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Information Foraging Across the Life Span: Search and Switch in Unknown Patches

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Abstract

In this study, we used a word search puzzle paradigm to investigate age differences in the rate of information gain (RG; i.e., word gain as a function of time) and the cues used to make patch-departure decisions in information foraging. The likelihood of patch departure increased as the profitability of the patch decreased generally. Both younger and older adults persisted past the point of optimality as defined by the marginal value theorem (Charnov, 1976), which assumes perfect knowledge of the foraging ecology. Nevertheless, there was evidence that adults were rational in terms of being sensitive to the change in RG for making the patch-departure decisions. However, given the limitations in cognitive resources and knowledge about the ecology, the estimation of RG may not be accurate. Younger adults were more likely to leave the puzzle as the long-term RG incrementally decreased, whereas older adults were more likely to leave the puzzle as the local RG decreased. However, older adults with better executive control were more likely to adjust their likelihood of patch-departure decisions to the long-term change in RG. Thus, age-dependent reliance on the long-term or local change in RG to make patch-departure decisions might be due to individual differences in executive control.

Keywords: Information foraging; Rate of information gain; Patch-departure behavior; Cognitive aging; Heuristics; Adaptive behavior

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1. Introduction

Because information is pervasive, often to the point of being overwhelming, search has become an important cognitive process to study for understanding how humans regulate their effort to different resources to achieve their goals. One of the critical questions is when to stop exploiting the current resource to switch to another (Stephens & Krebs, 1986). Search behavior has become an important topic in cognitive science as a framework for understanding performance in a number of arenas, such as simulated foraging tasks (e.g., Hutchinson, Wilke, & Todd, 2008; Mata, Wilke & Hutchinson, 2009), memory search (Hills, Jones, & Todd, 2012), word search (e.g., Chin, Fu, & Stine-Morrow, 2011; Hills, Todd, & Goldstone, 2008, 2010; Payne, Duggan, & Neth, 2007), and Internet search (Fu & Pirolli, 2007). A central focus in this research has been to address the extent to which people switch optimally among resources so as to maximize outcomes (e.g., Hills et al., 2012; Mata, Wilke, & Czienskowski, 2009; Payne et al., 2007).

Information foraging models are predicated on an analogy between human search for information and the way in which animals forage for food in the wild. Information foraging theory has been used to account for how people search for information in external environments, such as the World Wide Web (e.g., Fu & Pirolli, 2007; Hutchinson et al., 2008; Payne et al., 2007; Pirolli & Card, 1999; Wilke, Hutchinson, Todd, & Czienskowski, 2009) and in memory (e.g., Hills, Jones & Todd, 2012; Hills, Mata, Wilke & Samanez-Larkin, 2013; Hills, Todd & Goldstone, 2010). Information, like food, is often clustered into patches (e.g., particular forms of print resources, webpages) that vary in their profitability (i.e., potential yield). In patchy environments, foragers face frequent decisions about whether to continue exploitation of the current patch or to explore by departing the current patch to find resources in other patches. Such decisions must take into account a tradeoff between gaining nutrients from exploiting a patch and consuming energy from exploring for food (e.g., to move among patches). For example, when squirrels forage for berries among bushes, they will start with a particular bush. Food uptake will slow down as fewer berries are left. As the rate of gain (RG) decelerates, it will be ideal for a hungry squirrel to stop exploiting the current bush and to switch to a different bush, which offers the promise of higher initial gain. Hence, switch and uptake are highly connected.

Within the foraging framework, there is an interest in characterizing patch-departure policies. Under the assumption that the forager sequentially visits patches of random profitability, Charnov's marginal value theorem proposed that to maximize overall gain, foragers with perfect knowledge will depart a patch when the marginal RG (i.e., the amount of gain as a function of time) falls below the overall RG in the entire habitat (Charnov, 1976). However, the marginal value theorem only provides the theoretical optimal policy. Important empirical questions inspired by this approach include the extent to which foragers adopt patch-departure policies that optimize gain, and how they monitor the change in RG to guide the implementation of these policies. Optimal policies are difficult to apply in the real world, because foragers do not have perfect knowledge of the patch profitability and are often limited in computational abilities that would be needed to make optimal decisions (e.g., Simon, 1956). Thus, foragers must rely on heuristics.

Stephens and colleagues (Stephens, Brown, & Ydenberg, 2007; Stephens & Krebs, 1986) considered four heuristics that foragers might adopt to make patch-departure decisions: the fixed time rule, the fixed number of prey rule, the "give-up" time rule, and the assessment rule. The first two heuristics suggest that the forager will leave a patch if the time spent or the number of prey encountered in the patch exceeds a threshold; these two rules are typically straightforward and applicable in homogeneous patchy environments. The give-up time rule assumes that foragers depart a patch when the time since the forager has last found a prey (i.e., the give-up time) exceeds some threshold. Finally, the assessment rule (Green, 1984) considers both the time and prey uptake, such that the forager will stay in a patch as long as the accumulation of prey per unit time exceeds some threshold, and will be likely to depart a patch as the time without finding a prey increases. Therefore, foragers will adjust their time to stay in a patch according to the change in the rates of gain.

A rational analysis of information foraging, then, suggests that the time to leave a patch is determined by the expected information gain in the current patch and the cost of moving to a new patch (Pirolli & Card, 1999). For example, Fu and Pirolli (2007) implemented a computational model based on the rational analysis of information foraging theories showing that foragers leave websites when scores reflecting the mean information scent of a web page (i.e., the semantic relevance between information goal and web information) decreases beyond certain thresholds. Generally, in the cognitive search literature, empirical studies have found that the fixed time and the fixed number of prey rules cannot fully explain the variance of patch-departure time (e.g., Hutchinson et al., 2008; Mata et al., 2009; Payne et al., 2007). Furthermore, long give-up time might be a useful heuristic that foragers may terminate search or determine patch-departure when they cannot find a prey for a long time in combination with other heuristics (Harbison, Dougherty, Davelaar, & Fayyad, 2009; Payne et al., 2007). Instead, the assessment rule seems to be the most applicable policy to explain variance in patch-departure time among young adults (Payne et al., 2007; Wilke et al., 2009), with a body of research suggesting that people adjust time allocation to changes in rates of information uptake. For example, learners often selectively allocate their attention to materials as long as they perceive themselves to be learning, and disengage if they perceive their rates of learning to decrease below a threshold (e.g., Metcalfe, 2002; Metcalfe & Kornell, 2005). Older adults, who show slower rates of information uptake (Hartley, Stojack, Mushaney, Annon, & Lee, 1994; Stine & Hindman, 1994), also tend to disengage from sentence processing with relatively less thorough analysis of the meaning (Christianson, Williams, Zacks, & Ferreira, 2006; Stine-Morrow, Shake, Miles, & Noh, 2006).

Heretofore, research in cognitive search and information foraging has relied primarily on methodologies that enable the study of patch-departure policies at the level of the individual, in which researchers predict the patch-departure time between participants as a function of the available cues. With increasing indirect evidence that the foragers leave a patch as the RG drops (e.g., Payne et al., 2007; Wilke et al., 2009), there is little understanding of the dynamic relationship between the trajectory of gain and the patch-departure decision. In this study, we focused on the moment-to-moment change in the RG and its impact on search by examining behavior at the level of serial events within an individual. We used a word search puzzle paradigm (e.g., Chin et al., 2011; Payne, Duggen & Neth, 2007), in which participants were asked to maximize the number of items found across a set of four puzzles on an iPad. One puzzle was visible at a time and participants switched between puzzles at liberty, within a given time limit (see Fig. 1). With this paradigm, we were able to examine the patch-departure policy at both the macro (individual) level and the micro (event) level to understand how foragers with different cognitive profiles made use of cues representing the change in RG during exploitation to depart the patch and initiate search. In fact, individual differences in information foraging have rarely been investigated. Aging brings changes in both processing capacity and knowledge (Beier & Ackerman, 2005) that would likely impact both uptake rates and exploratory behavior. Older adults have been found to be less explorative in information search in decision making (Mata & Nunes, 2010) and web information search (Chin, Fu, & Kannampallil, 2009), and to show lower information uptake rates. However, the reasons for reduced exploration among older adults are unclear, with little empirical research examining age differences in patch departure policies. Therefore, our two major research questions in this study were as follows: (a) Do younger and older adults adopt a policy consistent with the marginal value theorem in switching between patches? (b) What cues do younger and older adults use to switch?

2. Method

2.1. Participants

Sixty-one participants were recruited from the community. Four participants (three young, one old) were excluded due to technical problem or failure to comply with the

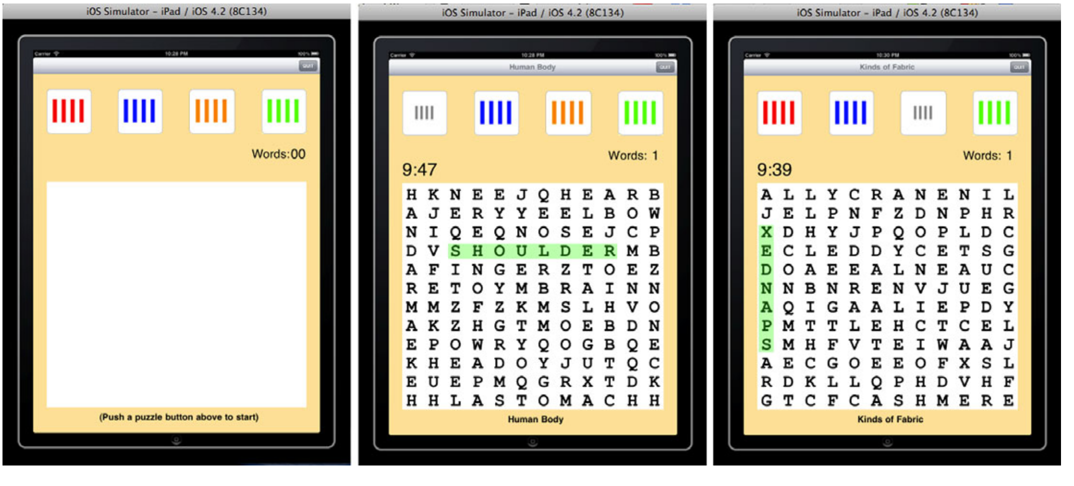

Fig. 1. Layout of the word search puzzle experiments.

instructions. Among the remaining 57 participants, 28 young adults (19 female) and 29 old adults (20 female) contributed data to the analysis. Descriptive statistics for variables characterizing the younger and older samples are presented in Table 1. All participants had graduated from high school. There was no age difference in the frequency of iPad use ($t(55) = 0.62$, $p = .54$). Young adults used computers more often than old adults ($t(55) = 2.78$, $p < .01$), and old adults did word puzzles more often than young adults ($t(55) = -2.81$, $p < .01$). Older adults were higher than the young on verbal ability (ETS Advanced Vocabulary; Ekstrom, French, & Harmon, 1976), but surprisingly, there were no age difference in executive control, measured as a composite score by averaging standardized scores of working memory and fluency (reading span; Stine & Hindman, 1994; FAS verbal fluency; Spreen & Strauss, 1998; verbal: $t(55) = 4.91$, $p < .05$; executive control: $t(55) = 0.79$, $p = .44$; r (working memory, verbal fluency) = .26, $p < .05$).

2.2. Materials

We manipulated profitability, or ease of finding words, to examine how participants interact with the patches of unknown properties. Ease was operationalized in terms of word orientation and prototypicality of category membership. Easy puzzles contained mostly high-prototypical category exemplars in canonical orientations in the puzzle (forward, down, diagonal); hard puzzles contained mostly low-prototypical exemplars in any orientation. There were three sets of four puzzles in the study, representing three experimental conditions: (a) the Easy set, containing four easy puzzles; (b) the Hard set, containing four hard puzzles; and (c) the Mixed set, containing two easy and two hard puzzles. Each puzzle had 16 words from a different semantic category. Measurement of exemplar prototypicality was based on category norms from Van Overschelde, Rawson, and Dunlosky (2004), in which prototypicality was indexed as the proportion of participants generating the word when given the category; the mean prototypicality of words was higher in the easy than in the hard puzzles ($F(1, 10) = 20.82$, $p < .001$). There were no differences in the mean log word frequency (Balota et al., 2007, $F(1, 10) = 0.69$,

Table 1
Descriptive statistics of participants

Measure	Mean (SD) Younger Adults	Mean (SD) Older Adults
Age	19.79 (1.23)	70.57 (6.33)
Education (years)	14.46 (1.47)	16.40 (3.52)
% of people used iPad at least three times a week	10.7%	10.3%
% of people use computer and Internet daily	100%	72.4%
% of people do word puzzles more than once a month	10.7%	31%
Working memory (WM)	4.15 (1.08)	3.46 (0.68)
Fluency	15.10 (3.23)	16.48 (3.87)
Executive control (composite of WM and fluency)	0.17 (1.65)	−0.16 (1.54)
Verbal	6.88 (2.53)	10.78 (3.39)

p = .42) or mean word length (F(1, 10) = 0.20, p = .66) between items in the easy and hard puzzles.

Prior to completing experimental conditions, there was a baseline puzzle that participants worked on for 5 minutes without the opportunity to make switches. The baseline puzzle contained 20 animal names in any orientation. The rate of information gain (RG) in the baseline puzzle was our measure of individual differences in information uptake.

The interface for the word search puzzle was programmed on an iPad (see Fig. 1). Participants first saw the interface with four colored buttons. Each button referred to a puzzle with words from a different semantic category. Participants could press any of the four buttons to start the experiment, at which point, a countdown timer of 10 min started (located in the upper left corner). A word search puzzle appeared with its category name shown on the top and bottom of the interface. Participants saw one puzzle at a time and used their fingers to swipe the words they found. The found words were highlighted in a different color and remained highlighted during the whole session. The number of words found in each puzzle was indicated by a counter at the upper right corner (but participants did not know the number of words remaining in the puzzle). During the experiments, participants could press the buttons to switch to the other puzzles at liberty. In the Mixed condition, the order of buttons of easy and hard puzzles was counterbalanced. Every meaningful touch (such as button touch, letter touch) on the iPad was recorded with timestamps.

2.3. Experimental design

The experiment followed a 2 × 3 mixed factor design with the between-subject variable, age (young vs. old) and the within-subject variable, task condition (Easy vs. Mixed vs. Hard). The order of the three task conditions was counterbalanced across participants. In data analysis, we also broke out performance into the easy and hard puzzles within the Mixed condition, in a 2 (Puzzle Difficulty: easy, hard) × 2 (Context: mixed, not mixed) design, to examine the effects of puzzle difficulty and how these effects varied as a function of whether the foraging environment offered patches that were uniform or variable in profitability.

2.4. Procedure

At the beginning of the experimental session, participants completed the battery of cognitive instruments after the consent process. Participants then practiced locating words in the puzzles and switching among puzzles for 10 min. After the practice, participants performed the baseline word search puzzle for 5 min. After a brief break, every participant completed three sets of four puzzles in a counterbalanced order. Each experimental condition (set of four puzzles) took 10 min. Participants were asked to maximize the total number of words found across all four puzzles and were told explicitly that some puzzles might be easier than others. Participants were not told how many words were available, but that they could go back and forth among the four puzzles, spending as much time in each puzzle as they liked. Participants were debriefed at the end.

3. Results

3.1. Search performance

The total number of words found in each condition is presented in Table 2. Younger adults found more words than older adults across all the conditions ($F(1, 55) = 35.37$, $p < .001$). The most words were found in the Easy condition, then the Mixed condition, followed by the Hard condition ($F(2, 55) = 191.78$, $p < .001$). Age differences in performance did not vary across condition ($F(2, 55) = 0.82$, $p = .45$).

However, younger and older adults varied in the extent to which they found words on their first encounter (Bout 1) versus successive encounters (Bout > 1) with the puzzles (Fig. 2). A 2 × 2 × 2 mixed design Analysis of Variance (age × ease × mixed or not) revealed a significant three-way interaction ($F(1, 54) = 6.29$, $p < .05$). Older adults generally relied more on persistence on the initial puzzle to find items, except when difficult puzzles were in the Mixed condition ($t(27) = 2.10$, $p < .05$). Interestingly, this is the condition in which persistence is least likely to pay off as it creates an opportunity cost for exploring the more profitable easy puzzles. In contrast, younger adults took differential advantage of the opportunity to revisit puzzles to increase the number of items found.

3.2. Age differences in rates of information gain (RG)

Nonlinear mixed effects modeling was conducted to estimate rates of information gain (RG) in the different puzzles using PROC NLMIXED in SAS. RG was defined as the cumulative number of words found as a function of time with data modeled based on 2-s intervals. Because participants generally found more words in their initial attempt to at each puzzle (see Fig. 2), modeling the cumulative gain by collapsing multiple attempts to the puzzles would underestimate their uptake performance. Therefore, for uptake behavior, we modeled cumulative gain for the first attempt to the puzzles only. We modeled gain within each puzzle type, yielding four models. Because the increment in number of words found over time showed exponential growth, we modeled the *cumulative number of words*, Y, with two parameters, *rate of change*, β_{1i}, and *asymptote*, β_{0i}, on i time bin (2-s time interval), as in formula (1). Given individual differences in rates of change, we decomposed this parameter into a fixed effect, γ, and a random effect, U, to estimate the average group performance as well as within-subject variance, as in formula (2).

Table 2
Mean (SD) number of total words found in each condition

	Mean (SD)			
	Easy	Mixed Easy	Mixed Hard	Hard
Young	38.93 (6.35)	20.14 (3.00)	11.71 (3.51)	23.39 (7.40)
Old	29.24 (6.95)	15.9 (3.99)	7.41 (3.62)	15.72 (6.15)

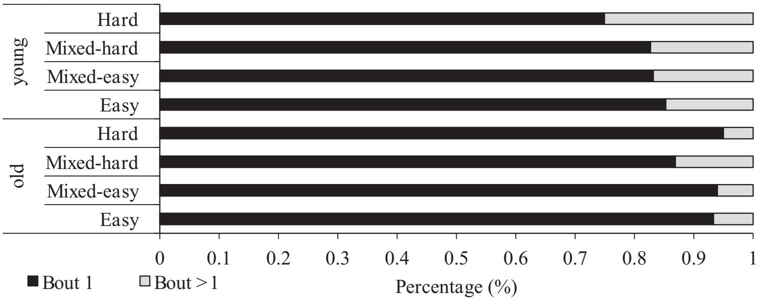

Fig. 2. Age difference in the percent of words found as a function of attempts at the same puzzle, comparing gain in the first bout with gain in successive bouts.

$$Y = \beta_{0i} - (\beta_{0i}\mathrm{EXP}(-\beta_{1i}\mathrm{Time})) \tag{1}$$

$$\beta_{1i} = \gamma_1 + U_{1i} \tag{2}$$

Table 3 provides the estimates and *t*-values for the rate of change parameters (β_{1i}) for easy and hard puzzles within different conditions. Results showed that the RG was modeled well with the exponential growth function. There was significant random variance in rates of change in the easy puzzles in both consistent and mixed conditions showing interindividual variability when the task was easy. For hard puzzles, the rate of change was also significantly fit well with the exponential growth model. The lack of random variance in the difficult condition suggests that participants may have been at a functional floor in the hard puzzles. The exponential functions of RG are plotted in Fig. 3.

The best linear unbiased predictors (BLUPs) of the rate of change (β_{1i}) were extracted for each participant for each of the four models, as the indices of RG. A 2 × 2 × 2 mixed design Analysis of Variance (age × ease × mixed or not) was used to examine the effects of puzzle type and age on RG. As expected, RG was higher in the easy puzzles than in the hard ones ($F(1, 54) = 807.73$, $p < .001$). Moreover, RG was higher for mixed sets than for consistent sets ($F(1, 54) = 726.05$, $p < .001$), especially for older adults ($F(1, 54) = 4.59$, $p < .05$). Perhaps surprisingly, while the difference in RG for

Table 3
Exponential growth parameters for each kind of puzzle

	Easy		Mixed Easy		Mixed Hard		Hard	
	Estimate	*t*	Estimate	*t*	Estimate	*t*	Estimate	*t*
Fixed effects								
	0.009	30.11*	0.012	27.52*	0.005	13.00*	0.0009	3.82*
Random variance								
	0.000003	2.89*	0.00001	4.34*	0.00000001	−0.53	0.000000004	1.1

Note. *$p < .0001$.

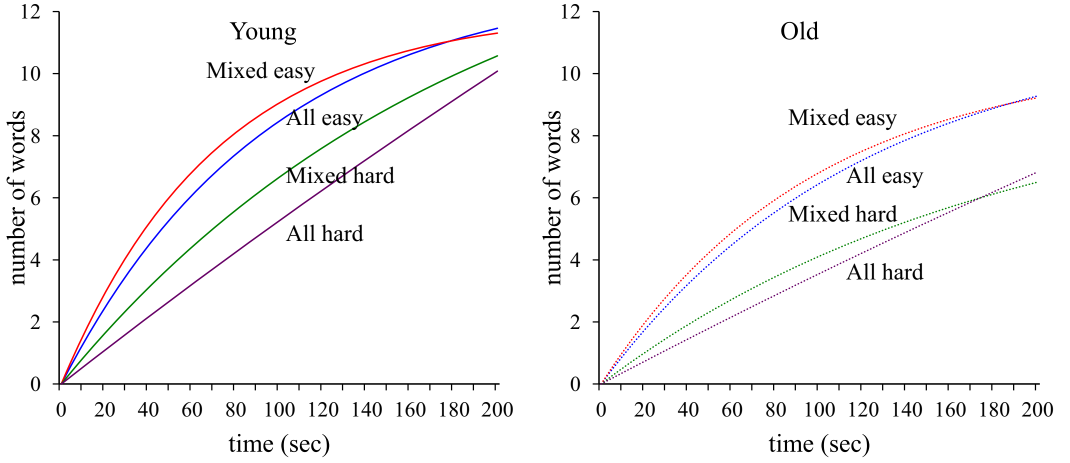

Fig. 3. Age differences in rates of information gain of easy and hard puzzles across conditions.

hard puzzles between mixed sets and consistent sets was equivalent for younger and older adults, the difference in RG for easy puzzles was larger for older than younger adults, showing that older adults experienced a differential advantage of mixed sets in uptake of easier puzzles ($F(1, 54) = 6.56$, $p < .05$).

3.3. *Macro analysis of age differences in switching*

We first examined the subject-level switching behavior as the Macro analysis. A 2 × 3 mixed design Analysis of Variance (age × condition) was conducted on the number of switches in the Easy, Mixed, and Hard conditions. There was a main effect of condition showing that people switched more often in the all hard condition ($M = 9.55$, $SE = 0.69$), then the mixed condition ($M = 8.61$, $SE = 0.53$), followed by the all easy condition ($M = 7.78$, $SE = 0.55$; $F(2, 55) = 5.21$, $p < .01$). Collapsing across conditions, younger adults ($M = 11.42$; $SE = 0.72$) switched more often than older adults ($M = 5.87$, $SE = 0.71$; $F(1, 55) = 30.39$, $p < .001$). The age differences in switches did not differ by condition ($F(2, 55) = 1.09$, $p = .34$).

Given that younger and older adults experienced different RGs and that switch behavior is hypothesized to depend on perceived deceleration in RG (e.g., Charnov's marginal value theorem), we reasoned that perhaps younger adults switched more often because their higher RGs would allow them to more easily detect deceleration in uptake. If that were true, individual foragers with higher switch rates should also be those with higher RGs. We tested this by estimating the RG from the *baseline puzzle* to predict frequencies of switch in the experimental sets of puzzles. The RG in the baseline puzzle was estimated using the same model (1) as the experimental puzzles, with the BLUPs for rate of change used in the analysis (Estimate of rate of change = 0.003, $t = 13.72$, $p < .001$; random variance of RG = 1.85, $t = 60.94$, $p < .001$).

The RG in the baseline puzzle was significantly correlated ($p < .05$) with the RGs in the experimental puzzles in the Easy ($r = .63$), Mixed easy ($r = .65$), and Hard ($r = .54$) puzzles, suggesting that RG is a reliable individual characteristic of foragers.

Multiple regression was conducted to examine the effects of age, RG, and their interaction on the number of switches in the experimental condition. In Model 1, Age and RG were entered as predictors, ($F(2, 54) = 13.47$, $p < .05$), $R^2 = .31$, and in Model 2, the interaction term was added, ($F(3, 53) = 11.75$, $p < .05$), explaining an additional 6% of the variance, $R^2 = .37$. As shown in Table 4, whereas RG did not have an overall effect on switching behavior, a significant Age × RG interaction suggested that there were age differences in the extent to which RG predicted the frequency of switch. The interaction term was decomposed into a simple regression of number of switches onto rate of change separately for younger and older adults (Preacher, Curran, & Bauer, 2006). Younger adults whose rates of change were higher tended to switch more (B = 4.99, $SE = 2.26$; $t(53) = 2.21$, $p < .05$), but for older adults frequency of switch was unrelated to the rate of change (B = −2.60, $SE = 2.29$; $t(53) = -1.26$, $p = .21$). In other words, younger adults who found words more quickly also switched more often, demonstrating a generally more flexible approach to alternating between search and switch; however, older adults made a similar number of switches regardless of individual differences in RG.

3.4. Marginal value theorem and empirical switch patterns

According to the marginal value theorem, the best patch-departure time is given by the marginal value—the time at which the marginal RG is equal to the mean RG in the entire habitat (Charnov, 1976). This theorem of optimality, of course, assumes that the forager has perfect knowledge of the average RG across patches in the habitat and is a perfect monitor of the current RG. In our study, the task was designed as a patchy environment with different puzzles (patches) in one condition set (habitat) with variable rates of gain. Following the analytic framework of Hills et al. (2012), we first analyzed the extent to which people followed the marginal value theorem, and then tested whether using the marginal value theorem was beneficial in our task given that foragers were unlikely to perfectly represent the profitability of the habitat or perfectly monitor their uptake. We divided the current interitem search time for successive words (IST; the amount of time

Table 4
Regression modeling the effects of age and rate of gain on number of switches

	Model 1		Model 2	
	β	*t*	β	*t*
Age	−0.53	−4.14*	−0.54	−4.46*
Rate of gain (RG)	0.06	0.66	0.08	0.66
Age × RG			−0.26	−2.42*

Note. Age and rate of gain were standardized to eliminate the collinearity among variables.
$^*p < .05$.

spent between finding successive words) by the mean IST of the cumulative items in that condition set up to the current item (Hills et al., 2012). Assuming that RG is high when the patch is initially encountered and then decelerates with time in the patch (cf. Fig. 3), it would be expected that the ratio between item IST and mean IST (cost of the current item relative to the average cost of an item in the habitat) would start off at some value less than 1 and then increase with time in the patch. When this ratio equals 1, it implies that the forager is at the point at which the cost (time) of finding the most recent items is equal to the average cost of items in the habitat. According to the marginal value theorem, this is the optimal point at which to make a switch. It is advantageous to stay when the ratio is smaller than 1 (i.e., the current item IST is shorter than the mean IST of the condition). On the other hand, it is advantageous to leave when the ratio is bigger than 1, which represents when the RG decelerates below the expected RG of the condition.

Fig. 4 shows the ratio between item IST and mean IST as a function of order of words found relative to switching. Both younger and older adults showed an increase in the ratio with time in the patch, and consistent with the marginal value theorem, both groups left the patch once the ratio exceeded one, however, relative to the predictions of the marginal value theorem, both groups left the puzzle late. The ratio of the last word before switch (word$_N$) was considerably larger than 1 for both younger and older foragers, suggesting that people left the puzzle when the IST of the last word exceeded the expected IST of the corresponding condition. In other words, people tended to leave the puzzle when the RG decelerated much more than the theoretical optimum. Given marginal value theorem, people should have left the puzzle one or two words prior to their current switch points (i.e., word$_{N-1}$ or word$_{N-2}$).

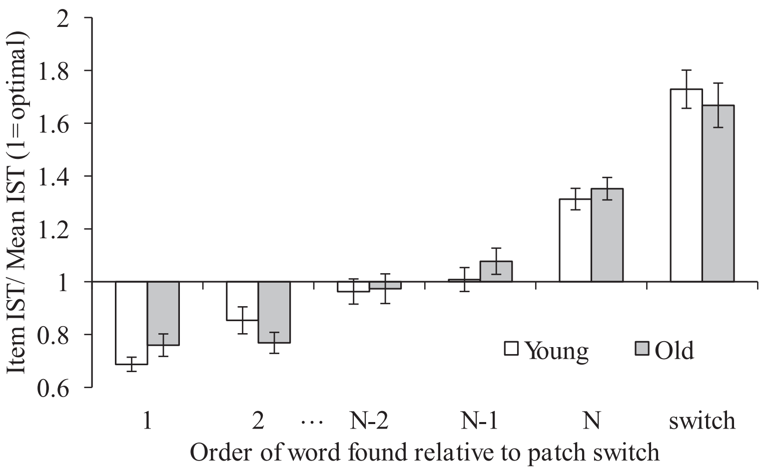

Fig. 4. The mean ratio between interitem search time (IST) for an item and the participants' mean IST over the entire task, as a function of the order of word found relative to puzzle switch for younger and older adults. 1, 2, $N-2$, $N-1$, N implied the first, second, last third, last second, and last word people found in a puzzle, respectively. Switch is the give-up time divided by the mean IST.

Given the imperfect knowledge of empirical foragers, it remained an open question as to whether it is suboptimal to deviate from the search policy implied by the marginal value theorem in the current task. Multiple regression was conducted to examine the effects of age and deviation from the theoretically optimal policy suggested by the marginal value theorem (absolute deviation between last item IST and mean IST, as operationally defined by Hills et al., 2012) on word search performance (i.e., total number of words). In Model 1, Age and Policy Deviation were entered as predictors ($F(1, 55) = 26.46$, $p < .05$), $R^2 = .48$, and in Model 2, the interaction term was added ($F(3, 53) = 19.54$, $p = .07$), explaining an additional 2% of the variance, $R^2 = .50$. As shown in Table 5, the marginal interaction between age and policy deviation suggested that the theoretical optimal policy did not predict the search outcome equally for younger and older adults. We decomposed the interaction into simple regressions of absolute deviation between last item IST and mean IST onto search performance separately for younger and older adults (Preacher et al., 2006). As Fig. 5 showed, the closer the younger adults were to following the optimal policy suggested by the marginal value theorem, the better their performance was (B = −2.07, $SE = 0.66$; $t(53) = -3.13$, $p < .01$). However, this association was nonsignificant for older adults (B = −0.51, $SE = 0.48$; $t(53) = -1.07$, $p = .29$); task performance among the old could not be predicted by adherence to the theoretical optimum as defined by the marginal value theorem. Therefore, younger and older adults not only switched differently according to their rates of gain but also obtained differential advantages to adjust their switch relative to the long-term RG in the task. Thus, the analysis in the next section explores individual differences in patch-departure policies that to some extent could account for age-related differences in overall performance.

3.5. Micro analysis on age-dependent predictors of switch decisions

The macro (subject-level) analysis of switching behavior examined the general inclination of patch-departure of an individual in response to his or her changes in rates of gain. However, for each individual, the likelihood of patch-departure may vary across the time course of search (as well as the changing profitability of the patches). Therefore, we

Table 5
Regression modeling the effects of age and deviation from the theoretically optimal policy on word search performance

	Model 1		Model 2	
	β	*t*	β	*t*
Age	−0.53	−4.96*	−0.49	−4.63*
Absolute deviation between last item IST and mean IST	−0.29	−2.70*	−0.37	−3.24*
Age × absolute deviation between last item IST and mean IST			0.19	1.84†

Note. Age and absolute deviation between last time IST and mean IST were centered to eliminate the collinearity among variables.
$*p < .05$, $^{\dagger}p = .07$.

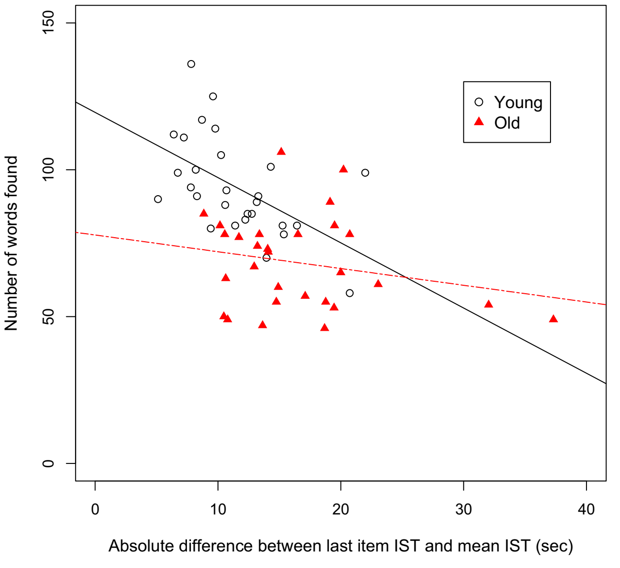

Fig. 5. The relationship between a participant's deviation from the marginal value theorem policy for patch departures and his or her total number of words found for younger and older adults. IST, interitem search time.

included the micro analysis to look at the item-level (moment-to-moment) switching behavior under each subject in addition to the macro (subject-level) analysis. The micro analysis was conducted to accomplish two aims that have not been addressed in previous literature: (a) identify how the moment-to-moment changes in rates of gain influence the immediate likelihood of patch departure, and (b) explain why younger and older adults switch at different time points. Previous research has used Cox proportional hazards regression to examine the contributors to patch-departure decisions (e.g., Hutchinson et al., 2008; Wilke et al., 2009). This technique can reveal factors that influence the likelihood of departure between patches, but it is unable to test the change in likelihood of patch-departure within a patch. Instead, generalized linear mixed models, such as multilevel logistic regression, can estimate the effects of individual differences and different decision rules on the likelihood of patch-departure over time, which can be used to capture the moment-to-moment dynamics of the interaction between the RG and switch decisions.

We used SAS PROC GLIMMIX to fit multilevel logistic regression models to examine the likelihood of puzzle departure based on different cues representing the change in RG over time for younger and older adults. As described above (e.g., Charnov, 1976), foragers are expected to leave the patch when the marginal RG drops to the average RG. Therefore, as the RG decelerates during the visit to a patch, the likelihood of departing a patch would be expected to increase. In the current search task, there were two kinds of events foragers experienced, word finding or switching, which would be followed by two kinds of decisions, exploitation (i.e., to continue finding words in the current puzzle) or exploration (i.e., to depart the current puzzle and switch to a new puzzle). To start the analysis, within each patch, we calculated the time for each event, finding a word or switching to a different puzzle (i.e., give-up time). The marginal rate of the events was computed (i.e., the marginal RG for each word and the inverse of give-up time for each switching event), and the dependent variable was the binary outcome, staying in or departing the puzzle.

First, participants did not use simple rules, such as fixed time, fixed number of prey, or give-up time, to make patch-departure decisions solely. The time people spent on each puzzle (fixed time) and the give-up time of each puzzle were not able to explain the age differences in patch-departure (fixed time: $t = -1.88$, $p = .06$; give-up time: $t = -1.61$, $p = .11$); the number of words people found in each puzzle (fixed number of prey) could not even explain the patch-departure behavior in this task ($t = 0.07$, $p = .94$). Although Green's assessment rule seems like a plausible decision rule that foragers may follow (e.g., Payne et al., 2007), it did not prove to be a useful proximal cue that adults used to switch to other patches. Therefore, we created cues to represent the change in RG which adults may adopt to monitor their uptake behavior for making patch-departure decisions. We examined whether different cues reflecting long-term change or local change in rates of information gain contributed to the patch-departure decisions. While some literature has assumed that foragers are able to measure time (and, therefore, rate) to make patch-departure decisions (Charnov, 1976; Stephens & Krebs, 1986), we assumed that there might be individual differences in the way foragers perceive the passage of time and relative uptake. Thus, indices of long-term and local change in RG were created based on the change in time and rate of information gain in the patch. We examined whether adults used these proximal cues for determining their time to switch, as suggested by assessment rules.

3.5.1. *Age differences in the use of incremental and local cues*

The results of these analyses are reported in Table 6. First, we fit a baseline model to verify that both younger and older adults were more likely to leave a puzzle as the elapsed time in the puzzle increased. There was no age × cumulative time interaction, suggesting that both age groups are equally likely to depart a patch as the time accumulates.

Then, we created two measures of cues to represent the long-term and local change in RG. Long-term change in RG is a continuous update of the "uptake experience" in the environment for learning the characteristics of the patch. We called this cue an "incremental cue," reflecting the deceleration in RG incrementally with the search. The incremental cue was defined as: (time of event$_N$−time of event$_{N-1}$)/(average time between event$_1$ up to event$_{N-1}$), where N is the current event. To take advantage of this cue, foragers would have to monitor the time of the most recent event relative to all events in the current patch. A large ratio implies that the current event takes much longer time than the preceding events. Therefore, the incremental cue to depart a given puzzle to explore a new one is when the ratio becomes larger.

Contrary to the incremental cue, a "local cue" reflects the local change in RG relative to the most recent experience in the patch. Unlike a strategy of monitoring and making patch department decisions based on incremental cues, a local cue strategy neglects past uptake experiences in the patch, except for the latest event. The local cue was defined as: (marginal RG at event$_N$)/(marginal RG at event$_{N-1}$), where N is the current event. If the ratio is small, this indicates that the marginal RG at current word is slower than the marginal RG at the previous word. Thus, the local cue to depart the puzzle is when this ratio becomes smaller.

Note that the long-term change in RG used time per item as the measure instead of the rate because the evidence showed that adults were not able to monitor the rates in a longer term as rate being a potentially more complex construct to update/learn over time.[1] The incremental and local cues were computed for each participant per patch, which captures the moment-to-moment change in RG for different individuals.

To model the effects of incremental cues on patch-departure decisions for both younger and older adults over time, we conducted a logistic mixed effects model on the likelihood of patch departure, including a random intercept across subjects. In addition to the fixed effects of cumulative time, age, incremental cue, and their interaction terms, the model also estimated the random variance of cumulative time across subjects, assuming that participants would vary in their time spent in each patch. Results showed a significant interaction of age × incremental cue and a marginal interaction of age × cumulative

Table 6
Generalized linear mixed models for the use of incremental and local cue strength for younger and older adults over time

	Baseline		Incremental Cue		Local Cue	
BIC	2,720.96		2,671.00		2,687.65	
	Estimate	*t*	Estimate	*t*	Estimate	*t*
Age	−0.06	−0.32	0.17	0.72	0.23	1.05
Cumulative time	0.027	11.05*	0.023	7.63*	0.023	7.91*
Age × Cumulative time	−0.003	−1.88	−0.004	−2.05*	−0.004	−2.18*
Predictor						
Incremental cue			−0.014	−0.18		
Age × Incremental cue			−0.11	−2.28*		
Cumulative time × Incremental cue			0.0007	1.00		
Age × Cumulative time × Incremental cue			0.0008	1.72†		
Local cue					−0.24	−2.43*
Age × Local cue					−0.144	−2.64*
Cumulative time × Local cue					0.002	2.39*
Age × Cumulative time × Local cue					0.0007	1.96*

Note. Incremental cue of event$_N$ (which can be either to stay for exploiting the next word or to leave for exploring a new puzzle) is the ratio between the (time of item$_N$ − time of item$_{N-1}$) and the average time from event$_I$ to event$_{N-1}$ (i.e., the time to find current word divided by the average time to find the first word till the previous one word) in the current patch. Local cue of event$_N$ is the ratio between the marginal rate of gain at event$_N$ and the marginal rate of gain at event$_{N-1}$ (e.g., the rate of current word divided by the rate of previous one word).
*$p < .05$. $^{\dagger}p = .08$.

time × incremental cue on the likelihood of patch-departure after controlling the likelihood of patch-departure increasing over time (i.e., the effect of cumulative time; Table 6). Younger adults were more likely to leave the puzzle than older adults when the incremental cue became larger. In addition, younger adults were influenced by this incremental cue earlier than older adults in the task. These interactions, plotted in Figs. 6A,B,

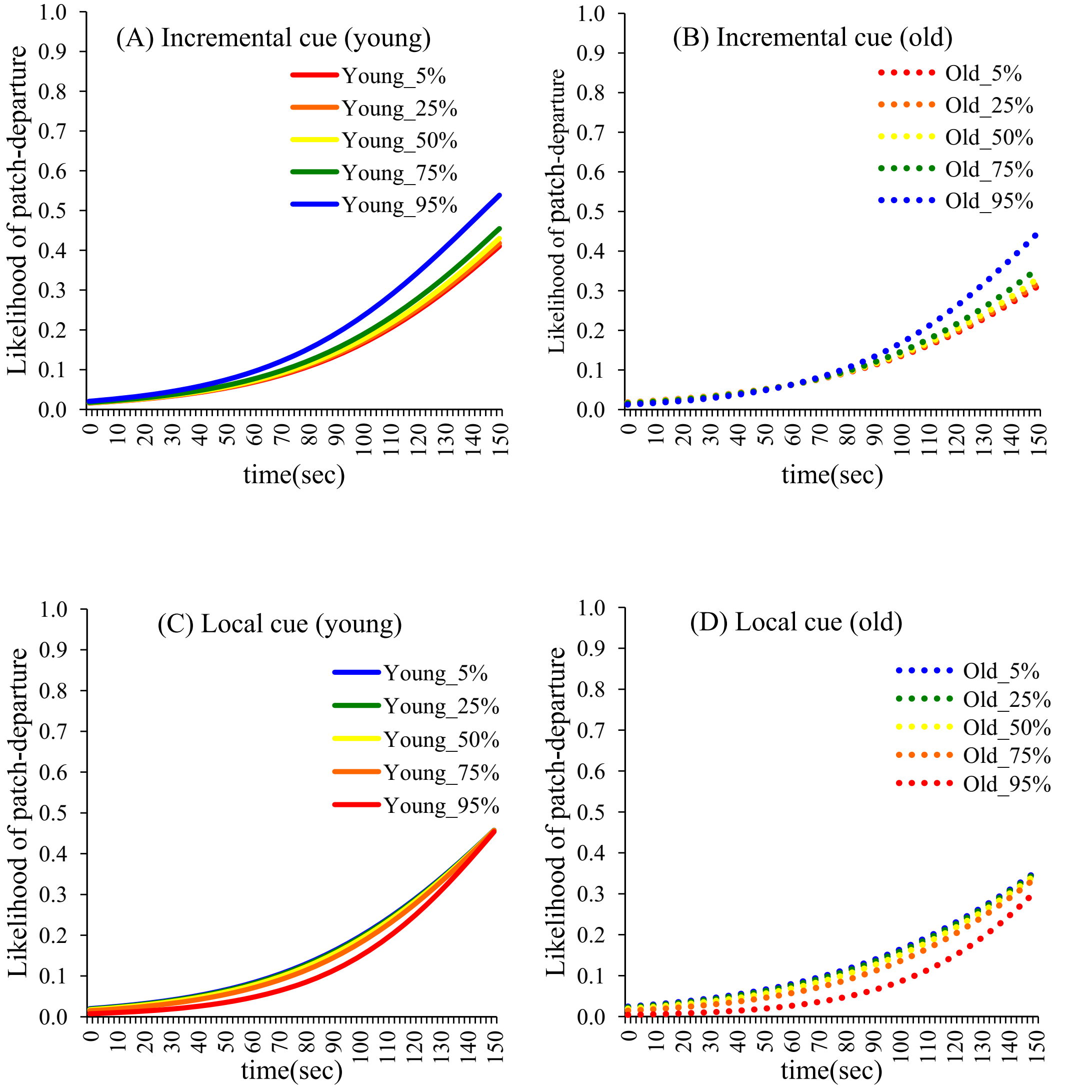

Fig. 6. Age differences in the use of incremental and local cues over time. (A) and (B) showed that younger adults adjusted their likelihood of patch-departure according to the incremental cue earlier in the search, whereas older adults less relied on the incremental cue to make the patch-departure decisions until the late stage. (C) and (D) showed that older adults relied on the local cue more than the younger adults over time. Percentiles show the size of incremental and local cue, which adults should leave a patch when the incremental is large or when the local cue is small.

show that younger adults were increasingly more likely to leave the puzzle as the cue of long-term change in RG declined at an earlier stage of search, compared to older adults. Older adults, in contrast, did not change their likelihood of puzzle departure in response to the incremental cue until the later stage of search. Therefore, younger adults were more sensitive to the long-term change in RG earlier in the task, which led to earlier and more frequent switch of younger adults.

To model the effect of local cues on patch-departure decisions, we conducted the same logistic mixed effects model with the random intercept of cumulative time on the likelihood of patch-departure (Table 6). As expected, there was a significant age $\times$ local cue interaction and age $\times$ cumulative time $\times$ local cue interaction on the likelihood of patch-departure (Figs. 6C,D), suggesting that older adults were more likely to depart a puzzle when the local cue became smaller over time. However, younger adults did not change their likelihood of patch-departure regardless of the size of local cue. In other words, older adults were more sensitive to the local change in RG in adjusting their likelihood of patch-departure, and younger adults were not responding to the local change in RG in terms of the tendency to depart a puzzle.

Given the evidence of age differences in the use of incremental and local cues over time, echoing the macro analysis and the analysis of marginal value theorem policy, the differential use of cues over time explained why younger and older adults switched differently.

3.5.2. The effect of condition on the use of incremental and local cues

From the analysis above, younger adults were likely to react to the long-term change in RG; older adults were likely to react to the local change in RG and may react to the long-term change in RG only at the later stages of search. The next question was whether younger and older adults adjusted their policies according to the contexts (i.e., the difficulty and heterogeneity of the puzzle environments). We examined the effect of condition (Easy, Mixed, Hard) on the use of cues to determine the likelihood of patch-departure over time. For each age group and cue type (incremental and local), the Logistic Mixed Effects Models were conducted on the likelihood of patch departure, with the following predictors: condition (Easy, Mixed, Hard sets), cumulative time, cue strength, and their interaction terms. For younger adults, to adjust their likelihood of patch-departure, they did not react differently to the cue strength across conditions (Incremental cue: comparing Easy to Hard: $t = 0.33$, $p = .74$; comparing Mixed to Hard: $t = 0.51$, $p = .61$; local cue: comparing Easy to Hard: $t = 0.16$, $p = .88$; comparing Mixed to Hard: $t = -1.28$, $p = .20$) over time (Incremental cue: comparing Easy to Hard: $t = -1.42$, $p = .16$; comparing Mixed to Hard: $t = -0.74$, $p = .46$; local cue: comparing Easy to Hard: $t = 0.68$, $p = .50$; comparing Mixed to Hard: $t = 1.46$, $p = .14$). Therefore, younger adults consistently responded to incremental cues on determining the patch-departure decisions across different conditions, and they consistently did not use local cues across conditions. As a result, young adults appeared to switch depending on the same amount of long-term change in RG regardless of the contexts, which previous research also had the same findings showing that adults did not change the policy across different patchy environments (Hutchinson et al., 2008).

For older adults, to adjust their likelihood of patch-departure, they did not react differently to the incremental cues across conditions (comparing Easy to Hard: $t = 1.3$, $p = .19$; comparing Mixed to Hard: $t = 0.34$, $p = .74$) over time (comparing Easy to Hard: $t = -1.76$, $p = .08$; comparing Mixed to Hard: $t = -0.67$, $p = .50$). Interestingly, although older adults reacted to the local cues similarly ($t = -1.04$, $p = .30$) between the constant conditions (Easy and Hard) over time ($t = 0.94$, $p = .35$), they did not use the local cues ($t = 2.43$, $p < .05$) in the mixed condition over time ($t = -2.43$, $p < .05$). The three-way interaction is shown in Fig. 7. While there was large variance among word search puzzles in the mixed condition, local change in RG may not be sensitive to capture the characteristics of the search environment. Hence, older adults may have been *adaptive* in not relying local cue strength given its relative lack of diagnosticity of profitability in the Mixed condition.

3.5.3. Executive control as a moderator of cue use to make patch-departure decisions

Lastly, we examined the potential moderator, executive control, on the use of local and incremental cues of younger and older adults. We adopted the random regression approach, first extracting the regression coefficient of the effect of cue on the likelihood of patch departure for each participant, and then did further analysis with these coefficients (Lorch & Myers, 1990).

Using the coefficients as the dependent variable, we conducted the multiple regression analysis with the predictors being centered age, centered executive control composite score, and their interaction term. Results showed that neither executive control nor the age × executive control interaction could explain the variance in the use of local cue (executive: B = −0.05, $t = -0.37$, $p = .71$; age × executive: B = −0.07, $t = -0.46$, $p = .65$). However, the age × executive control interaction approached significance for the use of incremental cues (B = 0.23, $t = 1.74$, $p = .08$). Younger adults showed a smaller association between executive control and the use of incremental cue strength to switch (B = 0.26), whereas older adults showed a relatively large association between

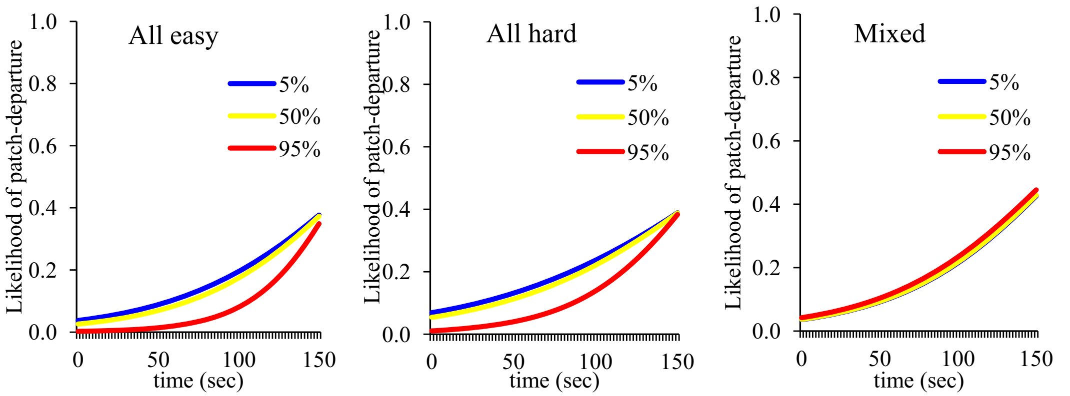

Fig. 7. Older adults less relied on the local cue in the mixed condition than the all easy and all hard conditions. Percentiles show the size of local cue that adults should leave when the ratio is small.

executive control and the use of incremental cue strength (B = 0.49). Although this marginally significant effect must be interpreted with caution, it is possible that executive control moderates older adults' switch strategy, such that older adults with higher executive function more likely to use the cue of long-term change in RG to determine when to switch.

4. Discussion

This study used a word search puzzle paradigm to investigate age differences in information foraging, specifically, information uptake and patch-departure behaviors. Results suggested that both younger and older adults had different rates of information gain as the profitability of puzzles varied. Younger adults experienced higher levels of exponential growth of information gain, which led them to switch more frequently in the task than older adults. Although both younger and older adults were likely to switch as information uptake decreased, their switch behavior was only partially consistent with the marginal value theorem. The likelihood of patch departure did increase as the patch became less profitable; however, foragers of all ages left the puzzles later than the theoretically optimum point across conditions. Furthermore, younger adults were likely to depart a puzzle depending on the long-term change in RG at the earlier stage of search, whereas older adults were likely to depart a puzzle depending on the local change in RG. These differences in use of uptake cues explained the age differences in switch behavior. Executive control was also found to be a potential moderator for older adults to adjust their patch-departure decisions to the long-term change in RG. Overall, this study provided new evidence showing the individual differences in the moment-to-moment dynamics of the interaction between changes in the rate of information gain and switch decisions over time.

Consistent with evidence from information foraging (e.g., Fu & Pirolli, 2007; Pirolli & Card, 1999) and animal foraging (e.g., Stephens & Krebs, 1986), people were sensitive to the diminishing rates of information gain in terms of making patch-departure decisions. However, results showed that adults did not accurately align their performance with the marginal value theorem as suggested by the previous studies (Charnov, 1976; Hills et al., 2012). Instead, people tended to persist in the face of diminishing returns, a strategy which creates an opportunity cost in not exploring for more profitable patches. Even though switches were not optimal, the findings suggested that information seekers tried to follow the rational decision rule, basing their patch-departure behavior on the change in rate of gain. Search is the adaptation to the environment through exploration and exploitation. Therefore, search tasks with different demands may result in modulated search behavior. The observed divergence from the marginal value theorem policy may be due to the different demands imposed by the search tasks. Particularly, the patch quality was relatively unknown to participants. In environments where adults do not have much knowledge about the patch quality, they may adopt a strategy of search using proximal cues, such as change in rates of gain, to estimate the reward structure of the environment and adjust their time allocation accordingly.

Also, the search tasks used in this study allowed participants to return to the prior patch. This feature was designed to represent information search in everyday life when information will likely not be depleted in the patches so that people may go back to the visited resource for obtaining information. For example, people may revisit the same health information webpage several times for obtaining information to meet their needs at different time points. People may learn new things or get new insights each time they reread the same information. Therefore, the current task allowed participants to revisit the puzzles for solving more words. However, the design of this task may be limited by underestimating RG in the first encounter of the puzzle compared to the situation in which participants were required to sequentially search for words in different puzzles. Despite this limitation, the design still enabled us to investigate how participants' decisions to leave a patch depends on the change in uptake behavior in contexts, in which patches varied in fruitfulness.

This study did not try to verify a particular decision rule for adults to make the patch-departure decisions consistently, which is different from prior research of patch-departure policies (Hutchinson et al., 2008). Instead of testing a particular decision rule, the current analysis allowed us to uncover how adults used different cues varying with different time points that led to different likelihood of patch-departure over time. Younger and older adults seemed to adopt strategies that relied on different cues to the change in RG in the search. Younger adults' switch decisions were mainly dependent on the long-term change in RG. In other words, younger adults interactively learned from their search experience about the properties of the patch quality that led to earlier switch. Interestingly, older adults were likely to react to the local change in RG in addition to the long-term change only at the later stage of search. Therefore, older adults were less accurate in terms of updating their RG over time. To support this argument, we also found that older adults with better executive control may be more likely to adjust their switch decisions depending on the long-term change in RG over time. This may suggest that executive control contributed to patch-departure decisions in terms of more accurate time estimation of RG, better updating mechanism of the change in RG, or the bigger span of memory for storing the previous search events over time, etc. Future work should be aimed at identifying the unsolved links between executive control and patch-departure behavior.

The other intriguing finding is that older adults were adaptive in adjusting their use of local cues according to the different task contexts. Like previous research, younger adults were found to use the same strategy regardless of the search environments (e.g., Hutchinson et al., 2008). As patch-departure decisions were mainly influenced by the change in RG from the cumulative experience in the current patch for younger adults, the incremental strategy itself would be sufficient for them to get information about the search environment. However, the reliance on local change in RG for determining the switch decisions may be risky in environments in which patches vary in enrichment, such as the mixed condition. Although older adults were not able to rely on incremental cues as much as younger adults, they were still adaptive in terms of reducing their use of local cues in the mixed conditions. In addition, older adults were less likely to revisit puzzles, which was consistent with the findings of Reader and Payne (2007), who found that readers were less likely to reread passages under time constraints. Given the task constraints in this study, older adults showed adaptation to search tasks in terms of persisting longer within a patch to accumulate information, instead of revisiting the patch. Thus, older adults were less explorative, but still adaptive to the search environments.

Even though diminishing returns shaped search and switch, our findings reinforce the point that foraging is, by its nature, interactive. At the macro level, individual differences in uptake lead to different foraging patterns (e.g., more exploration and less exploitation). At the micro level, the moment-to-moment change in the environments (which is reflected in uptake as well) leads to variation in foraging patterns within an individual. These dual routes of influences, individual differences, and environmental variation interactively build the search process. As suggested by Hills et al. (2008, 2010) search is ubiquitous in cognition and relies on a generalized executive control function that enables self-regulation in patchy environments. We also found robust connections between uptake and switch of search process residing in multiple levels of human behavior. These findings will shed light on the study of individual differences in adaptation to environments with multiple resources, such as in internet browsing. While research in age differences in web search consistently found that older adults browsed fewer pages for figuring out one topic, we found that not only the general slowing made older adults search less but older adults used different cues to make the patch-departure decisions. Thus, the less exploration of information among older population may be due to different perception of change in rate of information gain, which in turn made them persist more on exploiting one information source before exploring new one. However, information gain in the web search and puzzle search is quite different in terms of the process of gain consumption and whether the resource can be depleted. Future research should address how foraging theory can explain the higher level information search behavior.

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Note

1. Rate-based incremental cue (marginal rate at event_N/average rate at event_1 up to event_{N-1}) did not explain more variance than the cumulative time on the likelihood

of patch-departure decisions in the model ($t = -0.11$, $p = .9$), so we chose time-based incremental cue as the predictors in the model.

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