Look up what you cannot solve in your mind! Children increase information gathering to counteract imprecise planning abilities

Bowler A[1,2,3], Habicht J[1,2], Moses-Payne ME[4], Steinbeis N[5], Moutoussis M[1,2] & Hauser TU[1,2]

[1] Max Planck UCL Centre for Computational Psychiatry and Ageing Research, London WC1B 5EH, United Kingdom.
[2] Wellcome Centre for Human Neuroimaging, University College London, London WC1N 3BG, United Kingdom.
[3] Centre for Brain and Cognitive Development, Birkbeck, University of London, London WC1E 7HX, United Kingdom.
[4] UCL Institute of Cognitive Neuroscience, London WC1N 3AZ, United Kingdom.
[5] Division of Psychology and Language Sciences, University College London, London WC1H 0AP, United Kingdom.

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Corresponding author
Tobias U. Hauser
Max Planck UCL Centre for Computational Psychiatry and Ageing Research
University College London
10-12 Russell Square
London WC1B 5EH
United Kingdom
Phone: +44 / 207 679 5264
Email: t.hauser@ucl.ac.uk

Abstract

Knowing how the world works is critical for successfully navigating it. This requires two key components: knowledge about the world and the computational capacity to plan flexibly. Children are inherently limited in both domains but building a better understanding of the world is a functional imperative for development. To examine how youths overcome their constraints, we asked 107 children (8-9 years), early (12-13 years) and late adolescents (16-17 years) to perform a planning task. We find that children gather significantly more information before making a decision compared to adolescents, but only if it does not come with explicit costs. Using computational modelling, we find that this is because children have limited planning abilities, which they counteract by reduced subjective sampling costs. Our findings thus demonstrate how children level out their computational constraints by deploying excessive information gathering, a developmental feature that could inform aberrant information gathering in psychiatric disorders.

Keywords: cognitive development, information gathering, planning, computational modelling

Introduction

The world is complex and its inner workings sometimes appear impenetrable. To successfully navigate this intricate and complex maze, human and non-human animals use cognitive maps that reflect a model of their surrounding (Tolman, 1948; Whittington et al., 2019). Building and utilising such models is a key goal of development. Starting with only a few experiences for building a model in childhood, only a few years later adolescents are expected to be able to navigate the world independently without having to rely on their parents' guidance.

How do children learn to navigate the world so quickly, and how do they achieve this while taking into account the limited cognitive abilities they have available? It is widely acknowledged that children show an extraordinary aptitude to learn, but the mechanisms underlying their unique ability are still obscure (Gopnik et al., 2015). Children's ability to learn is even more noteworthy when acknowledging their protracted prefrontal development (Paus, 2005; Ziegler et al., 2019) and the delayed emergence of the cognitive skills that are needed to embed new experiences into a flexible cognitive model (Decker et al., 2016; Smid et al., 2020; Somerville et al., 2017; Vaghi et al., under review).

One area this conundrum applies to specifically is information gathering, in which one has to use a learnt model of the world/task, and balance between too much and too little reliance on this model and one's own inference abilities. Gathering too little information and relying too heavily on one's own (imprecise) beliefs and planning can lead to jumping to conclusions, commonly observed in patients with schizophrenia (Ermakova et al., 2018; Garety et al., 1991; Huq et al., 1988; Jepsen et al., 2018; Moutoussis et al., 2011; So et al., 2016). However, relying too little on one's model and inference can lead to excessive information gathering, as seen in patients with obsessive-compulsive disorder (OCD; Fear & Healy, 1997; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017; Voon et al., 2016), which in turn can lead to slow and debilitating decision making.

In recent years, cognitive neuroscience has started to reveal the mechanisms underlying information gathering and how healthy adults solve this challenge. A key finding is that humans use planning based on their current knowledge to determine the extent they engage in gathering information before making a decision (FitzGerald et al., 2014; Hauser, Moutoussis, Iannaccone, et al., 2017; Ma et al., 2019; Moutoussis et al., 2011), and that this process is flexible, adapting to the current demands (such as explicit costs for information gathering) to reach near optimal performance (Bogacz, Hu, et al., 2010; Hauser, Moutoussis, Iannaccone, et al., 2017). Moreover, a consistent finding across multiple approaches and tasks is that humans dynamically adjust their criteria for stopping the information gathering process, depending on how long they already have been sampling (Bogacz, Wagenmakers, et al., 2010; Gesiarz et al., 2019; Hauser, Moutoussis, Iannaccone, et al., 2017; Ma et al., 2019; Malhotra et al., 2017; Thura et al., 2014). Subjective sampling costs appear to increase as more information is gathered. When little is known, subjects only stop if there is strong evidence in favour of one option, but once lots of information has been sampled, participants become more lenient and are more willing to stop gathering information even if there is only slight evidence in favour of one option (Cisek et al., 2009; Hauser, Moutoussis, Iannaccone, et al., 2017; Malhotra et al., 2017; Moutoussis et al., 2011; Thura et al., 2014).

Little is known about how information gathering changes during childhood and adolescence. This is of particular importance because of the cognitive limitations children face. Given that children have much less knowledge of the world, generally increasing information gathering would be beneficial. However, known limitations in children’s planning abilities (Decker et al., 2016; Smid et al., 2020) may interfere with their inference process more fundamentally, maybe even leading to reduced information gathering behaviour. This is of particular importance because the psychiatric disorders known to have information gathering impairments are most likely to emerge during adolescence (Kessler et al., 2005). Here we investigate information gathering in three groups of children and adolescents and use computational modelling to show that children engage in an excessive information gathering to counteract their limitations in planning, but only if it is beneficial for them.

Materials and Methods

Subjects

To assess age-related differences in information gathering, we recruited children and adolescents from schools across London. In total, we recruited 107 youths (62 females) in three age groups: 30 children (aged 8-9 years old (yo), mean 9.34y), 41 young adolescents (12-13yo, mean 13.13yo), and 36 older adolescents (16-17yo, mean 17.19y). We determined the sample size assuming similar effect sizes as previous developmental studies and as our own studies with this task (e. g., Decker et al., 2016; Hauser et al., 2018; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017; Smid et al., 2020; Somerville et al., 2017; Stenson et al., n.d.). The groups did not differ in their age-adjusted IQ estimates (WISC; Wechsler, 1999) (children: 93.9±13.4 (mean±SD); young adolescents 98.5±13.5; late adolescents 97.2±10.3). All youths gave written informed consent, and parental consent was obtained for all participants below the age of 16. The study was approved by the UCL research ethics committee (No. 14261/001). Testing was conducted in a quiet room within the child's school and all subjects received a voucher for participating in the study (value £7). Different data from the same group of children is reported elsewhere (e.g., Dubois et al., 2020).

Task

To study information gathering, we used a modified information sampling task (Clark et al., 2006; Hauser et al., 2018; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017). For each game (Fig. 1A), subjects were presented with 25 covered cards and they needed to decide whether the majority of the cards were either yellow or blue (colours changed on every trial; cards could only ever be one of two colours on a given trial). Subjects were allowed to overturn as many cards as they wished (using a computer mouse) until they felt certain enough to make their choice. Once they reached that state, they could declare which colour was in the majority by clicking on a colour button below the card deck. After each game, subjects were informed of how many points they won in the game.

All subjects played two task conditions. In a fixed-win condition, a correct choice was rewarded with +100 points, while a wrong decision was penalised by -100 points. Turning over cards did not impose any explicit costs. In the decreasing-win condition, subjects started with a potential gain of +250 points. However, each overturned card led to a reduced potential win by -10 points (e.g. after 3 draws, a potential win is +220 points). If subjects chose the wrong colour, they always lost 100 points, irrespective of how many cards they had already sampled.

Statistical analyses

For the behavioural analyses, we ran repeated-measures ANOVAs with a within-subject factor condition (fixed, decreasing) and a between-subject factor group (children, young adolescents, late adolescents). Significant effects were further explored using (independent samples) t-tests. For comparison of the model parameters, we used one-way ANOVAs with the between-subjects group factor. We report effect sizes of all analyses using Cohen's d for t-tests and partial eta-squared η^2 for ANOVAs.

Computational model

To investigate the computational mechanisms underlying age-related change in information gathering, we fitted computational models that we have previously developed for this task. We provide a summary of the model with key equations in the Supplementary Material. For a detailed discussion of the model, please see (Hauser et al., 2018; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017). Here we provide a description of the model and the key model parameters.

In this model, the agent makes a decision between three possible choice options: declaring for yellow, declaring for blue, or continuing with sampling (i.e. non-declaring). To make this choice, the agent assigns a value to each of these choice options. The value for declaring for blue or yellow are made based on the agent's current belief that given colour will win, multiplied with the potential win and loss amount. The agent forms this belief based on the cards that they have already opened. For example, if the agent already opened six cards and five of them were yellow, then the agent thinks it is much more likely that yellow will form the majority of cards, than if only three of the six cards were yellow.

To assign a value to the non-declaring choice option, the agent uses planning to project themselves into the future and evaluate how valuable future choices could be. It does that by thinking ahead and considering how clear a decision will be if they continue sampling another x cards, based on what the agent already knows (i.e. the cards it already opened). The quality of this planning process is thereby governed by the decision temperature parameter τ, which governs how precisely the agent plans and accounts for its current beliefs.

An additional factor that influences the value of the non-declaring option is the emergence of subjective sampling costs. Model comparison (cf Supplementary Material) showed that subjects internally represent costs for continuing sampling, even when they are not imposed by the experiment (e.g. in the fixed condition). These costs are added to the non-decision value and render it less attractive to continue sampling if the costs are high. These costs are determined by two model parameters: the scaling parameter *cs* describes how large the costs can maximally become, while parameter *p* describes when these costs start to emerge. A low *p* means that these costs incur early in the sampling process, thus promoting an early decision.

For each sample, the agent arbitrates between these three choice alternatives and hence makes predictions about what a subject should choose based on specific model parameters. To compare the model parameters between age groups, we fitted each computational model and parameter to each subject, which then provided us with the best fitting parameters for a given subject (cf Supplementary Material for details). These fitted parameters were subsequently used to make inference about the underlying development-related processes.

Results

Children gather more information when it's free

Three groups of children (8-9yo), early (12-13yo), and late adolescents (16-17yo) performed an information gathering task that we had extensively examined previously in adults and patients (Fig. 1A) (Hauser et al., 2018; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017). Youths were tasked to decide whether the majority of 25 covered cards were yellow or blue. Prior to making a decision, subjects could uncover as many cards as they wished, until they felt 'certain enough' with their decision. In the 'fixed' win condition, no points were deducted for gathering information prior to declaring for a colour, whereas in the 'decreasing' win condition the potential wins steadily decreased as a function of sampling (cf methods for more details).

To assess developmental change in information gathering, we investigated whether the groups differed in the number of cards they opened before making a final decision. We found both a highly significant age group effect (Fig. 1B; $F(2,104)=11.28$, $p<.001$, $\eta^2=.178$) as well as a highly significant interaction with condition ($F(2,104)=20.43$, $p<.001$, $\eta^2=.282$; main effect of condition: $F(1,104)=293.75$, $p<.001$, $\eta^2=.739$). Subsequent t-tests revealed that this was driven by a significant increased information gathering in children as compared to adolescents in the fixed (vs early adolescents: $t(69)=4.61$, $p<.001$, $d=1.10$; vs late adolescents: $t(64)=5.59$, $p<.001$, $d=1.36$), but not in the decreasing condition (vs early adolescents: $t(69)=-.50$, $p=.617$, $d=.12$; vs late adolescents: $t(64)=.54$, $p=.589$, $d=.13$). No differences between the adolescent groups were observed in any of the analyses. This means that children gather significantly more information than adolescents when there is no explicit cost associated with information gathering, but show equal information gathering when sampling information is expensive. This also suggests that children deploy their information gathering in a strategic way to optimise outcomes.

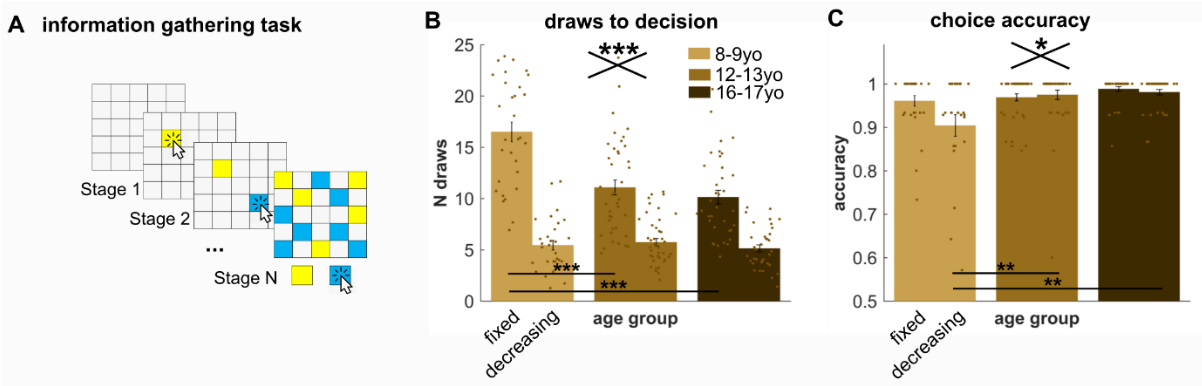

Figure 1. Increased information gathering in children. (A) Task procedure: Youths played an information gathering task in which they were allowed to overturn as many cards as they needed before making a decision and declaring whether the yellow or blue cards formed the majority of the 25 originally covered cards. (B) The 8-9 year-old children opened more cards than the early (12-13yo) and late (16-17yo) adolescents in the fixed condition, in which opening cards was not associated with explicit costs. There was no difference in sampling in the decreasing condition, in which their earnings decreased when opening more cards. (C) Moreover, children were slightly worse at choosing the colour that was currently more plentiful in the decreasing condition, indicating worse inference abilities. *** p<.001; ** p<.01; * p<.05; yo year-olds.

Developmental differences in inference

Next, we investigated whether the age groups differed in other aspects of their performance. In particular, we investigated how accurate their decisions were, relative to the opened cards, i.e. whether subjects chose the colour that was more plentiful according to what they had drawn so far. We found that subjects in general performed close to ceiling, but despite this were more accurate in the fixed than in the decreasing condition (Fig. 1C; $F(1,104)=4.28$, $p=.041$, $\eta^2=.039$). Interestingly, we found both a group main effect ($F(2,104)=8.73$, $p<.001$, $\eta^2=.144$) and a group-by-condition interaction ($F(2,104)=3.88$, $p=.024$, $\eta^2=.069$). Post-hoc t-tests showed that children were less accurate than adolescents and that this difference was primarily driven by differences in the decreasing (vs early adolescents: $t(69)=-2.87$, $p=.005$, $d=.66$; vs late adolescents: $t(64)=-3.24$, $p=.002$, $d=.78$), but much less so in the fixed condition (vs early adolescents: $t(69)=-.58$, $p=.564$, $d=.15$; vs late adolescents: $t(64)=-2.23$, $p=.030$, d=.54). This means that children were less precise in their decisions, primarily in the decreasing condition where information gathering per se was already costly.

Excessive information gathering counteracts inference imprecision

To further understand how these behavioural effects came about and what mechanisms were underlying them, we fitted a range of different computational models to subjects' behaviour and then analysed the model parameters of the best-fitting computational model (cf Supplementary Methods; Hauser et al., 2018; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017). This means that the winning model was fitting the data better than the alternative models and was able to correctly predict >75% of choices (cross-validated data; chance level performance: 33%). More details can be found in Figure S2 and the Supplementary Material.

To characterise the computational aspects that differed between the age groups, we compared the free model parameters, which can be subdivided roughly into two families. The first set of parameters (*cs*, *p*) describe the emergence of the subjective sampling costs that control the extent of information gathering prior to declaring for a colour. The other set of parameters govern the precision of the inference and decision process (ξ, τ). They determine how precisely one plans into the future, but also how this information is then used to inform decision making.

Altered costs drive excessive information gathering in children

One key parameter that governs when in a sampling process subjective costs start to matter (i.e. when it gets subjectively expensive to open further boxes) is parameter *p* (using separate parameters for the fixed-win and decreasing-win conditions). We have previously found that this parameter is sensitive to dissociate different groups that show differences in the number of draws (psychiatric patients, drug groups (Hauser et al., 2018; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017)).

In our developmental sample, we found a significant difference between the groups in parameter *p* of the fixed condition (Fig. 3B; $F(2,104)=11.72$, $p<.001$, $\eta^2=.184$). Subsequent tests revealed that this was because children had larger parameter values than young and late adolescents (vs early adolescents: $t(69)=3.63$, $p=.001$, $d=.90$; vs late adolescents: $t(64)=5.13$, $p<.001$, $d=1.29$). There was no difference in the decreasing condition (Fig. 3E; $F(2,104)=.49$, $p=.615$, $\eta^2=.009$). In alignment with our behavioural data, this means that a critical driver underlying the increased information gathering in children is the later arising of subjective costs in the fixed condition.

Interestingly, there was also a group effect on the scaling of the costs *cs* (Fig. 3A; $F(2,104)=7.92$, $p=.001$, $\eta^2=.132$). This was driven by a reduced maximal cost (i.e. smaller scaling parameter *cs*) in children compared to the older groups (vs early adolescent: $t(69)=2.903$, $p=.005$, $d=.69$; vs late adolescents: $t(64)=3.88$, $p<.001$, $d=.95$). This suggests that there may be multiple mechanisms at work in children, not only a delay in when these costs arise (parameter *p*), but also that sampling costs are generally perceived as less costly.

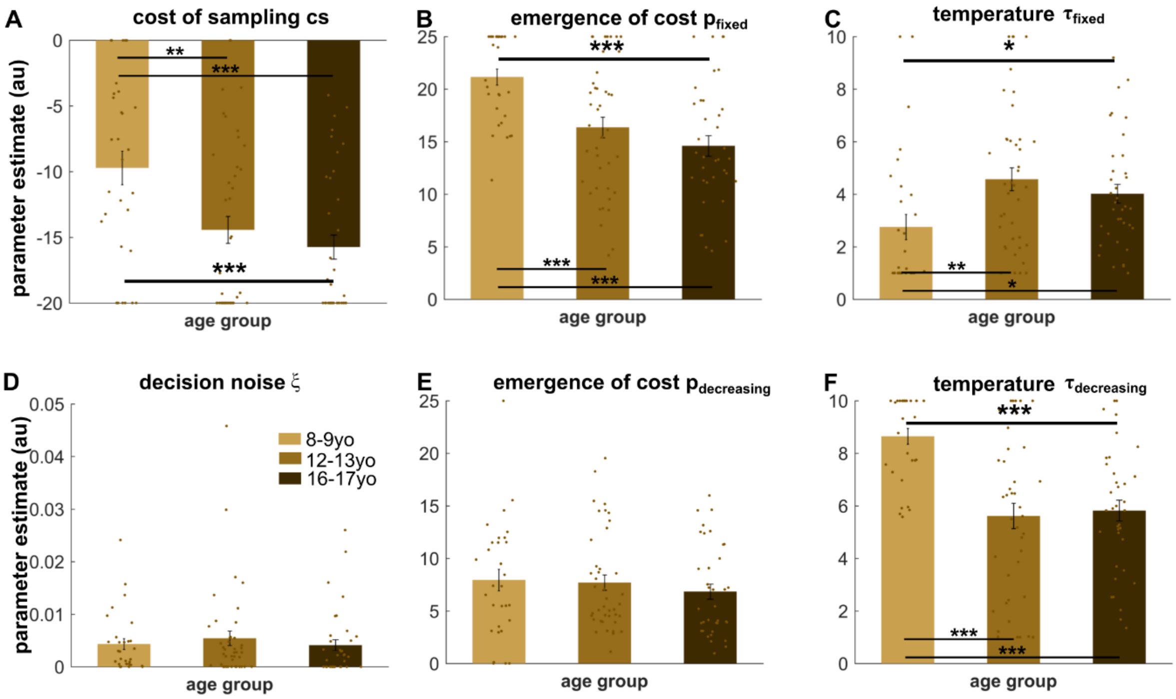

Figure 3. Model parameters reveal multiple distinct processes change with age. The parameters of the best-fitting model reveal that children differed from the adolescent groups across multiple model parameters. (A) Children have a lowered maximal subjective cost parameter as well as a later emergence of these costs in the fixed (B), but not in the decreasing (E) condition, which is underlying the increased information gathering behaviour in the former condition. Children also had an increased decision temperature, primarily in the decreasing (F) and less so in the fixed (C) condition. The higher decision temperature for the decreasing condition suggests that in this more demanding setting, children perform less precise inference. We found no difference in decision noise between the groups (D). *** $p<.001$; ** $p<.01$; * $p<.05$.

Reduced inference precision in children

Next, we investigated the parameters related to the precision of their inference and action. The first parameter ξ characterises a decision noise or noise floor, which accounts for decisions that were unguided by any traceable reasoning process in our model. We did not find any difference in this parameter between the three groups (Fig. 3D; $F(2,104)=.37$, $p=.695$, $\eta^2=.007$). Next, we investigated whether parameter τ differed between age groups. This parameter not only governs how strictly you stick to the best possible option, but also how precisely your future planning is executed. The groups differed in this parameter both in the fixed condition (Fig. 3C; $F(2,104)=4.49$, $p=.013$, $\eta^2=.080$) as well as in the decreasing condition (Fig. 3F; $F(2,104)=14.76$, $p<.001$, $\eta^2=.221$). This was mainly driven by an increased τ in the children compared to the adolescents (fixed condition: vs early adolescents: $t(69)=2.77$, $p=.007$, $d=.70$; vs late adolescents: $t(64)=2.15$, $p=.035$, $d=.52$; decreasing condition: vs early adolescents: $t(69)=4.88$, $p<.001$, $d=1.23$; vs late adolescents: $t(64)=5.51$, $p<.001$, $d=1.39$). Our findings are thus in line with previous findings of reduced planning abilities in children (Decker et al., 2016; Smid et al., 2020), confirming that children were less accurate in their planning abilities (esp. in the long horizon) and this process was driven by an altered τ parameter.

Discussion

How can children solve complex decision making tasks despite their limited cognitive resources and skills? Here, we show that children compensate for limited planning abilities by increasing their information gathering, but only if this is beneficial for their performance. Our results thus suggest that children take their limited capacities into account and are able to deploy compensatory strategies to make up for these limitations.

In our data, we find two distinct behavioural differences between children and adolescents. Firstly, we find excessive information gathering in children when gathering information comes at no additional explicit costs (fixed wins condition). Our findings thus contradict the notion that children are generally more impulsive and avoid long deliberation (Moutoussis et al., 2016; Olson et al., 2007; Peters & Büchel, 2011; Steinberg et al., 2009). In the costed condition, where gathering each piece of information incurs an explicit cost, children did not differ in their sampling behaviour. This means that children (as well as adolescents) are able to flexibly adjust their information gathering based on the external incentive structure. In the costed condition, excessive information gathering would not have been beneficial for children, because sampling more information would have led to a reduction in possible wins, thus leading to worse overall performance (cf Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017). The condition-specific findings also rule out an alternative explanation that children inherently need stronger evidence difference to make a decision, which would have led to a similar effect in both conditions. Interestingly, the excessive information gathering behaviour in children allowed them to perform marginally better than both adolescent groups (see Figure S1), demonstrating that their excessive information gathering was indeed beneficial and highlights the adaptive nature of this strategy.

The second behavioural difference was that children's inference and decision making process was less precise. We found that the children's accuracy was lower than the adolescents', particularly in the decreasing condition, in which they did not show a difference in sampling. This is not surprising because our information gathering task requires planning ahead using the current knowledge, and children have been found to be limited in their abilities for these complex computations (Decker et al., 2016; Smid et al., 2020). In particular, in this task subjects make inference about 'what will be if I were to open all cards', rather than 'what is currently the case'. This means that one needs to plan ahead and infer how it will be in the future by taking the current evidence (number of yellow vs blue) into account. The more precise one can perform this inference, the less strong the current evidence has to be. As children's inference process seems limited, we find that they seem to compensate for this limitation by gathering additional information when this comes for free. This means that they are outsourcing the highly demanding planning process and investing in further information gathering, which simplifies the decision problem (because the difference between yellow and blue gets stronger with further sampling).

Our computational modelling revealed that the behavioural differences were driven by different mechanisms. Analysing the model parameters, we found that the reduced planning was driven by a reduced inference precision as captured by the decision temperature parameter. In our model, this parameter not only governs how strongly the actual choices depend on their individual valuation. More importantly, this parameter also determines how precisely you think about the future and thus how well you can rely on the current information you have already gathered. Our finding is thus likely to align with a slow emergence of model-based reasoning (Decker et al., 2016; Smid et al., 2020; Vaghi et al., under review) and related aspects of higher-order cognitive computations (e.g., Bolenz & Eppinger, 2020; Decker et al., 2016; Hauser et al., 2015; Somerville et al., 2017; Tymula et al., 2012; van den Bos et al., 2015) that require the flexible utilisation of cognitive maps and which seem to mature only later in adolescence.

A reduced planning ability, however, also means that already gathered information is not taken into account as adequately, which is what we see in the reduced accuracy in the decreasing condition in children. It is thus most compelling that children are able to compensate for this by boosting their information gathering in the fixed condition. Analysing the model parameters, we found that this is driven by a strong developmental effect on when the subjective costs arise during sampling (parameter *p*). This means that children are gathering more information because their subjective costs (time costs, tiredness, etc.) kick in later. Interestingly, we also found a general scaling effect of these costs with children having a lower cost scaling parameter *cs*, which affects all conditions of the task. This means that even when the costs of gathering information kick in, children still perceive these costs as less grave than adolescents. The exact nature of these intrinsic costs (e.g. time costs vs cognitive effort vs fatigue), and how they relate to the externally imposed costs remains unclear and could be studied in more detail in future studies. Nevertheless, our findings thus suggest that children deploy multiple, potentially distinct, processes to compensate for their reduced planning abilities. Some of these processes seem to be condition-specific and primarily apply when there are no explicit costs associated with gathering information. Other processes are more general, affecting all conditions similarly.

Relatively little is known about the neural mechanisms underlying information gathering and the associated sampling costs. Studies in perceptual decision making suggest that these costs work as a gating signal by boosting neural activity in motor and premotor cortex, in addition to the information that has been accumulated in these same areas (Cisek et al., 2009; Thura et al., 2012, 2014; Thura & Cisek, 2014, 2016). However, it is unclear where this cost signal itself originates from: some models suggest contributions from basal ganglia and associated loops (Lo & Wang, 2006). Other recent findings highlight the role of different neurotransmitters, such as serotonin or noradrenaline, and their selective effect on different aspects of subjective cost computations (Hauser et al., 2018; Michely et al., in prep). A more detailed investigation of the neural mechanisms as well as the neurotransmitters underlying the developmental effect we observed in our study would thus be desirable.

As an aberrant information gathering behaviour is also a key feature of psychiatric disorders that often emerge during adolescence, it is interesting to speculate how the development of mental health problems and the development of information gathering skills might co-occur. On the one hand, we see increased information gathering behaviour in (juvenile) OCD patients (Chamberlain et al., 2007; Dar et al., 2000; Fear & Healy, 1997; Grassi et al., 2015; Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017; Jacobsen et al., 2012; Pélissier & O'Connor, 2002; Volans, 1976; Voon et al., 2016). Their information gathering seems to be as excessive as what we see in the children's behaviour in this study. In our previous studies (Hauser, Moutoussis, Dayan, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017), we also found that an increase in information gathering was primarily driven by the model parameter p that governs when subjective costs arise in the fixed condition. Whether this is because failing to reduce information gathering during the transition to adolescence is driving the emergence of OCD symptoms needs to be addressed in longitudinal studies.

The opposite information gathering pattern, jumping to conclusions, is frequently found in psychosis/schizophrenia (Ermakova et al., 2018; Garety et al., 1991; e.g., Huq et al., 1988; Jepsen et al., 2018; Moutoussis et al., 2011; So et al., 2016), a disorder that traditionally emerges during late adolescence. However, the developmental trajectories underlying this aberrant process remain entirely unclear. While adult patients have shown an altered temperature parameter, similar to our children (Moutoussis et al., 2011), a study with adolescent first-episode patients did not observe any jumping to conclusion behaviour (Jepsen et al., 2018). Whether jumping to conclusions in schizophrenia thus arises from a similar aberrant developmental process needs to be determined. Moreover, our findings suggest that there is considerable developmental heterogeneity between different forms of impulsivity, and maybe these different developmental trajectories can help explain different transdiagnostic symptoms of psychiatric disorders (Berg et al., 2015; Story et al., 2015).

In summary, we show that information gathering behaviour decreases between childhood and early adolescence. Using computational modelling, we show that children gather information excessively to compensate for their reduced ability of precise inference and planning. This increased information gathering during childhood might be a driving factor that helps children to learn rapidly and accurately about the world around them, and may help them to successfully navigate the world as they get more independent. Our findings may also help understand how different information gathering impairments arise in adolescence-related psychiatric disorders and to understand the underlying neurobiology.

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Data and code availability: Data is available from the corresponding author upon reasonable request. A toolbox with the computational model is currently in preparation.

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