions. Further, adolescents continued to sample more information than adults even as effort costs increased, suggesting that adolescents may be less averse to effort costs. The additional sampling observed in adolescents did not result in substantial improvements in task performance, indicating that the calibration of sampling effort for decision accuracy continues to improve into adulthood. Computational models indicated that both adolescents and adults relied on simple sampling strategies, making decisions once reaching a certain evidence threshold or after sampling a certain amount. Our findings shed light on the complexity of factors influencing adolescent decision-making. The impulsive decision-making observed in adolescence via other paradigms may not be due to an aversion to effort costs in gaining information but instead may be due to other factors, such as reward sensitivity, impulsivity, and improvements in working memory.

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