



ELSEVIER

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Cognitive Development

journal homepage: [www.elsevier.com/locate/cogdev](http://www.elsevier.com/locate/cogdev)

## Quitting rules in hybrid foraging search: From early childhood to early adulthood

Beatriz Gil-Gómez de Liaño<sup>a,b,\*</sup>, Adrián Muñoz-García<sup>a</sup>, Elena Pérez-Hernández<sup>c</sup>,  
Jeremy M. Wolfe<sup>d</sup>

<sup>a</sup> Department of Social Psychology and Methodology, Universidad Autónoma de Madrid, Spain

<sup>b</sup> Department of Experimental Psychology, Basic Processes and Logopedic, Complutense University of Madrid, Spain

<sup>c</sup> Department of Developmental Psychology and Education, Universidad Autónoma de Madrid, Spain

<sup>d</sup> Brigham & Women's Hospital, Harvard Medical School, USA

### ARTICLE INFO

#### Keywords:

Quitting-Search Rules  
Hybrid Foraging  
Visual Search  
Attention  
Development  
Marginal Value Theory

### ABSTRACT

In hybrid foraging, observers search for multiple instances of multiple target types. Children regularly perform such tasks (e.g., collecting LEGO pieces or looking for different teammates within a game). Quitting rules (When do you leave the search?) are important in foraging (e.g., I found enough LEGOs or teammates). However, the development of quitting behavior has not yet been experimentally studied, and it could give us significant information about executive function development. We tested 279 observers (4–25 years old) using classic feature and conjunction foraging. The results show that while children's performance improved with age, all groups made similar "quitting" decisions roughly following optimal choices as defined by Charnov's Marginal Value Theorem (MVT), with the youngest 4–5 years old children quitting slightly earlier. It seems that mature quitting rules in search operate relatively early in development, suggesting that those rules are quite basic aspects of the human cognition.

When we think about visual search, we typically think about the act of finding something. Understanding how we get our attention to a target has been the topic of years of research (Cho & Chong, 2019; Wolfe, 2020). Also important, but less studied is the question of ending search. When do we quit? If we find nothing, at some point we must decide to end the search (Chun & Wolfe, 1996). If we do not know how many targets are present in a scene, we still need to quit when we think we have found enough (Hong, 2005). In a target rich environment, where we are 'foraging' for many targets (like berry picking, shopping at the grocery, finding the different LEGO bricks required to a construction, or looking for teammates within a game to pass a ball), we need to decide when we have reached a point of diminishing returns, so it would be worth the cost of leaving and moving to the next "patch" (Wolfe, 2013). While basic visual search tasks have been studied developmentally (e.g., Gil-Gómez de Liaño, Quirós-Godoy, Pérez-Hernández & Wolfe, 2020; Hommel, Li, & Li, 2004; Müller-Oehring, et al., 2013), foraging tasks have not received the same attention. Foraging is a variant of visual search in which observers search for multiple instances of the target (e.g. picking berries or apples, see Wolfe, 2013). In *Hybrid Foraging* (HF) tasks, observers look for several instances of several target types (e.g., picking all of the British & American coins out of mixed collection of coins; see Wolfe, Cain & Aizenman, 2019). Foraging tasks have been much less studied compared to typical visual search tasks. Foraging extends visual search tasks beyond single-target visual search by incorporating decisions about when to terminate the search

\* Correspondence to: Departamento de Psicología Social y Metodología, Facultad de Psicología, UAM, C/ Ivan Pavlov, 6, Ciudad Universitaria Cantoblanco, 28049 Madrid, Spain.

E-mail address: [bgil.gomezdeliaño@uam.es](mailto:bgil.gomezdeliaño@uam.es) (B. Gil-Gómez de Liaño).

<https://doi.org/10.1016/j.cogdev.2022.101232>

Received 31 August 2021; Received in revised form 23 July 2022; Accepted 6 August 2022

Available online 13 September 2022

0885-2014/© 2022 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

and move on to a new search patch. Incorporating the study of these quitting processes using foraging tasks can help us to depict and understand executive functions development from a broader perspective by including the study of decision-making within a visual search task, besides the already studied attentional control, information processing, or working memory processes in development in visual search (Gil-Gómez de Liaño et al., 2020). Thus, the present study aims to understand how quitting rules in hybrid-foraging search operate during development from early childhood to early adulthood.

To our knowledge, there are three studies from a single lab that examine children's development using a foraging task in a controlled experimental setting.<sup>1</sup> Ólafsdóttir et al. (2016); Ólafsdóttir, Gestsdóttir & Kristjánsson (2019) and Ólafsdóttir & Kristjánsson (2020) compared behavior of kindergarteners, pre-adolescents, adolescents and adults in a set of studies using feature and conjunction hybrid foraging tasks. Different foraging patterns were found in younger children and adults. For conjunction searches, observers first tended to look for all the targets of one type (e.g., all red circles), in one long run. Then, the other target type was picked in another long run. In feature foraging, younger children (about 4–5 years old) behaved similarly showing those long runs, while older children and adults showed more shifts between the two target types. These were studies of 'exhaustive' foraging in which participants were required to look for and find the very last target in each visual display/patch before leaving that patch and beginning to forage in a new one. This exhaustive foraging task can be very useful and helpful in the study of a number of different aspects of search (attentional control, search strategies, etc.), but eliminates the option to study quitting decision. To do so, we need to allow the participants to freely move to another patch of targets at will. In this way, we can study the rules governing these patch-leaving decisions and any changes in those rules over development.

Referring to the decision to move to the next screen as 'patch leaving' is a nod to the animal literature where the task involves foraging in one patch of food before leaving to find another (Stephens & Dunlap, 2009). Patch leaving behavior is characteristic of human, real-world foraging tasks, too. If we were picking blackberries, for example, we would not typically be required or inclined to collect every single blackberry from one bush before moving to the next. Moreover, different bushes would contain different numbers of berries. In this berry-picking style of foraging, the decision of when to leave a patch/bush/screen in order to look for more berries in a different bush becomes a key aspect of the behavior; one that has not been addressed in previous studies of foraging with children. In the present study, we use the Wolfe et al. (2019) modification of the Kristjánsson et al. (2014) and Ólafsdóttir et al. (2016, 2019, 2020) paradigm to allow us to examine foraging behavior in a paradigm that requires patch leaving. There were three significant differences between the Kristjánsson and Wolfe paradigms: 1) In Wolfe's version and also in ours, the number of distractors and targets can vary from one patch to another, simulating set size manipulations in classical visual search, and more real-world environments like berry picking where all bushes do not contain the same number of berries. This set size manipulation will also allow us to study set size differences within foraging that previous works in development did not consider. As distractors do not disappear in the foraging while picking targets, we could expect earlier quitting behavior under larger set size conditions since more distractors could result in more difficulties detecting the remaining targets. 2) Our stimuli moved at random around the screen in order to thwart systematic scanning of the image, following Wolfe et al. (2019) paradigm used with adults and Wiegand, Seidel, and Wolfe (2019) with older adults. This motion manipulation will help us to avoid strategies of search (like reading-style search left-right/up-down), but importantly, since the search is more difficult in terms of finding targets when they are in movement than in a static task like in Ólafsdóttir's studies, it will incline participants to leave the patches in a more variable behavior, depending on adaptable decision rules upon different conditions (e.g. easier versus more difficult search, previous different set sizes...), or based on their cognitive flexibility. We expect to find developmental differences, with younger children leaving patches earlier since items in movement do not allow them to search as efficiently as if they would if they were static. 3) Finally, and most critically for our purposes, the observer was required to decide when it was time to move to the next patch, rather than being required to collect every target within a patch. This change from the Kristjánsson paradigm undoubtedly alters overall foraging search strategies by altering components like goal setting, cognitive flexibility, and decision making. We are not arguing that this paradigm is the "correct" foraging paradigm; merely that it allows to study quitting rules that cannot be evaluated using an exhaustive paradigm adding richness to the picture of development to study executive functions.

The analyses in the present study rely on the predictions of the Marginal Value Theorem (MVT) from Charnov's Optimal Foraging Theory (Charnov, 1976; Stephens & Krebs, 1986). Although initially based on animal studies, the MVT has been proven useful in explaining quitting rules in human adults (e.g., Hutchinson, Wilke and Todd, 2008; Wiegand, Seidel & Wolfe, 2019; Wolfe et al., 2019). Other theories in animal foraging have been proposed to model quitting rules in search, like the Potential MVT (McNamara, 1982), the Giving-up time rule (Krebs, Ryan, & Charnov, 1974), or the Assessment rule (Green, 1980, 1984). For a review on theories on foraging and quitting rules in search, the interested reader can examine a recent extensive review on the topic (Bella-Fernández, Suero-Suñé & Gil-Gómez de Liaño, 2021). However, the general MVT seems to be a good fit for tasks that involve continuous foraging (like berry picking) as opposed to tasks with more intermittent rewards (e.g. truffle hunting) (e.g. Hutchinson, et al., 2008; Wolfe, 2013). Thus, since our interest is to look for changes in quitting rules in experimental foraging tasks over the course of development, we will focus our analysis on the Charnov's MVT, since previous research with adults and older adults (Wolfe et al., 2019, Wiegand et al., 2019) has found MVT to be a useful theoretical framework for understanding quitting rules in adults performing visual foraging tasks.

<sup>1</sup> There are some observational studies focused in the analysis of foraging behavior in children, but from a behavioral/ecological point of view, and to study observational learning (e.g., Bird & Bliege-Bird, 2002; Whiten et al., 1996). There are also a series of experiments with young infants which are focused on how young infants forage for general visual information from the moment of birth onward, essentially focused on the understanding of perceptual development (e.g., Robertson, Watamura, & Willbourn, 2012). None of those works are interested in the understanding of how foraging tasks can help us to study search termination rules in visual search in development.

Charnov's MVT is focused on the idea that as an animal searches a given area (for food, for instance), the resources in that area are depleted. At some point, the animal's rate of return drops below the average rate of return for the whole task. That is the point at which MVT predicts that the animal will move on to a new region to continue searching for more resources (Charnov, 1976). Wolfe et al. (2019) found that, although there were conditions that violated MVT, in general, MVT provided a reasonable account of when, on average, observers left the current patch. In the present work, we ask how MVT fares as a model of quitting rules in foraging in a sample of 4–25 year old observers' search for simple stimuli (colored circles and squares) within a video game-like hybrid foraging task. To our knowledge, this is the first experimental work studying quitting rules in foraging in children and adolescents, and importantly from a developmental perspective, comparing young children from as young as 4 years old to adolescents and young adults. Since MVT has proven to provide a good account for basic quitting behavior both in animals and adult humans, we expect to find similar results in children and adolescents' quitting search behavior.

## 1. Method

### 1.1. Participants

We tested a sample of 313 children, adolescents and adults from schools and colleges in Madrid, Spain, with a final sizeable cohort between 21 and 33 observers at each age group from 4 to 25. Other data collected from part of this sample of observers are reported in Gil-Gómez de Liaño, et al. (2020). From previous studies in adults and older adults (Wolfe Aizenman, Boettcher & Cai, 2016; Wiegand et al., 2019) on quitting rules, the sample size used to get reliable results was between 11 and 12 participants per group. Given that we have more than double that number in each age group, we can be confident that the sample size used in the present study is adequate. All observers with any history of neurological or sensorial damage or motor impairments, or with a diagnosis of schizophrenia or generalized developmental disorder were excluded from analysis. Anyone with scores over three standard deviations above the published mean in the administered clinical tests (CPT, BASC or BRIEF, see materials below) or who had an estimated IQ of less than 70 (RIST, see materials below) were also excluded, though they were tested to avoid any sense of publicly singling out a child.

The final sample was composed of 279 typically developing observers (49% female, 179 children from junior kindergarten and elementary school, 67 adolescents from middle and high school, and 33 university college students). Age bins are 1 year wide for ages 4–10. We would expect behavior to change less as children become adolescents and adults (Gil-Gómez de Liaño, et al., 2020), so the rest of the cohorts after 10 years involve more than one year range. As mentioned above, this partitioning of the data allowed for cohorts of 21–33 observers in each age group. Details are found in Table 1.

All participants had normal or corrected-to-normal vision. Parents/guardians gave written informed consent for each minor, and each participant over age 7 gave verbal or written assent/consent, after ethical committee acceptance at Universidad Autónoma de Madrid, Spain (Code of approval CEI 67–1193).

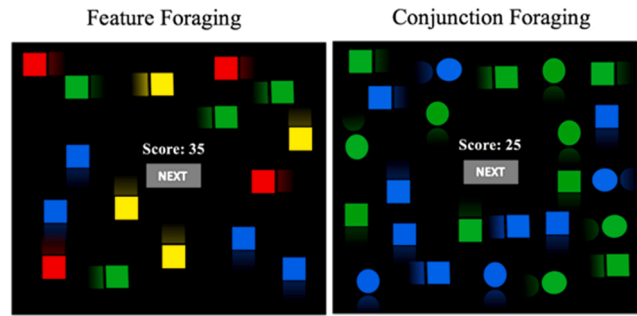
### 1.2. Materials

Experiments were written in Matlab 7.10 (The Mathworks, Natick, MA, USA) using the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997, Kleiner, Brainard, & Pelli, 2007) version 3. Stimuli were presented on a Microsoft Surface pro i5, and observers gave responses by touching the screen. Monitor resolution was 1400 × 1050 pixels. As in Wolfe et al. (2019), stimuli were green, blue, yellow and red squares for the feature condition, and blue and green squares and circles for the conjunction condition (see Fig. 1). These are essentially the same as the stimuli originally used by Kristjánsson et al. (2014). Each item subtended approximately 0.75° at an approximately 60 cm viewing distance. The stimuli were randomly moving at a constant velocity of 44 pixels/sec (approximately 1.2° of visual angle per second) following the methods of Wolfe et al. (2019). As mentioned above, search is more difficult in terms of finding targets when they are in motion than in a static task like in Olafsdóttir's studies. The motion prevents participants from forming a systematic strategy such as "reading" the display from top left to bottom right. They must decide to move on to following patches using a quitting decision rule that can be influenced by different conditions (e.g. task difficulty, previous set size, etc.).

The standardized tests used to assess typical development were:

**Table 1**  
Sample size for each age group, mean, standard deviation (Sd), and range for age quoted in years; Months.

Age group	Sample size	Mean age	Sd	Range
4	28	4;6	0;4	1;0
5	26	5;5	0;3	0;10
6	23	6;7	0;3	0;10
7	28	7;5	0;3	0;10
8	26	8;5	0;4	0;11
9	27	9;7	0;3	0;11
10	21	10;3	0;3	0;10
11–12	21	12;1	0;6	1;6
13–14	21	13;11	0;6	1;8
15–17	25	16;3	0;8	2;1
18–25	33	20;7	1;8	7;5



**Fig. 1.** Example of Stimuli for Feature and Conjunction conditions following Wolfe et al. (2019). Note. In this figure we show how stimuli looked in both Feature and Conjunction tasks. They moved around the screen in pseudo-random order. This image is for illustrative purposes, but set size was larger for the actual task (60, 100, 140 and 180 specifically).

#### 1.2.1. The Conners Kiddie Continuous Performance Test 2nd Edition™ (Conners K-CPT 2™) and the Conners Continuous Performance Tests 3 (CPT).

The K-CPT test is usually used for assessing attention deficits in children ages 4–7 years old. The test takes 7.5 min for a performance-based assessment using familiar object pictures (e.g. boat, soccer ball, train) to young children. The child must press the space bar to all objects except for the soccer ball. For the older children, adolescents and adults (8 and older), the CPT is similar but uses letters instead of pictures and takes about 15 min. Both the K-CPT and the CPT are used in clinical diagnosis of Attention Deficit/Hyperactivity Disorder (ADHD), as well as other psychological and/or neurological disorders of attention. The test-retest reliability reported from the Conners CPT’s manual varies from 0.62 to 0.90 depending on the study and the population of interest. The median test-retest reliability reported from Conners K-CPT manual is 0.57.

#### 1.2.2. The Reynolds intellectual screening test (RIST)

To assess Intelligence quotient (IQ) we used the Reynolds Intellectual Screening Test (RIST; Reynolds & Kamphaus, 2003). It is a short test (takes around 30 min or less) and shows high reliability with other measures of intelligence (the correlation with the WISC-IV is 0.68, and 0.62 with the WAIS-IV). The internal consistency median coefficient reported by the RIST-2’s manual (Cronbach’s alpha: 0.92) seems more than sufficient for screening purposes.

#### 1.2.3. The behavioral assessment scale for children (BASC-II)

Also, we used the parent report form of The Behavioral Assessment Scale for Children (BASC; Reynolds & Kamphaus, 2004) to look for potential behavioral problems. The test was created to evaluate the behavior and self-perception of children and young adults. It is structured in several dimensions measuring essentially adaptive skills and behavioral problems (hyperactivity, conduct problems, anxiety, depression, etc.). As reported in the BASC-II’s manual, Test-retest reliability varies from 0.77–0.90. The questions essentially follow a 4-choice Likert-Scale from “Never” to “Almost Always”. Some examples of the items are: *My child cannot wait to take turns*, *He/She interrupts others when they are speaking*, *He/She seems lonely*, *He/She is easily stressed*, etc.

#### 1.2.4. The behavior rating inventory of executive function (BRIEF)

The Behavior Rating Inventory of Executive Function- BRIEF (Gioia, et al., 2000) looks for potential problems with executive functions in everyday life with different versions adapted to different children age’s. Like the BASC, it is a test with items that are answered using a Likert-Scale. The BRIEF uses three options for each question: “never, sometimes, and often”. Example of items in the test are: *His/Her school work is careless or neglected*, *She/He acts before thinking*, *He/She speaks out of turn*, *She/He gets lost in details and does not pay attention to the big picture*, etc. The latent variables of the BRIEF are essentially seven: Inhibition, Self-Monitoring, Shifting, Emotional Control, Task Completion, Working Memory, and Plan/Organization of Materials. In a recent re-evaluation of the test, the test-retest reliability varied from 0.67–0.92 (Hendrickson & McCrimmon, 2019).

Finally, parents also provided information about their child’s development and medical history.

### 1.3. Design and procedure

Observers were asked to collect 200 points as quickly as possible by picking up targets in each *feature* and *conjunction* motion foraging tasks. They received 2 points for every target picked, and lost 1 point for every distractor. When a correct target was tapped, it disappeared from the screen. If a distractor was erroneously tapped, a red cross was displayed on the distractor, but the distractor remained on the screen and the red cross disappeared. In the *feature* task, observers had to look for the blue and green squares among yellow and red ones, while for the *conjunction* task they had to look for green circles and blue squares, among green squares and blue circles. *Feature* and *Conjunction* conditions were run separately and randomly counterbalanced, with half of the observers running first *feature* and then *conjunction*, and the other half first the *conjunction* trials and then the *feature* ones. A score counter in the center of the screen was updated every time they picked a target, and each condition ended when the observer got 200 points (Thus, requiring 400

total points for the whole task). Since the counter interpretation for the youngest children of 4–5-years-old was a bit complicated for them, those children were also updated about their score during the experimental phase to make sure they attended to the counterpoints during the task. The word “next” was present in a gray square below the score, as is shown in Fig. 1. Touching the next button moved observers to a new screen. Set size was random within subjects, following Wolfe et al. (2019) (and unlike in Ólafsdóttir et al., 2016, 2019, 2020) with set sizes of 60, 100, 140 & 180 items in the displays. Targets constituted 20–30 % of all items in each display. Observers were unaware of the specific number of targets in each display. Thus, observers were asked to look for two different types of targets (green and blue squares in the *feature* conditions, and blue squares and green circles in the *conjunction* one) that could appear an undetermined number of times in each display and for each blocked and counterbalanced feature/conjunction condition. They could move to another patch to look for more targets whenever they chose. The “travel time” – the time from the touching of the “Next” button to the appearance of the next screen – was set to 2 s. The task finished when the 200 points were reached in each of the feature and conjunction conditions. The standardized tests and the hybrid foraging task were run in different sessions on different days. Each session took between about 20–40 min each one, including rest times as needed by the participants and practice trials. All observers had a practice phase prior to the experimental phase with feedback for the items left behind when moving to the next trial. This highlighted the fact that observers indeed could leave those targets behind when they went to the next patch, at their discretion. We checked to ensure that each observer had understood the instructions, especially those for the free-quitting search within patches, and especially for the younger children. For the youngest ones, the experimenter asked them to describe the task objectives before starting the experimental paradigm and made sure that the children clearly understood the task before the end of the practice phase. The practice phase required observers to get 50 points before moving to the experimental phase in both feature and conjunction blocked conditions, in order to assure that observers were trained and familiarized with the task.

## 2. Results

### 2.1. MVT predictions

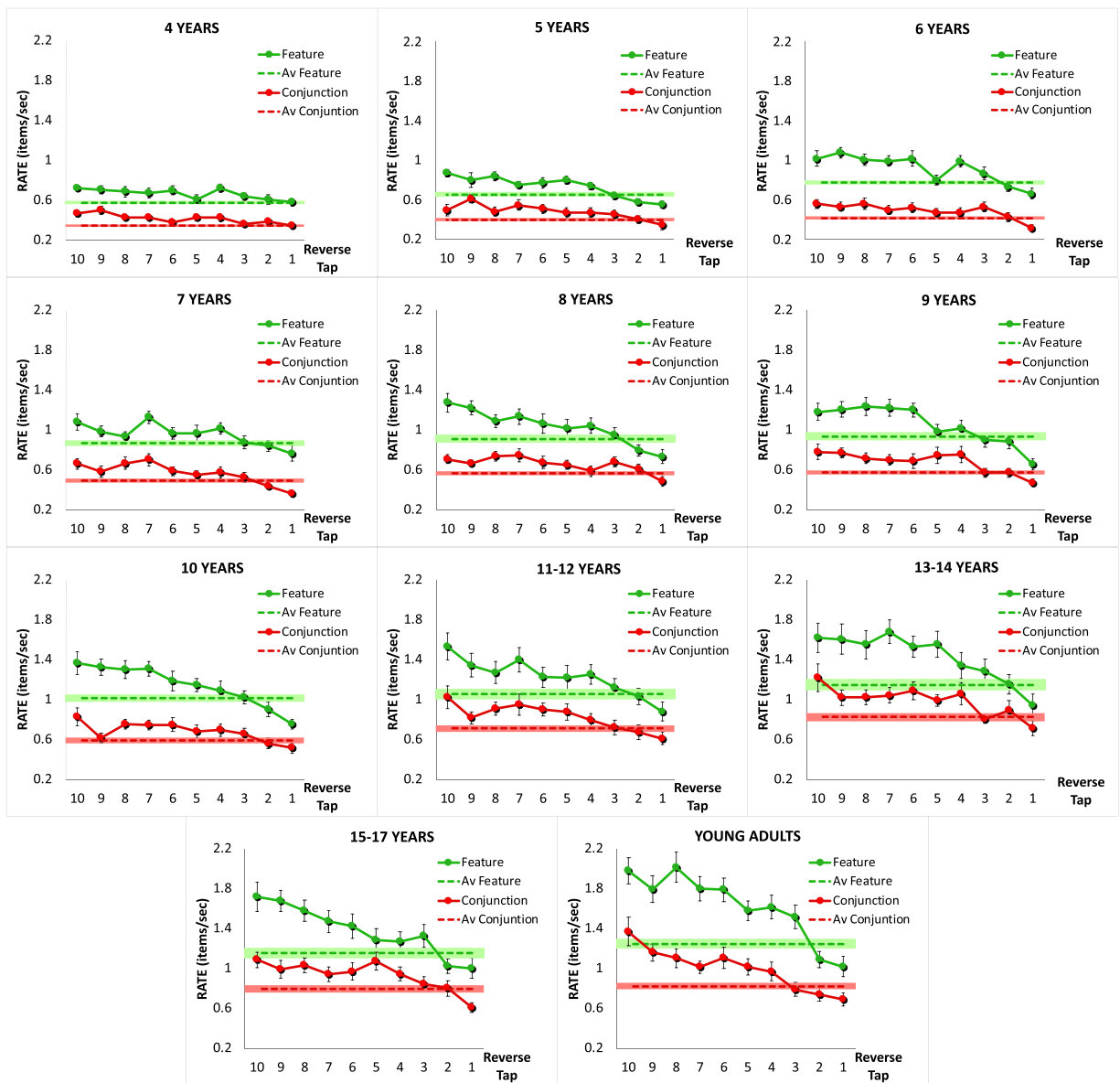
According to MVT, an observer, following an optimal quitting rule would opt to move to the next frame/patch when the instantaneous rate of target collection (the inverse of the time between successive target collections) meets or falls right below the average rate of collection in the task (Charnov, 1976). Following the previous work with younger adults (Wolfe et al., 2019) and older adults (Wiegand, et al., 2019), the *average rate* is calculated as the total number of points collected divided by the time spent in the whole task (including travel times). The *instantaneous rates* are the inverse of the average RTs for a specific time point multiplied by the proportion of hits at that time point. These RTs are calculated for each one of the last 10 items tapped, counting in *reverse* order from the item tapped just before the “Next” button. We will refer to the position in the order as the “reverse tap”, so that reverse tap 1 is the last item tapped before leaving the patch, reverse tap 2 is the previous one, and so forth. One could go further than 10 taps back but, at that point, numbers of trials begin to decrease markedly (especially for children, as we will later see) and, for present purposes, the earlier taps do not tell us much about the quitting behavior. Following previous work with a similar task (Wolfe et al., 2019 & Wiegand et al., 2019), we plotted the rate of picking by the reverse tap from the final tap in the patch to 10 taps earlier. Results are shown in Fig. 2 for each of the eleven age groups from 4 to 25 described in Table 1. They are divided into feature (green lines) and conjunction (red lines) conditions for each age bin.

Fig. 2 shows overall results that are broadly consistent with MVT. The instantaneous rate drops as the trial progresses from Reverse Tap 10 to the final selection from the current screen. When the rate drops to or below the average rate (dashed lines), the observers move to the next patch/screen. In Table 2, we show the T-tests for the comparisons for each instantaneous rate with the average rate to see the progression of those functions shown in Fig. 1.

As seen both in Table 2 and Fig. 2, for *feature conditions* instantaneous rates are usually significantly higher than the average rate for Reverse Taps 5–10 ( $p < .05$  in most of the cases and for all ages). For *conjunction conditions* (red lines in Fig. 2) the results are similar, although not as clear as for feature conditions. Interestingly, we can also see in Fig. 2 that it seems that observers leave the patches more quickly than in feature conditions once the instantaneous rate reaches the average rate. That is, in general, observers seem to dip further below the average rate before quitting in the feature case. To test this, we computed the difference between the average rate and the instantaneous rate for the last tap (reverse tap 1), and used it as the dependent measure for a linear regression with age as the independent measure. There is a significant effect of age with older observers showing higher values than younger observers in this measure of absolute rate: This is true for feature [ $F(1,278)=7.02$ ;  $p = .009$ ;  $r = .16$ ] and conjunction conditions [ $F(1,278)= 10.28$ ;  $p = .001$ ;  $r = .19$ ]. The regression equations found are: Average Rate – Instantaneous Rate reverse tap 1 =  $0.065 + 0.001$  (Age in months), and Average Rate – Instantaneous Rate reverse tap 1 =  $0.024 + 0.001$  (Age in months), respectively for feature and conjunction conditions. Both the correlation and the regressions are showing rather small effects though.

In Fig. 3, we display the results with the instantaneous rate plotted against the average rate for each task, age group, and for the last 2 taps before leaving the patch (in Table 3 we show the direct values with its corresponding SEs). The diagonal line marks a match between the instantaneous and average rates. Points below the line show cases where the instantaneous rate falls below the average rate. As we can see (especially in feature conditions), there is a subtle but clear developmental trend. Age is shown by color with younger groups scores in blue, turning red for groups' scores with increasing age.

The graph shows that at Reverse Tap 2, the penultimate tap on the screen, observers' instantaneous rate reaches the average rate. With age, the rates get faster, as seen in the increase upon the diagonal as age increases. On the last click in the patch (Reverse Tap 1), the instantaneous rate has fallen below the average rate (except for age 4). The distance below the line of equality grows in absolute terms with age. However, the roughly linear form of the function showing change over age (blue to red) is consistent with observers



**Fig. 2.** Mean instantaneous rate for the last 10 reverse taps. Note. In this figure we show the mean instantaneous rate for the last 10 reverse taps (1 being the last one, 2 the previous one, and so forth) for each condition (feature in green and conjunction in red). Dashed lines represent the average rate for each condition (again green for feature and red for conjunction). Error bars show one Standard Error (SE). Shaded areas for average rates also represent one SE.

quitting when the instantaneous rate falls to a roughly constant fraction of the constant rate. Fig. 4 shows the average ratio in each age group of the final instantaneous rate divided by the average rate, separately for feature and conjunction items (data also derived from Table 3, where both the instantaneous and average rate is shown for each age group).

A repeated measures ANOVA<sup>2</sup> with condition as a within-subject variable and age-group<sup>3</sup> as a between-subject variable shows a

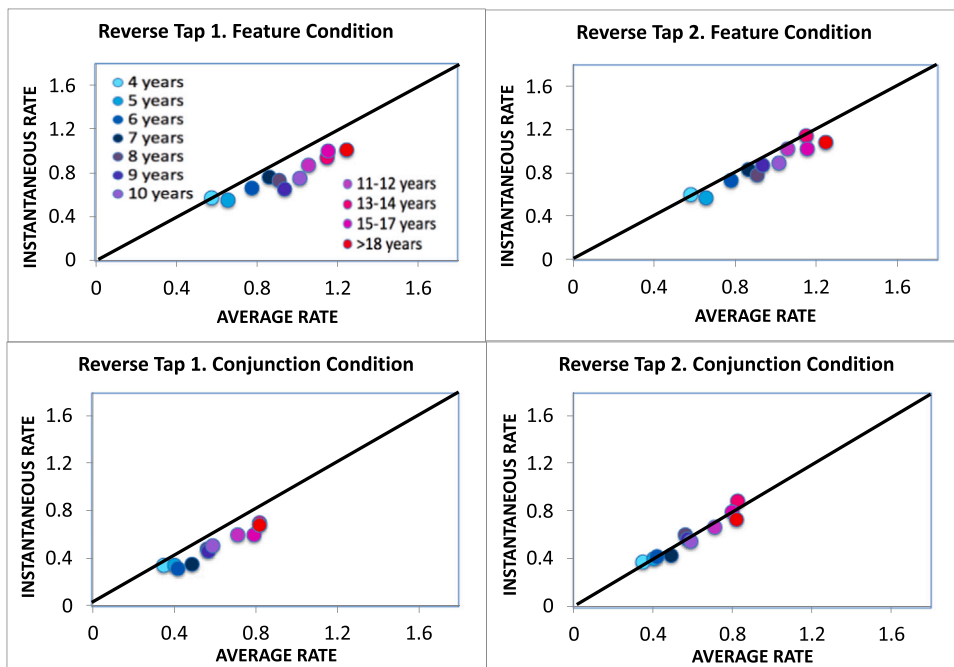
<sup>2</sup> All ANOVAs in the manuscript show essentially the same results as those found when using Linear Mixed Models (LMM). Our large sample allows to find the same results using maximum likelihood estimations (LMM) or least-square estimations (ANOVA). Since many age effects are not following a linear function in our study, and the effect sizes (partial Eta-square indexes) for potential meta-analytic studies are more useful, we decided to report ANOVA results. Remarkably, the results of LMMs are the same, so conclusions do not vary.

<sup>3</sup> Similar results were found when including Age in months as covariate, and thus treating it as a continuous factor in the analysis, maintaining the same conclusions as those derived from the Age-Group analysis. Moreover, since for some of these analysis, age does not usually show a linear function, it seems rather more correct to use it as a categoric factor using bin-age groups (Age-Group factor).

**Table 2**

T-test comparisons for every instantaneous rate with its average rate at every reverse tap (see Fig. 2) for feature and conjunction conditions and for each group of age. T (Student-T), df (degrees of freedom), p (p-value).

Reverse Click	4 YEARS OLD						5 YEARS OLD						6 YEARS OLD						7 YEARS OLD					
	FEATURE			CONJUNCTION			FEATURE			CONJUNCTION			FEATURE			CONJUNCTION			FEATURE			CONJUNCTION		
	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p
1	0.02	27	0.98	-0.07	27	0.94	-2.03	25	0.05	-1.38	25	0.18	-3.06	22	0.01	-3.45	22	0.00	-1.55	27	0.13	-5.24	27	0.00
2	0.92	27	0.36	2.10	27	0.04	-1.84	25	0.08	0.08	25	0.94	-0.99	22	0.33	0.25	22	0.80	-0.64	27	0.53	-2.22	27	0.04
3	1.42	27	0.17	0.94	27	0.35	-0.36	25	0.72	1.80	25	0.08	1.61	22	0.12	2.50	22	0.02	0.14	27	0.89	0.78	27	0.44
4	4.17	27	0.00	2.27	27	0.03	1.70	25	0.10	1.98	25	0.06	4.14	22	0.00	1.13	22	0.27	2.94	27	0.01	1.57	27	0.13
5	0.97	27	0.34	2.91	27	0.01	3.09	25	0.00	1.82	25	0.08	0.69	22	0.49	1.60	22	0.12	1.43	27	0.17	1.46	27	0.16
6	2.76	27	0.01	1.30	27	0.20	2.55	25	0.02	2.65	25	0.01	3.71	22	0.00	2.17	22	0.04	2.05	27	0.05	2.42	27	0.02
7	2.54	27	0.02	3.61	27	0.00	1.83	25	0.08	4.35	25	0.00	5.65	22	0.00	1.99	22	0.06	4.75	27	0.00	3.81	27	0.00
8	2.32	27	0.03	3.44	27	0.00	4.44	25	0.00	1.74	25	0.09	4.93	22	0.00	2.66	22	0.01	1.64	27	0.11	3.11	27	0.00
9	2.74	27	0.01	4.00	27	0.00	3.86	25	0.00	3.09	25	0.00	5.73	22	0.00	2.87	22	0.01	2.58	27	0.02	1.67	27	0.11
10	3.57	27	0.00	3.93	27	0.00	3.96	25	0.00	2.44	25	0.02	3.77	22	0.00	3.39	22	0.00	2.81	27	0.01	3.97	27	0.00
Reverse Click	8 YEARS OLD						9 YEARS OLD						10 YEARS OLD						11-12 YEARS OLD					
	FEATURE			CONJUNCTION			FEATURE			CONJUNCTION			FEATURE			CONJUNCTION			FEATURE			CONJUNCTION		
	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p
p1	-3.01	25	0.01	-1.81	25	0.08	-6.85	26	0.00	-3.28	26	0.00	-5.46	20	0.00	-2.18	20	0.04	-3.30	20	0.00	-2.31	20	0.03
2	-2.54	25	0.02	0.87	25	0.39	-1.22	26	0.23	-0.01	26	0.99	-2.01	20	0.06	-0.68	20	0.50	-0.43	20	0.67	-0.67	20	0.51
3	0.54	25	0.59	2.61	25	0.02	-0.88	26	0.39	-0.01	26	0.99	0.13	20	0.90	1.56	20	0.13	1.07	20	0.30	0.13	20	0.89
4	1.63	25	0.12	0.60	25	0.55	1.50	26	0.15	2.51	26	0.02	0.72	20	0.48	2.29	20	0.03	2.35	20	0.03	1.42	20	0.17
5	1.70	25	0.10	2.01	25	0.06	0.91	26	0.37	2.15	26	0.04	2.53	20	0.02	1.93	20	0.07	1.71	20	0.10	2.87	20	0.01
6	1.83	25	0.08	2.20	25	0.04	4.83	26	0.00	1.82	26	0.08	1.87	20	0.08	2.71	20	0.01	2.36	20	0.03	3.51	20	0.00
7	3.66	25	0.00	3.47	25	0.00	5.05	26	0.00	2.68	26	0.01	3.87	20	0.00	4.12	20	0.00	3.99	20	0.00	2.27	20	0.03
8	3.19	25	0.00	3.63	25	0.00	4.13	26	0.00	3.15	26	0.00	4.07	20	0.00	3.81	20	0.00	2.25	20	0.04	3.17	20	0.00
9	6.06	25	0.00	3.28	25	0.00	4.71	26	0.00	4.85	26	0.00	4.54	20	0.00	0.54	20	0.60	3.30	20	0.00	1.62	20	0.12
10	4.51	25	0.00	3.04	25	0.01	3.92	26	0.00	2.91	26	0.01	3.07	20	0.01	2.87	20	0.01	4.53	20	0.00	3.22	20	0.00
Reverse Click	13-14 YEARS OLD						15-17 YEARS OLD						> 18 YEARS OLD											
	FEATURE			CONJUNCTION			FEATURE			CONJUNCTION			FEATURE			CONJUNCTION								
	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p	t	df	p						
1	-3.10	20	0.01	-2.23	20	0.04	-2.30	24	0.03	-6.19	24	0.00	-3.10	32	0.00	-2.95	32	0.01						
2	0.05	20	0.96	0.78	20	0.44	-3.05	24	0.01	0.12	24	0.91	-2.84	32	0.01	-1.87	32	0.07						
3	1.44	20	0.16	-0.43	20	0.67	2.32	24	0.03	0.79	24	0.44	3.24	32	0.00	-0.68	32	0.50						
4	1.99	20	0.06	2.57	20	0.02	2.00	24	0.06	2.68	24	0.01	3.74	32	0.00	1.93	32	0.06						
5	4.65	20	0.00	3.34	20	0.00	1.77	24	0.09	4.09	24	0.00	4.37	32	0.00	2.55	32	0.02						
6	4.48	20	0.00	4.42	20	0.00	3.43	24	0.00	3.04	24	0.01	6.29	32	0.00	3.19	32	0.00						
7	5.42	20	0.00	4.01	20	0.00	4.41	24	0.00	2.37	24	0.03	5.21	32	0.00	3.72	32	0.00						
8	4.17	20	0.00	3.11	20	0.01	5.46	24	0.00	3.45	24	0.00	6.14	32	0.00	3.62	32	0.00						
9	4.25	20	0.00	2.85	20	0.01	7.31	24	0.00	2.30	24	0.03	4.93	32	0.00	4.68	32	0.00						
10	4.32	20	0.00	3.15	20	0.01	4.89	24	0.00	4.32	24	0.00	7.83	32	0.00	4.33	32	0.00						



**Fig. 3.** Mean Instantaneous rate plotted by Average Rate by Age for the last 2 reverse taps. Note. The plots show mean instantaneous rate for the last 2 tapped items before quitting the search in a patch (reverse taps 1–2 for each graph, left and right, respectively) against the mean average rate for each group of age by condition (feature in the upper graphs and conjunction at the lower ones). The diagonal line indicates equality between both instantaneous and average rates.

significant though small effect of age [ $F(10,268) = 2.10, p = .03, \eta^2 = .07$ ], no effect of condition [ $F(1,268) = 0.33, p = .57, \eta^2 = .001$ ], and no interaction [ $F(10,268) = 0.97, p = .47, \eta^2 = .04$ ]. The age effect is entirely due to the higher ratio at Age 4. Tukey-correct pairwise comparisons show that Age 4 is significantly different from other ages. No other paired-comparisons are significant. If the Age 4 data are removed, the age effect is no longer significant ( $F < 1$ ). These results indicate that children and adults tend to continue picking until the instantaneous rate falls to about 80 % of the average rate, independent of age or condition. Then they leave for the next patch. The exception may be the youngest children (4 years old) in the group who appear to leave sooner. However, the 4 years old children's picking rate is relatively slow and does not change much with reverse click number (Fig. 2). The ratio of  $\sim 1.0$  may be the product of this slow, unvarying click behavior. Overall, it is interesting that, while picking becomes swifter with age, the foraging rules appear to be very similar, at least from age 5 on.

The increase in the picking rate as a function of age can be seen for individual observers in Fig. 5 where we plot the average rate for each observer as a function of age (the mean values with standard deviations for each age group can be found in Table 3). A regression analysis both for feature and conjunction on the average rate, with age as the predictor variable showed significant effects for both tasks; Feature: [ $F(1,278) = 232; p < .001; r = .68$ ], and conjunction: [ $F(1,278) = 358; p < .001; r = .75$ ] (see Fig. 5). The regression equations are for feature: Average Rate =  $.53 + .003$  (Age in months), and for conjunction: Average Rate =  $.26 + .003$  (Age in months).

To compare the functions between conditions we also performed a repeated measures ANOVA with condition (feature/conjunction) as the within-subjects variable and age-bin as a between-subjects variable. We found main effects for Condition [ $F(1,268) = 1397; p < 0.001; \eta^2 = 0.84$ ] and for Age [ $F(10,268) = 39.78; p < 0.001; \eta^2 = 0.60$ ]. The interaction was also significant [ $F(10,268) = 4.24; p < .001; \eta^2 = .14$ ]. Bonferroni-corrected comparisons show that the functions were steeper for older observers, and that this effect was bigger for the feature conditions (Fig. 5).

Taken together, these results indicate that children, adolescents and young adults are, on average, broadly optimal, in MVT terms, in their patch-leaving decisions in these hybrid foraging tasks. Youngest children (4 years old) seem to leave the patches a bit earlier compared to the older ones, but from 5 years onwards, they leave the patch similarly regardless of age. The main change with age is in the rate of picking which becomes steadily faster over time.

To more deeply investigate those quitting rules differences between different ages, we performed two further analyses. As our experiment used different set sizes, we can study if the set size interacts with quitting rules, conditioned by age. Since set size was randomized for every observer, there might not be data for all set size conditions for all observers because it was possible to collect 200 points before seeing a patch of each set size. Thus, given that some cells in the ANOVAs are empty for certain observers, Linear Mixed Models are a better way to perform this analysis in this particular case. We performed LMM separately for Feature and Conjunction conditions with Set size and Age Group as factors for mean average ratios shown in Fig. 4, but separated by Set size. The results show no main effect of Set size for Feature ( $F < 1$ ), nor any significant interaction [ $F(30,651) = 1.26; p = .16$ ]. For Conjunction, although the main



**Table 3**  
Mean Values and SEs for the Average Rate and Instantaneous Rates 1 and 2, for Feature and Conjunction in each Age Group Cohort.

Age Group	Feature							Conjunction						
	N	Average Rate		Instantaneous Rate 1		Instantaneous Rate 2		Average Rate		Instantaneous Rate 1		Instantaneous Rate 2		
		Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	
4	28	0.58	0.02	0.58	0.04	0.61	0.03	0.35	0.01	0.35	0.02	0.39	0.02	
5	26	0.66	0.02	0.56	0.05	0.58	0.04	0.40	0.02	0.35	0.04	0.41	0.03	
6	23	0.78	0.03	0.67	0.05	0.74	0.05	0.42	0.01	0.32	0.03	0.43	0.05	
7	28	0.87	0.03	0.77	0.08	0.84	0.05	0.49	0.02	0.36	0.03	0.44	0.03	
8	26	0.91	0.04	0.73	0.07	0.79	0.06	0.56	0.02	0.49	0.05	0.61	0.05	
9	27	0.94	0.04	0.66	0.06	0.88	0.07	0.57	0.02	0.47	0.04	0.57	0.05	
10	21	1.02	0.04	0.76	0.05	0.90	0.07	0.59	0.03	0.51	0.05	0.56	0.05	
11–12	21	1.06	0.05	0.88	0.09	1.03	0.08	0.71	0.03	0.61	0.06	0.67	0.07	
13–14	21	1.15	0.06	0.95	0.11	1.15	0.10	0.82	0.04	0.71	0.08	0.89	0.10	
15–17	25	1.16	0.05	1.00	0.10	1.02	0.07	0.80	0.04	0.61	0.05	0.80	0.08	
18–25	33	1.25	0.05	1.02	0.10	1.09	0.08	0.82	0.03	0.69	0.06	0.74	0.06	

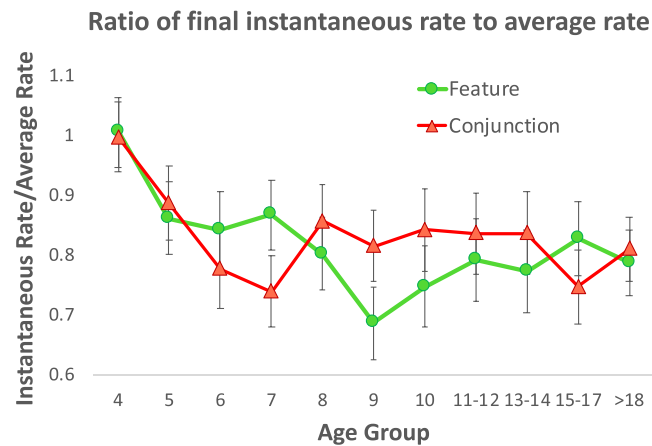


Fig. 4. Final instantaneous rate (at reverse tap 1) divided by the average rate for each age group for feature (green circles) and conjunction (red triangles) conditions. Note. Error bars show one SE.

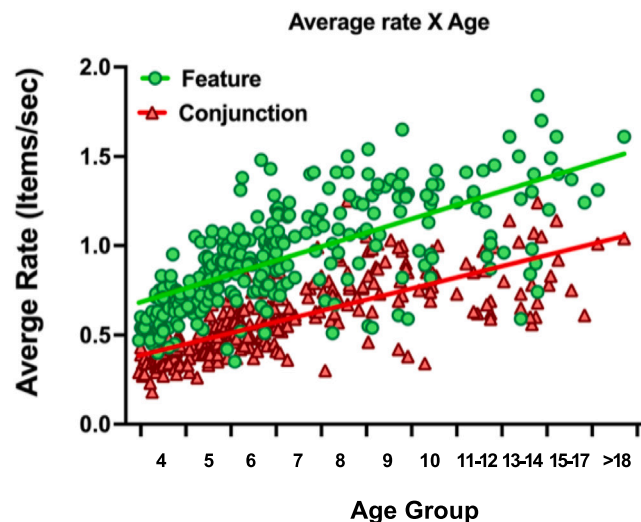


Fig. 5. Average rate as a function of Age and Condition for each observer (Feature – green circles - and Conjunction – red triangles).

effect of Set size did not reach significance [ $F(3,668) = 2.17$ ;  $p = .09$ ], the interaction [ $F(30,664) = 1.51$ ;  $p = .04$ ] as well as the main effect of Age Group [ $F(10,336) = 4.02$ ;  $p < .001$ ] were significant. The interaction showed that 4-year-olds left the patches with more distractors (140 & 180) significantly earlier than patches with fewer distractors ( $p < .001$ ). For the remaining age groups, there were no differences in the patch quitting behavior based on Set size.

In our second analysis, to check for a change in strategy over the course of the experiment, we divided the task by patches in the first half and the second half (for odd number of patches, we included one more in the first half, being conservative looking for a potential change for the second half of the task) and performed an ANOVA as before for average ratios with Time as another within-subjects factor (plus Condition and Age-Group, as before). The results showed no significant differences between time bins [ $F < 1$ ;  $F(1,268) = .09$ ;  $p = .77$ ], nor any interaction between Bin-Time and any other factor: Bin-Time by Age [ $F(1,268) = 1.50$ ;  $p = .14$ ], or the three-way interaction [ $F < 1$ ;  $F(10,268) = .50$ ;  $p = .89$ ]. Thus, we do not see evidence that the first half of the task is different from the second.

## 2.2. How many items are picked? How many items are left behind?

A forager's patch leaving rule interacts with their picking speed and the travel time to change the average number of items that they will pick in a patch. Fig. 6 shows the average proportion of targets picked for each observer. It is clear that almost no one forages exhaustively in this task, again, illustrating an important difference with the earlier work of Ólafsdóttir et al. (2016, 2019) that required observers to collect all of the targets in every patch before moving to the next one. Freed from that constraint, observers are clearly willing to abandon a substantial proportion of targets. This does not mean that one method is superior to the other. It demonstrates that foraging behavior is very responsive to the specific rules of the task. These results may serve as an illustration of the MVT

pressures that make it very hard to find *everything* in a foraging task, even if the forager wants to be exhaustive (think about finding typos in your manuscript).

As we can see in Fig. 6, the proportion of items picked declines as a function of age, more dramatically for feature foraging than for conjunction foraging. Over the ages from 5 to 16, the linear regression of proportion as a function of age is significant for feature [ $F(1,203) = 84.1$ ,  $p < .001$ ;  $r = .54$ ] and conjunction [ $F(1,203) = 13.08$ ,  $p < .001$ ;  $r = 0.24$ ]. If all data are included, the regressions remain significant (both  $p < .005$ ).

### 2.3. False positive-false alarm error rate

While items left behind are not miss errors in this task, distractors that are selected do constitute false positive or false alarm errors and could be informative. In Fig. 7 we show the distribution of false alarms by age. False alarm errors are typically quite rare in simple search tasks (e.g. Wolfe, Palmer, & Horowitz; 2010). Fig. 7 shows that this adult behavior develops over time with linear regression showing that errors decrease with age: Feature [ $F(1,278) = 37.37$ ;  $p < .001$ ;  $r = 0.24$ ] and Conjunction: [ $F(1,278) = 44.36$ ;  $p < .001$ ;  $r = .37$ ]. In line with the data on items left behind, these data also suggest that four year old observers are quite sloppy in their performance of this task. The ANOVAs confirmed the regression results: There is a significant main effect of Age [ $F(1,268) = 10.33$ ;  $p < .001$ ;  $\eta^2 = .28$ ]. There is also a main effect of Condition, showing that the conjunction condition is harder than the feature condition [ $F(1,268) = 55.64$ ;  $p < .001$ ;  $\eta^2 = .17$ ]. The significant interaction of age and Condition [ $F(1,268) = 2.76$ ;  $p = .003$ ;  $\eta^2 = .09$ ] shows that the differences between conditions become insignificant when children get older, as false alarms become rare in older children and young adults for both tasks.

### 2.4. Response times and target type switching

Fig. 8 shows mean Response Times (RTs) for hits plotted by condition and age for each observer. Taken together, Figs. 7 and 8 show a speed-accuracy covariance as a function of age. Children become faster and more accurate as they get older. This is supported by an ANOVA for RTs with Condition as within-subjects and Age-Group as between subjects, where all effects were significant: Condition [ $F(1,268) = 1495$ ;  $p < .001$ ;  $\eta^2 = .85$ ], Age-Group [ $F(10,268) = 44.25$ ;  $p < .001$ ;  $\eta^2 = .62$ ], and the interaction [ $F(10,268) = 14.74$ ;  $p < .001$ ;  $\eta^2 = .36$ ].

Because there are two targets in each patch, we can look at the decision to stay with the same target type (a "run") or to "switch" to the other target type. Using the exhaustive foraging paradigm, Ólafsdóttir et al. (2016, 2019) found that conjunction searches generate a pattern in which observers look for all the targets of one type first, in one long run, followed by all the items of the other type. In feature foraging, Ólafsdóttir's observers switched back and forth much more often. Interestingly, younger children (about 4–5 years old) produced longer runs in the feature conditions, probably showing that the feature search is not as easy for them as it is for older children and adults.

Our non-exhaustive foraging task does not produce the same dramatic differences between feature and conjunction tasks. Older children and adults produce somewhat greater numbers of switches in the Feature case. Younger children show very similar rates of runs and switch (Fig. 9, left panel). This is reflected in an ANOVA that shows a significant effect for condition [ $F(1,268) = 43.37$ ;  $p < .001$ ;  $\eta^2 = .14$ ], no effect for Age [ $F(10,268) = 1.61$ ;  $p = .104$ ;  $\eta^2 = .06$ ] and a significant interaction of condition with age [ $F(10,268) = 2.99$ ;  $p = .001$ ;  $\eta^2 = .10$ ].

It is interesting that the rates of switching are similar, because the cost of switching is markedly higher in conjunction than feature searches. This can be seen by comparing the RTs for switch trials in the right panel of Fig. 9 with the overall RTs in Fig. 8. The cost of

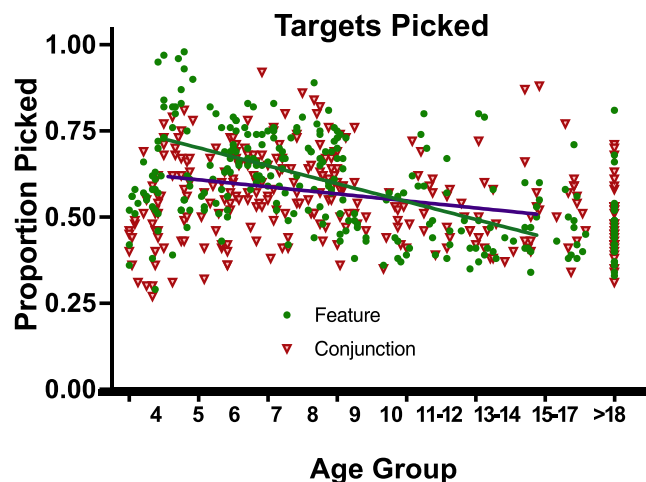


Fig. 6. Average proportion of items picked in each patch as a function of age. Note. Each datapoint represents one observer. Circles show feature foraging results. Triangles show conjunction foraging.

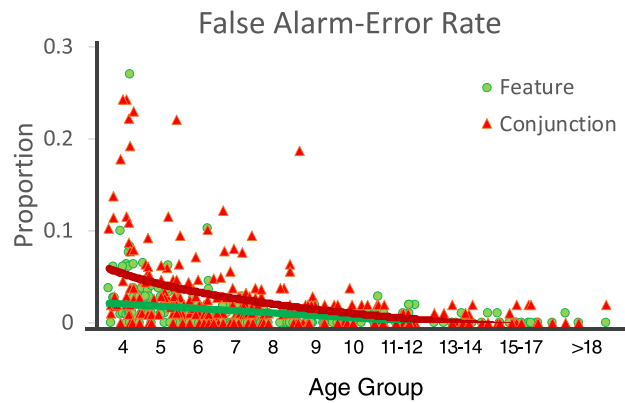


Fig. 7. Distribution of errors for each condition (feature in green-circles, conjunction in red-triangles) by age.

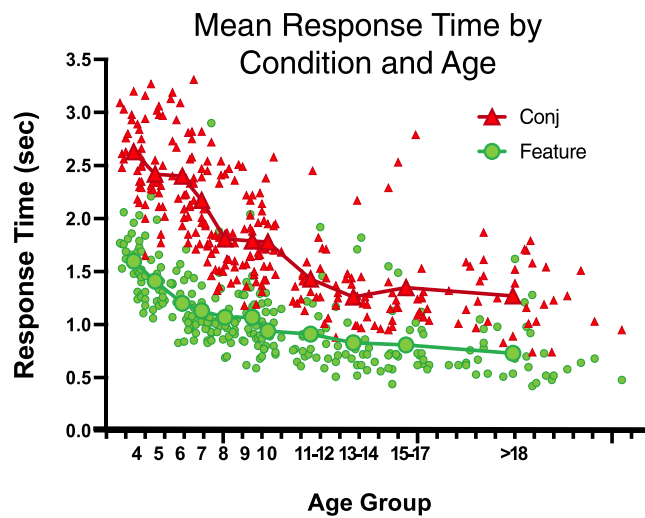


Fig. 8. Mean Response Times (RTs) for each condition (feature in green-circles, conjunction in red-triangles) by age.

switching in the feature case is on the order of 100 msec while it is several 100 msec in the conjunction condition. An ANOVA for switch response times shows significant effects for Condition [ $F(1,268) = 1575; p < .001; \eta^2 = .86$ ], Age Group [ $F(10,268) = 46.47; p < .001; \eta^2 = .63$ ], and their interaction [ $F(10,268) = 12.19; p < .001; \eta^2 = .31$ ]. The interaction is showing that the cost of a switch for the

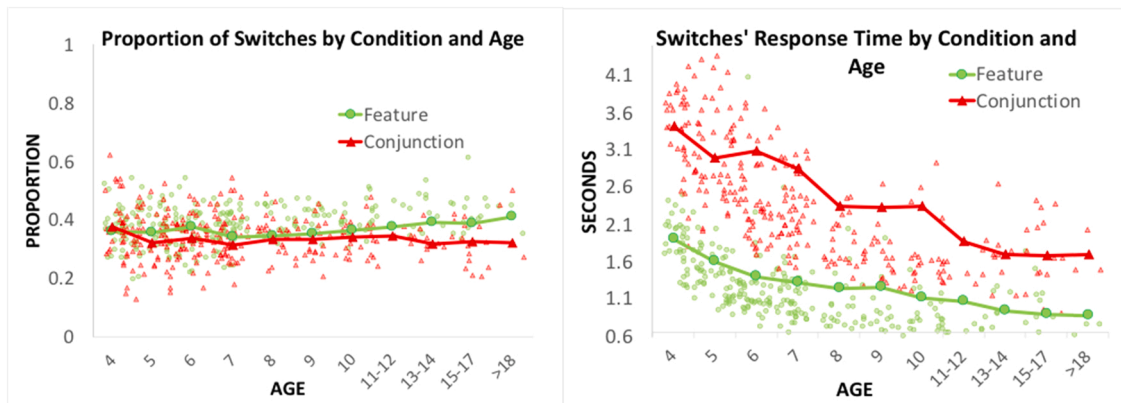


Fig. 9. Distribution of runs by age and condition (feature in green-circles, conjunction in red-triangles) on the left panel. On the right panel, the distribution of response times associated to runs and switches by age and condition feature in green-circles, conjunction in red-triangles).

conjunction condition is stronger for younger children compared to the older ones.

Finally, how do these error, RTs, and run-switch patterns relate to the quitting behavior in the foraging task? As shown in the previous analyses, younger children are less efficient in their search and strategies, but not in the quitting decision behavior, so, is there any relationship between the efficiency in search and the quitting decisions? Calculating the correlations between quitting ratios and efficiency in the search (FA-errors, RTs for runs and switches, misses, etc.) we only found a significant correlation between quitting ratios of feature and conjunction ( $r = .19$ ;  $p < .001$ ), and a small correlation between quitting ratio in the conjunction condition with FA-errors ( $r = .13$ ;  $p = .03$ ). That is, quitting before or after in the feature condition is related to quitting before or after in the conjunction one. We found no other significant correlations, showing no clear relationships between quitting rules and the efficiency in the search.

### 2.5. Quitting rules and individual differences

Table 4 shows the average results for the neuropsychological tests administered to our observers (CPT, RIST, BRIEF and BASC, see methods section). For the adult observers (those over 18 years old) we have no measures for the BRIEF and BASC tests, since they were the family versions filled out by parents/guardians of the minors, so not used for our adults.

We examined the correlation of these scores with the ratio of instantaneous rate to average rate. The lower this ratio, the longer observers stayed in the patch.

Only the BRIEF test was significantly correlated with the rate ratio for Feature [ $F(1,245) = 4.03$ ;  $p = .046$ ;  $r = .13$ ] and Conjunction [ $F(1,245) = 5.52$ ;  $p = .02$ ;  $r = .15$ ]. The equations have positive slopes (Feature: Rate Ratio =  $0.68 + .003$  (BRIEF Global EF index); Conjunction: Rate Ratio =  $0.67 + .003$  (BRIEF Global EF)). The bigger the average ratio, the earlier the observers quit the search. Here we found that the higher the EF index in the BRIEF, the higher the average ratio. Thus, those individuals with higher EF levels in the BRIEF tend to leave the searches earlier. Since higher EF values in the BRIEF indicate potential problems in executive functions, the higher the tendency to show EF problems, the higher the tendency to spend less time than needed in the search. As the CPT did not reveal any tendency with quitting rules, nor the BASC, it seems that the effect found for the BRIEF does not rely on attentional, inhibitory, or behavioral problems. Indeed, when considering the single measures of every latent variable in the BRIEF test, only Self-Monitor reached significance in the linear regression [ $F(1,182) = 3.57$ ;  $p = .06$ ;  $r = .14$ ; intercept =  $.59$ ; beta =  $-.004$ ] and Organization of Materials is marginally significant also for the Conjunction condition [ $F(1,245) = 5.52$ ;  $p = .02$ ;  $r = .15$  intercept =  $.62$ ; beta =  $-.004$ ].

**Table 4**  
Mean statistics for each age group for CPT, RIST, BRIEF, and BASC tests.

Age group	Statistics	CPT response style	Rist (IQ)	Global EF index (BRIEF)	Global behavioral index (BASC)
4	N	28	28	28	28
	Mean	53.96	103.96	78.34	45.41
	SD	7.21	9.09	12.24	9.20
5	N	26	26	26	26
	Mean	55.62	109.04	74.78	40.93
	SD	9.73	12.18	13.26	8.56
6	N	23	23	23	23
	Mean	55.96	112.13	52.37	45.71
	SD	9.21	13.79	11.67	5.86
7	N	28	28	28	28
	Mean	50.00	113.61	49.87	47.12
	SD	7.54	13.94	11.15	8.13
8	N	26	26	26	26
	Mean	53.35	114.50	51.73	50.31
	SD	11.45	13.32	8.72	10.86
9	N	27	27	27	27
	Mean	50.70	109.04	51.91	47.72
	SD	8.77	13.43	8.66	8.31
10	N	21	21	21	21
	Mean	53.81	108.48	48.16	45.29
	SD	6.56	12.04	9.52	8.85
11–12	N	21	21	21	21
	Mean	51.76	103.57	46.28	41.92
	SD	7.92	10.71	8.38	7.56
13–14	N	21	21	21	21
	Mean	53.00	94.95	50.43	44.33
	SD	7.09	14.08	13.87	9.08
15–17	N	25	25	25	25
	Mean	52.12	96.12	47.40	42.52
	SD	5.66	11.52	7.88	8.18
18–25	N	33	33		
	Mean	43.63	99.03		
	SD	8.54	13.29		

N (sample size)  
SD: Standard Deviation

The results support the assumption that quitting rules could be based on aspects of executive functions related to monitoring the task and organization, rather than attentional control or working memory.

### 3. Discussion

There is a modest literature on foraging in humans. There is an even smaller literature on foraging behavior during childhood. The present study is the first (to our knowledge) to examine quitting rules in foraging in a developmental context. The principal result of our study is that average foraging behavior is roughly optimal as defined by the Marginal Value Theorem (MVT) for children aged 4–16. This is similarly to what was found for younger (Wolfe et al., 2019) and older (Wiegand et al., 2019) adults. Charnov's (1976) MVT proposes that the optimal moment to leave a search is when the rate of picking meets or drops below the average rate for the whole task. We see this behavior across ages 4–25 years old in our experiment using hybrid foraging tasks in which observers are looking for either of two types of target. The results show there is a tendency for our youngest children (age 4) to leave patches somewhat earlier than older observers, though even these youngest observers behave roughly optimally in MVT terms. Interestingly, Wiegand et al. (2019) found that older adults although also roughly optimal in terms of MVT, tend to leave patches a bit later compared to younger adults. When expressed as a ratio between the final instantaneous rate and the average rate, everyone beyond the 4-year-old group tended to leave the current patch when the instantaneous rate dropped to about 80 % of the average rate. It is interesting that this measure is quite stable, even as the rate of picking, and the percent of items left behind increased with age (Figs. 5–8), and strategies in terms of *runs* and *switches* were less optimal for younger children (Fig. 9). Age does not appear to produce substantial changes in quitting rules after age 5.

One might expect earlier quitting with larger set sizes, especially with younger children, since the task becomes harder. However, only the 4 year old group shows earlier quitting behavior with larger set sizes. For older participants, there was no set size effect on quitting rules. Moreover, although there is within-subjects variability in the quitting behavior during the task, it does not seem to be related to any other systematic factor. We found no learning effects between the first and last halves of the experiment. Individual differences analysis correlating quitting results with neuropsychological tests (CPT, RIST, BRIEF, and BASC) showed a modest correlation with BRIEF results for children, 6–10 years old; perhaps showing a relationship between poorer executive functions and earlier quitting behavior. Thus, the evidence presented here seems to show that, beyond age 4, any trial by trial variability in quitting rules seems to be related to random variations during the task.

As in prior results from other visual search and foraging developmental studies too (Gil-Gómez de Liaño et al., 2020; Ólafsdóttir et al., 2016, 2019, 2020), executive functions like attentional control, and working memory capacity seem to be related to search behavior as seen in Figs. 5–9, but not to quitting rules. The results for false alarms/error rates and response times essentially replicate those previously found in foraging and visual search tasks in development (e.g., Gil-Gómez de Liaño, et al., 2020; Ólafsdóttir et al., 2016, 2019, 2020). For instance, the effects of age on response times are not linear (see Fig. 8). Indeed, there is a suggestion of abrupt, step-like changes between age bins in development (Anderson, 2002). Similar patterns are seen in other developmental studies of executive functions and attention in visual search (as discussed in Gil-Gómez de Liaño et al., 2020), indicating that these cognitive changes may appear in spurts rather than in a linear progression in development.

These and other results mirror results from more applied neuropsychological studies of development (Anderson, 2002), showing typically lower performance for our younger children, as attentional control and information processing skills are still developing from 4 to 5 years-old to about 11–12 years-old before reaching near adult performance. Recent findings have tied aspects of personality traits using the Big Five questionnaire to search behavior (differences in response times in conjunction search in target-absent trials, for instance; see Lange-Küttner & Puiu, 2021). However, in the present data, the BASC measures that can be related to some aspects of personality traits do not show any correlation with quitting rules. Although these factors could be related to some search behavior aspects in foraging (more research would be needed to test for this hypothesis), they do not seem to influence quitting rules.

As we have also seen, the results from the BRIEF support that quitting rules could be based on aspects of executive functions related to monitoring the task and organization, rather than attentional control or working memory. Indeed, the study of the organization of the task has recently shown a relation to age maturation, with organization improving between the age of 6 and 12 in foraging tasks (Ólafsdóttir, Gestsdóttir, & Kristjánsson, 2021). However, Ólafsdóttir et al. (2021) did not directly test for quitting rules in foraging since their task was exhaustive foraging, not allowing the participants to leave the search until all targets were gathered. Thus, although more research is needed to support this idea (since it is just based on the correlation with quitting behavior in our task and the results of the BRIEF family reported measures), it seems that quitting rules could also be related to organizational aspects in foraging. Future studies should test this potential relationship between quitting rules and the search organization. On the other hand, attentional control and working memory have been related to search behavior during foraging (e.g., Ólafsdóttir, et al., 2019, 2020), but, according to our results, not directly related to the decision of when it is time to leave a patch. Any firm link between development of foraging behavior and other executive functions would need to be the topic of future research. For now, the present results altogether demonstrate that besides the replication of previous results in search developmental tasks, even the youngest observers in our sample were able to do the present hybrid foraging tasks (both feature and conjunction) competently according to their age, with the expected improvements over time, but while being essentially optimal at their decisions of when it is time to quit the search.

At the other end of the age spectrum, older adults show different patch leaving behavior compared to young adults. They leave the search later (Wiegand, et al., 2019). There are several differences between the tasks used in the present study and those used in Wiegand et al. (2019). These include the number of targets to search for (many more in the older adults study compared to the current study), the type of stimuli used (simple colored squares and circles in our study, and real-world items in Wiegand et al., 2019), and a few others. Thus, more research would be needed to properly compare children with young and older adults. The present results

support the hypothesis that there is a relatively constant rule from early in childhood (5 years-old) to young adulthood following MVT, with perhaps a change to more conservative quitting times for older adults.

It would be interesting to see how infants and toddlers would behave in foraging tasks, since our 4 years-old observers showed indications of a more liberal, early quitting rule compared to the rest of the observers. This might represent use of something like a “giving-up” rule (Krebs, et al., 1974; see Bella-Fernández et al., 2021, for a review). Thus, it could be that there is a lifespan shift from relatively early giving-up to a type of perseverance in later years. Importantly, if something like MVT is shaping adult behavior, it also appears to be shaping behavior of children as young as 4–5 years old. This suggests that the decision making process behind quitting rules in these hybrid foraging tasks is a basic piece of our cognitive hardware. It seems that these quitting rules are not laboriously learned over the lifetime or based on some slow process of maturation. Instead, MVT-style quitting either comes with the system or is learned in early childhood. This seems reasonable, given that MVT also applies to other less cognitive developed species (e.g., Krebs et al., 1974) though it would be worth more extensively testing with a broader range of foraging tasks. Other variables could also be of interest. Time pressure and/or the consequences of the searching behavior can also shape quitting behavior. Wolfe et al. (2019) found deviations from simple MVT predictions when reward rules were changed (Zhang, Gong, Fougny & Wolfe, 2017) or when targets are sparse (Ehinger & Wolfe, 2016). It could be informative to systematically vary “travel times”, the time after leaving one patch and before the next patch can be foraged. Longer travel times lower the average rate of return since one cannot collect targets while ‘traveling’. Consequently, MVT predicts that observers should stay longer in each patch. Animals and human adults show this behavior (see Bella-Fernández et al., 2021, for a review). It would be interesting to know if children do as well. Further, Wiegand et al. (2019) found no substantial differences in behavior when participants’ memory was loaded with up to 64(!) targets. This, too, would be interesting to test with children. A goal of future developmental foraging research would be to see if the quitting behavior of children responds to these variables in an adult manner.

#### 4. Conclusions

In the present study, we show how quitting rules in visual foraging search tasks change (or do not change) during development, from age 4 to adulthood. Children as young as 4–5 years of age show approximately optimal quitting behavior as defined by Charnov’s Marginal Value Theorem. Other results from these foraging tasks replicate previous work on response times, error rates, and efficiency in the use of strategies during search from previous developmental studies of visual search. Foraging tasks allow us to extend developmental study to decision rules governing quitting / “patch-leaving” behavior. The results of the present study using foraging tasks show that adult-like quitting rules in search seem to operate quite early in development (as early as 4–5 years old), suggesting that those rules are quite basic aspects of human cognition.

#### Context Paragraph

The present study is part of a long-lasting research collaboration between Beatriz Gil-Gomez de Liaño lab (UAM) and Jeremy Wolfe’s lab (BWH-Harvard Medical). The aim was to study visual search in children and adolescents (within a MINECO/FEDER grant in Spain), since the literature has shown inconclusive results and few studies within a developmental viewpoint (see Gil-Gómez de Liaño et al., 2020; PBR; as part of this project). Hybrid Foraging has been an interesting task in adults within our research interests (see Wolfe et al., 2019 and Wolfe, 2013). At the moment we started, there were no other foraging experiments with children, and the studies currently published after we started this project did not pay attention on quitting rules in search. For us, functioning of quitting rules is a key question to understand visual search in our daily life (Wolfe, 2013). Then, a bigger project within the EU (Marie Skłodowska-Curie Actions: FORAGEKID 793268) was framed as a new way to understanding those rules and executive function development during childhood. We studied hybrid foraging in a more realistic context where observers can decide when it is time to leave the search from a developmental viewpoint.

#### Funding

This work was supported by the Research Grant Project PSI2015–69358-R (MINECO/FEDER) “Ministerio de Economía y Competitividad” (MINECO), and “Fondo Europeo de Desarrollo Regional” (FEDER), given to Beatriz Gil-Gómez de Liaño as PI. Also, part of the research of this study was done thanks to the Fulbright Commission, and the European Union’s Horizon 2020 research and innovation program, Marie Skłodowska-Curie Actions, under grant FORAGEKID 793268, also granted to Beatriz Gil-Gómez de Liaño at the University of Cambridge, Universidad Complutense de Madrid and BWH-Harvard Medical School, and by NIH EY017001 given to Jeremy M. Wolfe.

#### Acknowledgments

The authors are grateful to Public Schools of Madrid, Spain, Principe de Asturias School and Los Ángeles School, and Corazón Inmaculado de Madrid (Spain) Charter school for their help in data collection. Also, we would like to thank María Quirós-Godoy, Chiara Castelletti, Nieves Pérez-Mata, Patricia Díaz Baena, and Ignacio Sifre for their assistance during data collection, comments, and suggestions on the present work.

## References

- Anderson, P. (2002). Assessment and development of executive function (EF) during childhood. *Child Neuropsychology*, 8(2), 71–82. <https://doi.org/10.1076/chin.8.2.71.8724>
- Bella-Fernández, M., Suero-Suné, M., & Gil-Gómez de Liaño, B. (2021). Foraging behavior in visual search: A review of theoretical and mathematical models in humans and animals. *Psychological Research*. <https://doi.org/10.1007/s00426-021-01499-1>
- Bird, D. W., & Bliege Bird, R. (2002). Children on the reef. *Human Nature*, 13, 269–297. <https://doi.org/10.1007/s12110-002-1010-9>
- Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, 10, 433–436. <https://doi.org/10.1163/156856897x00357>
- Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, 9, 129–136.
- Cho, J., & Chong, S. C. (2019). Search termination when the target is absent: The prevalence of coarse processing and its intertrial influence. *Journal of Experimental Psychology: Human Perception and Performance*. <https://doi.org/10.1037/xhp0000686>
- Chun, M. M., & Wolfe, J. M. (1996). Just say no: How are visual searches terminated when there is no target present? *Cognitive Psychology*, 30, 39–78.
- Ehinger, K. A., & Wolfe, J. M. (2016). When is it time to move to the next map? Optimal foraging in guided visual search. *Attention, Perception & Psychophysics*, 78, 2135–2151.
- Gil-Gómez de Liaño, B., Quirós-Godoy, M., Pérez-Hernández, E., & Wolfe, J. M. (2020). Efficiency and accuracy of visual search develop at different rates from early childhood through early adulthood. *Psychonomic Bulletin & Review*. <https://doi.org/10.3758/s13423-020-01712-z>
- Gioia, G. A., Isquith, P. K., Guy, S. C., & Kenworthy, L. (2000). Test review behavior rating inventory of executive function. *Child Neuropsychology*, 6(3), 235–238. <https://doi.org/10.1076/chin.6.3.235.3152>
- Green, R. F. (1980). Bayesian birds: a simple example of Oaten's stochastic model of optimal foraging. *Theoretical Population Biology*, 18, 244–256.
- Green, R. F. (1984). Stopping rules for optimal foragers. *The American Naturalist*, 123, 30–40.
- Hendrickson, N. K., & McCrimmon, A. W. (2019). Test review: Behavior rating inventory of executive function®, second edition (BRIEF®2) by Gioia, G.A., Isquith, P. K., Guy, S.C., & Kenworthy, L. *Canadian Journal of School Psychology*, 34(1), 73–78. <https://doi.org/10.1177/0829573518797762>
- Hommel, B., Li, K. Z., & Li, S. C. (2004). Visual search across the life span. *Developmental Psychology*, 40(4), 545. <https://doi.org/10.1037/0012-1649.40.4.545>
- Hong, S.-K. (2005). Human stopping strategies in multiple-target search. *International Journal of Industrial Ergonomics*, 35, 1–12.
- Hutchinson, J. M. C., Wilke, A., & Todd, P. M. (2008). Patch leaving in humans: can a generalist adapt its rules to dispersal across patches? *Animal Behavior*, 75, 1331–1349. <https://doi.org/10.1016/j.anbehav.2007.09.006>
- Kleiner, M., Brainard, D.H., & Pelli, D. (2007). What's new in Psychtoolbox-3? Perception, 36, ECVF Abstract Supplement.
- Krebs, J. R., Ryan, J. C., & Charnov, E. L. (1974). Hunting by expectation or optimal foraging? A study of patch use by chickadees. *Animal Behavior*, 22, 953–964. [https://doi.org/10.1016/0003-3472\(74\)90018-9](https://doi.org/10.1016/0003-3472(74)90018-9)
- Kristjánsson, Á., Jóhannesson, O. I., & Thornton, I. M. (2014). Common attentional constraints in visual foraging. *PLOS One*, 9(6), Article e100752. <https://doi.org/10.1371/journal.pone.0100752>
- Lange-Küttner, C., & Puiú, A. A. (2021). Perceptual load and sex-specific personality traits: The impact of the Big Five personality dimensions and the autism quotient on visual search. *Experimental Psychology*, 68(3). <https://doi.org/10.1027/1618-3169/a000520>
- McNamara, J. (1982). Optimal patch use in a stochastic environment. *Theoretical Population Biology*, 21, 269–288.
- Müller-Oehring, E. M., Schulte, T., Rohlfing, T., Pfefferbaum, A., & Sullivan, E. V. (2013). Visual search and the aging brain: Discerning the effects of age-related brain Vol. shrinkage on alertness, feature binding, and attentional control. *Neuropsychology*, 27(1), 48–59. <https://doi.org/10.1037/a0030921>
- Ólafsdóttir, I. M., Gestsdóttir, S., & Kristjánsson, A. (2019). Visual foraging and executive functions: A developmental perspective. *Acta Psychologica*, 193, 203–213. <https://doi.org/10.1016/j.actpsy.2019.01.005>
- Ólafsdóttir, I. M., Gestsdóttir, S., & Kristjánsson, A. (2020). Age differences in foraging and executive functions: A cross-sectional study. *Journal of Experimental Child Psychology*, 198. <https://doi.org/10.1016/j.jecp.2020.104910>
- Ólafsdóttir, I. M., Gestsdóttir, S., & Kristjánsson, A. (2021). Age differences in foraging organization. *Journal of Vision*, 21, 1932. <https://doi.org/10.1167/jov.21.9.1932>
- Ólafsdóttir, I. M., Kristjánsson, T., Gestsdóttir, S., Jóhannesson, O. I., & Kristjánsson, A. (2016). Understanding visual attention in childhood: Insights from a new visual foraging task. *Cognitive Research: Principles and Implications*, 1(1), 18–29. <https://doi.org/10.1186/s41235-016-0016-5>
- Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision*, 10(4), 437–442. <https://doi.org/10.1163/156856897x00366>
- Reynolds, C.R., & Kamphaus, R.W. (2003). RIST Reynolds intellectual screening test. Interpretative manual. Torrance, CA: Western Psychological Services ([In RIST Test de Inteligencia breve de Reynolds (P. Santamaria, & I. Fernandez Pinto, Adapters), 2009, Madrid, Spain: TEA Ediciones].
- Reynolds, C.R., & Kamphaus, R.W. (2004). BASC – Behavior assessment system for children, Second Edition. Interpretative manual. Circle Pines, MN: American Guidance Service. [In BASC-2 Sistema de evaluación de la conducta de niños y adolescentes. Manual de interpretación (J. Gonzalez, F. Fernandez, E. Perez-Hernandez, & P. Santamaria, Adapters), 2004, Madrid, Spain: TEA Ediciones].
- Robertson, S. S., Watanabe, S. E., & Wilbourn, M. P. (2012). Attentional dynamics of infant visual foraging. *Proceedings of the National Academy of Sciences of the United States of America*, 109(28), 11460–11464. <https://doi.org/10.1073/pnas.1203482109>
- Stephens, D. W., & Dunlap, A. S. (2009). Why do animals make better choices in patch-leaving problems. *Behavioural Processes*, 80(3), 252–260. <https://doi.org/10.1016/j.beproc.2008.11.014>
- Stephens, D. W., & Krebs, J. R. (1986). *Foraging theory*. Princeton, New Jersey: Princeton University Press.
- Whiten, A., Custance, D. M., Gomez, J.-C., Teixidor, P., & Bard, K. A. (1996). Imitative learning of artificial fruit processing in children (Homo sapiens) and chimpanzees (Pan troglodytes). *Journal of Comparative Psychology*, 110(1), 3–14. <https://doi.org/10.1037/0735-7036.110.1.3>
- Wiegand, I., Seidel, C., & Wolfe, J. (2019). Hybrid foraging search in younger and older age. *Psychology and Aging*, 34(6), 805–820. <https://doi.org/10.1037/pag0000387>
- Wolfe, J. M. (2013). When is it time to move to the next raspberry bush? Foraging rules in human visual search. *Journal of Vision*, 13(3), 1–17. <https://doi.org/10.1167/13.3.10>
- Wolfe, J. M. (2020). Visual search: How do we find what we are looking for. *Annual Review of Vision Science*, 6. <https://doi.org/10.1146/annurev-vision-091718-015048>
- Wolfe, J. M., Aizenman, A. M., Boettcher, S. E. P., & Cain, M. S. (2016). Hybrid foraging search: Searching for multiple instances of multiple types of target. *Vision Research*, 119, 50–59. <https://doi.org/10.1016/j.visres.2015.12.006>
- Wolfe, J. M., Cain, M. S., & Aizenman, A. M. (2019). Guidance and selection history in hybrid foraging visual search. *Attention, Perception and Psychophysics*, 81(6), 637–653, 2019. <https://doi.org/10.3758/s13414-018-01649-5>
- Wolfe, J. M., Palmer, E. M., & Horowitz, T. S. (2010). Reaction time distributions constrain models of visual search. *Vision Research*, 50(14), 1304–1311. S0042-6989(09)00502-110.1016/j.visres.2009.11.002.
- Zhang, J., Gong, Xue, Fougny, D., & Wolfe, J. M. (2017). How humans react to changing rewards during visual foraging. *Attention, Perception, & Psychophysics*, 79, 2299–2309. <https://doi.org/10.3758/s13414-017-1411-9>