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Information Foraging in the Unknown Patches across the Life Span

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Abstract

This study used a word search puzzle paradigm to examine the effects of task environment and individual differences in ability on information foraging. Younger and older adults attempted to maximize the number of items found in a set of 4 puzzles in which they were at liberty to search within a puzzle or switch between them. Younger adults demonstrated faster uptake (i.e., number of words found as a function of time) from individual puzzles than older adults but experienced more deceleration of rates during the search. Additionally, older adults switched less often and their switching was less dependent on the uptake rate compared to younger adults. Both younger and older adults stayed longer than was optimal in a patch, older adults were especially likely to persevere suboptimally. Collectively, these results suggest that individuals may differentially optimize information gain through self-regulation of exploration and exploitation.

Keywords: Information foraging; information uptake; cognitive aging; adaptive behavior.

Introduction

Self-regulation of cognition in natural environments almost always involves alternating phases of *exploration*, which entails search in the service of deciding how effort will be allocated, and *exploitation*, or task engagement in which effort is allocated to meet task-specific goals. Information Foraging (IF) models are predicated on an analogy between these regulatory processes and the way in which animals forage for food in the wild. Information foraging has been used to account for how people search for information in external environments, such as the WWW (e.g., Fu & Pirolli, 2007; Payne et al., 2007; Pirolli & Card, 1999) and in memory (Hills et al., 2010, 2012). However, even though IF presents a compelling metaphor, there is actually very little empirical research investigating the alignment between IF principles and how people interact with the environment to search and make use of information sources (Metcalf & Jacobs, 2010). There is also little work that has examined how individual differences afford or constrain search in and uptake from information sources. In this study, we used a simple word search puzzle to explore these issues.

According to the IF theory (Fu & Pirolli, 2007; Pirolli & Card, 1999), certain basic properties of animal foraging can be applied to the way human seek and consume information. First, food is distributed in the wild in clusters, or “patches,” that vary in their profitability (i.e., potential yield) and in

their tractability (i.e., how much of an investment of resources is needed for exploitation; e.g., apples on low branches or high branches). Resources in the patch are often finite and unknown to the foragers in advance, though “scent cues” may provide hints about profitability of the patch. Second, as patches become depleted, the rate of uptake decelerates. Third, the forager faces a tradeoff between gaining nutrients from exploiting a patch and consuming energy from exploring for food (e.g., to move among patches). The optimal foraging theory predicts that animals will stay in a patch until the expected rate of gain falls below the overall rate of gain, which takes into account the cost of moving to a new patch (Charnov, 1976; Stephens & Krebs, 1986). Finally, because food is crucial to survival, foragers work to maximize their food uptake and rarely revisit a depleted patch (Stephen, Brown & Ydenberg, 2007; Stephens & Krebs, 1986).

There are similarities and differences between animal foraging and human information foraging. For example, information is often clustered into patches (e.g., particular forms of print resources, webpages), though units of information are often hard to quantify in everyday life. Although information seekers may sometimes find it difficult to estimate profitability and tractability before visiting a patch, they may judge the richness or relevance of information based on their knowledge or expertise. Learners often selectively allocate their attention to materials as long as they perceive themselves to be learning, and disengage if they perceive their rate of learning to decrease below a threshold (e.g., Metcalfe, 2002; Metcalfe & Kornell, 2005). While information seekers have been found to adjust their search behavior to the statistical structures of the task environments (e.g., Fu & Pirolli, 2007), given the limited computational capacity and imperfect knowledge of human beings, the decision to explore a new task or exploit the current one is often suboptimal due to the biased representation of the local environment (e.g., Simon, 1956). For example, Payne, Duggan and Neth (2007) found, in a series of cognitive foraging experiments, that switch decisions could not be entirely predicted by the rate of gain from a patch. Rather, people tended to switch more than optimal without monitoring the real-time change of expected gain. Finally, empirical studies show that information seekers often revisit information patches (e.g. Payne et al., 2007). In fact, unlike food, information will not be exhausted after consumption. Therefore, the benefit of

“revisiting a patch” is particularly ecologically important in information foraging.

Little research has examined adult age differences in foraging behavior. Aging brings changes in both processing capacity and knowledge that would likely impact both uptake rates and exploratory behavior (Beier & Ackerman, 2005). In fact, older information seekers have been found to adopt different strategies to adapt to the environment. Mata, Wilke and Czienskowski (2009) showed that older adults were adaptive to the task characteristics in a fish foraging task, such as staying longer in one pond while between-ponds travel time was high. Interestingly, older adults have been found to search/explore less information but use simple heuristics or knowledge-driven strategies to achieve good performance in decision-making or ill-defined information search tasks (e.g., Chin, Fu & Kannampallil, 2009; Mata & Nunes, 2010). However, older adults’ information uptake behavior in a foraging task has generally received little attention. To investigate information foraging behavior in unknown environments, the goals of the current research were to examine: 1) the effects of task environments and individual differences on information uptake (measured as the rate of information gain), and 2) the effects of task environments and individual differences on the decisions to switch between sources.

Methods

The word search puzzle paradigm was modified from previous research (e.g., Chin, Fu & Stine-Morrow, 2011; Experiment 4 in Payne, Duggen & Neth, 2007). Participants were asked to maximize the number of items found in a set of 4 word search puzzles on an iPad. One puzzle was visible at a time and participants switched between puzzles at liberty, with a 10-minute limit (See Figure 1).

Participants

Sixty-one participants were recruited from the community. Four participants (3 young, 1 old) were

excluded due to technical problem or failure to comply with the instructions. Among remaining 57 participants, 28 young adults (Mean Age = 19.79, SD = 1.23; 19 female) and 29 old adults (Mean Age = 70.57, SD = 6.33, Range = 62-85; 20 female) were analyzed. All participants had graduated from high school. There was no age difference in the frequency of iPad use ($t(56)=0.55$, $p=0.59$). Young adults used computers more often than old adults ($t(56)=2.83$, $p<.01$), and old adults did word puzzles more often than young adults ($t(56)=-2.63$, $p<.05$). Older adults had better vocabulary than younger adults as measured by the Advanced Vocabulary Test (Ekstrom et al., 1976) ($t(56)=-4.77$, $p<.001$). On the other hand, younger adults had better working memory than older adults, as measured by Reading Span task (Stine & Hindman, 1994) ($t(56)=2.87$, $p<.01$).

Materials

The 4 puzzles, each containing 16 words from a different semantic category, were presented in three conditions: all easy, containing mostly high-prototypical category exemplars in canonical orientations in the puzzle (forward, down, left-right diagonal); all difficult, containing mostly low-prototypical exemplars in any orientations; and mixed (2 easy, 2 difficult). 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; there was significant difference in the mean prototypicality of words in the easy and hard puzzles ($F(1,10)=20.82$, $p<.001$). There were no differences in the mean log word frequency (Balota et al., 2007, $F(1,10)=0.69$, $p=.42$) or mean word length ($F(1,10)=0.20$, $p=.66$) between items in the easy and hard puzzles. Thus, given that the words in the easy puzzles were easier to generate from semantic memory and in a canonical orientation, they were more likely to “pop-out” than those in the hard puzzles. While controlling the density of the easy



Figure 1. Layout of the word search puzzle experiments

and hard puzzles, we manipulated the profitability of the puzzles to see if participants were effective in monitoring their uptake rates.

The interface for word search puzzle was programmed in iPad (see Figure 1). Participants first saw the interface with four colored buttons. Each button referred to a puzzle of different semantic category. Participants could press any of the four buttons to start the experiment. When the participant pressed any of the four buttons, a countdown timer of 10 minutes started. 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 different colors and remained highlighted during the whole session. Participants could check the number of words they found in each puzzle on the right corner, but would not know the number of words remaining in each puzzle. During the experiments, participants could press the button to switch to the other puzzles. In the mixed condition, the order of buttons of easy and hard puzzles was in counterbalanced order. Every meaningful touch (such as button touch, letter touch) on the iPad was recorded with time stamps.

Experimental Design

The experiment followed a 2 x 3 mixed factor design with between-subject variable, age (young vs. old) and within-subject variable, task condition (all easy vs. mixed vs. all hard). The order of the three conditions was counterbalanced across participants.

Procedures

At the beginning of the experiment, participants completed cognitive measures after the consent process. Participants then practiced locating words in the puzzles and switching among puzzles for 20 minutes. After the practice, participants performed the experimental task. Each condition took 10 minutes. Participants had been told explicitly that some puzzles might be easier than others, and they could go back and forth among four puzzles and decide how long they want to spend in each puzzle on their own. After all three conditions, the experimenter briefly interviewed the participants about their self-observed search and switch strategies. Participants were debriefed at the end.

Results

A 2 x 3 Repeated Measures Analysis of Variance showed significant main effects of age and condition on the number of words found in each condition (Age: $F(1,55)=35.37$, $p<.001$; Condition: $F(2,55)=191.78$, $p<.001$). Both younger and older adults found the most words in the Easy condition, then the Mixed condition, followed by the Hard condition. Younger adults found more words than older adults across all the conditions. The Age by Condition interaction was not significant (see Table 1). 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 (Figure 2). Older adults tended to find most words in their first bout at

the puzzle, while younger adults tended to find relatively more words in later bouts (i.e., more revisiting), especially in the hard puzzle (Age: $F(1,54)=11.00$, $p<.005$).

Table 1. Descriptive statistics of word search performance

Mean (SD)	Easy	Mixed	Hard
Young	38.93(6.35)	31.86(5.63)	23.39(7.40)
Old	29.24(6.95)	23.34(5.47)	15.72(6.15)

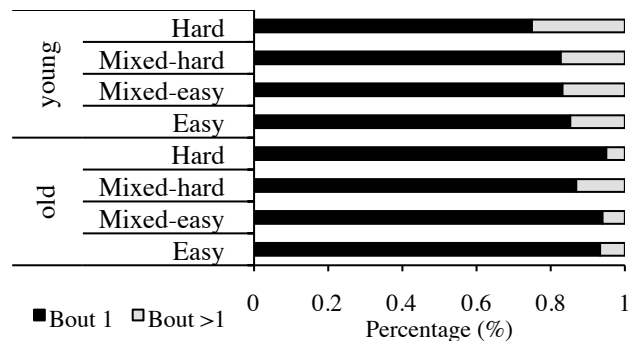


Figure 2. Age difference in the percent of words found in the first attempt

Age Differences in Uptake Rates

Mixed-effects modeling was conducted to estimate uptake rates in the different conditions. Uptake rate was defined as the cumulative number of words found as a function of time with data modeled based on 2-sec intervals. As showed in Figure 2, participants found most words in their first bouts across different conditions; thus, we modeled the uptake rates for the first bout only. There were 37,763 observations in total. Following the growth curve analysis method (Mirman, Dixon & Magnuson, 2008), we started with the

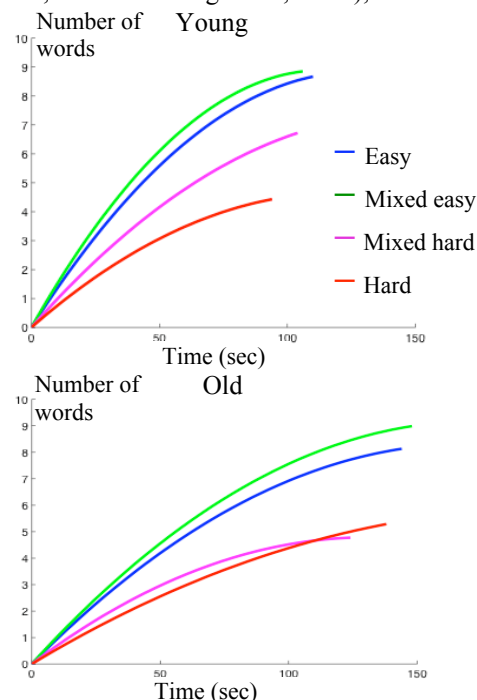


Figure 3. The uptake rates for younger and older adults in different puzzles

“average uptake rate model.” The uptake rate function (cumulative number of words per unit time) was calculated as :

$$Y_{ij} = \gamma_1(\text{time}) + \gamma_2(\text{time}^2) + U_{1j}(\text{time}) + U_{2j}(\text{time}^2) + e_{ij} \quad (1)$$

In (1), Y_{ij} , γ , U , and e_{ij} represented the cumulative number of words, the fixed effects, the random effects of subjects, and the error term respectively. Because we are interested in capturing both the linear and non-linear components of the random effects of subjects, it was divided into: U_{1j} – the linear “rate” and U_{2j} – the non-linear “rate of change”. Then we added fixed effects of age and condition and its interaction terms to the model “conditional uptake rate model”, as follow:

$$Y_{ij} = \gamma_1(\text{Time}) + \gamma_2(\text{Time}^2) + \gamma_3(\text{Age} \times \text{Time}) + \gamma_4(\text{Age} \times \text{Time}^2) + \gamma_5(\text{Condition} \times \text{Time}) + \gamma_6(\text{Condition} \times \text{Time}^2) + \gamma_7(\text{Age} \times \text{Condition} \times \text{Time}) + \gamma_8(\text{Age} \times \text{Condition} \times \text{Time}^2) + U_{1j}(\text{time}) + U_{2j}(\text{time}^2) + e_{ij} \quad (2)$$

The condition update rate model in (2) was developed to test how uptake rates changed (both linearly and non-linearly) with conditions and age. The model shows that the uptake rate (which measured how quickly subjects found a word in a puzzle) for the easy puzzles was higher than for the hard ones ($F=2377.28$, $p<.001$). Interestingly, the uptake rate for the hard puzzles was higher when they were embedded in the mixed condition with easier puzzles relative to those in the pure condition. This was true for both younger and older adults, suggesting a facilitation effect in the mixed condition, in which there were 2 easy and 2 hard puzzles. Figure 3 showed best fitting curves of uptake rates of younger and older adults in four puzzles to the empirical data. The length of curves represents the mean duration of uptakes (exploitation). As shown in these plots, older adults stayed longer in the puzzle than younger adults.

Younger adults had higher uptake rates than older adults, especially in the easy puzzles (Age x condition x time: $F=108.32$, $p<.001$). Younger adults also showed a larger rate of change, such as quicker deceleration of uptake rate across time, than older adults ($F=16.30$, $p<.001$). The difference in rates of change was larger in the easy, mixed puzzles than the hard ones ($F=93$, $p<.001$). Thus, the uptake rates grew more quickly for younger adults but reached the asymptote quicker (with larger reduction of rates across time) than older adults.

Age Differences in Switch

Given the individual difference in uptake rates across different conditions, we examined whether age differences in uptake rates were related to frequency of switching. A 2 x 3 Repeated Measures Analysis of Variance (Age x Condition) was conducted on the number of switches in the easy, mixed, and hard condition. Younger adults switched more often than older adults in all conditions (Figure 4)

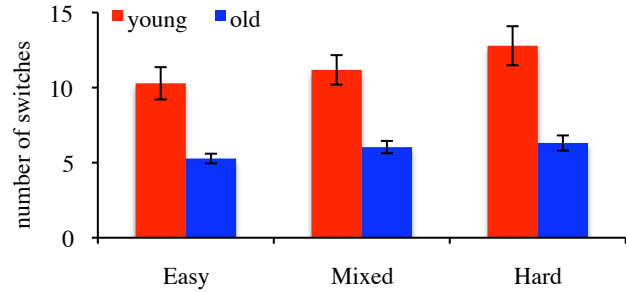


Figure 4. Age differences in number of switches of different conditions

($F(1,55)=30.39$, $p<.001$). There was also a main effect of condition showing that people switched more in the hard condition, then the mixed condition, followed by the easy condition ($F(2, 55)=5.21$, $p<.01$). The Age x Condition interaction was not significant.

Given that younger and older adults experienced different degrees of rates of change, we examined if the age differences in rates of change over time were associated with their switch behavior, and the extent to which they were moderated by individual differences in working memory and verbal ability. We first extracted the best linear unbiased predictors of rates of change from the average uptake rate model (U_{2j}). Then we did a median split on the estimates of rates of change to create two groups – those with uptake rates dropping more and those with uptake rates dropping less. We did a 2 (Age) x 2 (dropping more or less) ANCOVA to examine the relationship between the number of switches and the deceleration of uptake rates across time by treating individual differences in working memory and verbal ability as covariates.

Results showed a significant Age x Rate of change interaction ($F(1,51)=7.21$, $p<.01$) in addition to the effects of age, rate of change, and working memory (Age: $F(1,51)=19.29$, $p<.001$; Rate of change: $F(1,51)=9.87$, $p<.01$; Working memory: $F(1,51)=6.28$, $p<.05$). The interaction of Age x Rate of change on the number of switches was shown in Figure 5. People with more reduction of uptake rates (the dropping more group) across time tended to switch more, and the difference was bigger in younger adults than older adults. In the other words, older adults were less sensitive to their rates of change in uptake—they were less likely than younger adults to switch puzzles as the rate of uptake diminished. On the other hand, younger adults were more sensitive to changes in uptake rates, which led to more switches. Also, the covariates of working memory had association with switch behavior – people with higher working memory capacity tended to switch more often. However, the age-differences in associations between rates of change and switch behavior were shown regardless of the individual differences in working memory.

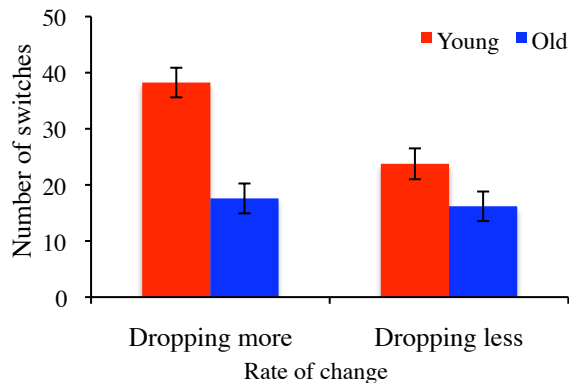


Figure 5. Interaction of age and rate of change on switch

Suboptimal Leaving and Longer Perseverance for Older Adults

Given that younger adults switched more than older adults, and also showed higher uptake rates and rates of change, the next question we addressed was whether younger and older participants switched optimally. According to the optimal foraging theory, the marginal value theorem predicts the optimal patch departure time – the time at which the marginal uptake rate is equal to the mean uptake rate of the entire habitat (Charnov, 1976). We calculated the ratio of marginal uptake rate at each word and the mean uptake rate of the corresponding patch for each participant. The optimal time to switch to a different puzzle is when the ratio equals 1. When the ratio is larger than 1, it is advantageous to stay because the current marginal rate is higher than the average expected return (estimated based on previous experiences). As the marginal value decreases with decelerated uptake rates, the value becomes increasingly smaller than 1, and it is advantageous to switch because the expected uptake from the habitat as a whole exceeds the current marginal value.

Both younger and older adults were suboptimal based on the criterion derived from the marginal value theorem, as they left the puzzle late (Figure 6a). Mean ratio of the last word in the puzzle was smaller than 1, suggesting that the marginal uptake rate of the last word was slower than the mean uptake rate in the corresponding puzzle. Though people tended to leave the puzzle when the uptake rate was low, Figure 6a shows that participants would have been more optimal if they left the puzzle about 2 words earlier (the ratio of the third word back was close to 1). Additionally, among puzzles of different profitability, people tended to switch more optimally in the hard puzzles than in the easier puzzles. This finding suggests that both younger and older adults were more sensitive to the change of uptake rates and switched earlier in the hard puzzle condition (Figure 6b).

While both younger and older adults switched later than was optimal, they persevered differently in the puzzles. Perseverance was measured by the give up time, which was defined as the duration from finding the last word to leaving

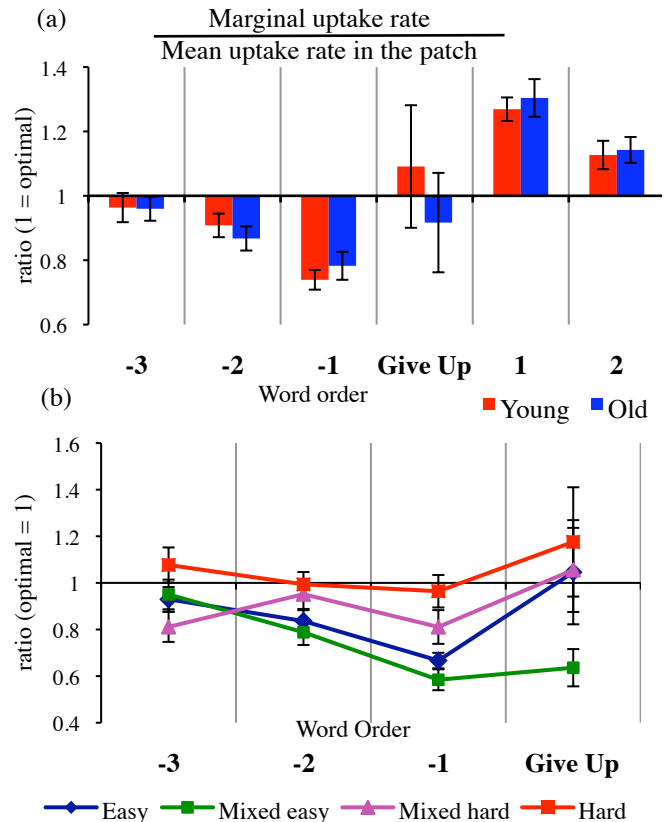


Figure 6. The ratio of marginal uptake rate of the word and mean uptake rate in the corresponding patch for younger and older adults (a) and different puzzles (b)

the puzzle (e.g., Payne et al, 2007) – i.e., the amount of time participants persevere in a patch without finding a word.

A 2 x 4 Repeated Measures Analysis of Variance (Age x Puzzle type: easy, mixed easy, mixed hard, hard) was conducted to explore the effects of age and puzzle type on give up time. Give up time was longer for older adults than for younger adults. In other words, older adults persevered longer in the current patch before moving to a new patch compared to younger adults. Figure 6a also showed that while younger adults tended to persevere for a shorter time than their mean uptake time for the puzzle, older adults tended to persevere longer than their mean uptake time. Furthermore, people persevered longer in the hard puzzles than the easy ones (puzzle type: $F(1,53)=2.55$, $p<.05$; age: $F(1,53)=13.15$, $p<.001$). Interestingly, the give up time in the mixed easy puzzles was relatively longer than the time in the all easy condition, suggesting that participants were influenced by the mixed context.

Conclusion

The study used the word search puzzle paradigm to study the information search behavior of younger and older adults in the patches of different profitability. Although the gain functions of puzzles were unknown to the participants, individuals were able to allocate their effort to uptake and switch when uptake decreased. Older adults showed slower

uptake rates and smaller change of rates than younger adults across different puzzles. Thus, older adults relied less on the deceleration of uptake rates to decide when to switch to a different puzzle. Older adults switched less often and persevered longer in the puzzles, especially in the difficult condition. To maximize the search performance, older adults allocated more time to exploitation (i.e., task engagement in the puzzles) and younger adults did more exploration to the new puzzles than the older adults. Overall, older and younger adults showed adaptive self-regulation patterns through differential attention to exploitation and exploration.

Older adults were found to be less explorative in information search in decision making (Mata & Nunes, 2010) and web information search (Chin, Fu & Kannampallil, 2009), and they explored (i.e., switched to another puzzle) less often in the current study as well. Less exploration might be adaptive given the heavy demands on processing capacities of switching behavior in information search (e.g., Chin et al., 2009, 2011). In addition to the higher switch cost of older adults, results suggested that older adults seemed to use different policies (i.e., less relying on the rates of change) to make switch decision than younger adults. As the optimal foraging model suggests, foragers will leave while the marginal uptake rates is lower than the mean uptake function of a patch. However, given the uptake function of the puzzles were unknown to the participants, people needed to track their uptake behavior after entering a puzzle across time to estimate the expected gain of the puzzle. This process was so information intensive and resource demanding that older adults might experience more difficulty executing which was partly shown in our results. Thus, age differences in learning from experiences in a given information patch and the corresponding patch-leaving policy should be further examined in future studies.

Despite the age differences in switch, both younger and older adults were suboptimal in terms of the later departure time in the patches. Interestingly, past studies also found that foragers were suboptimal in external search task (e.g., Mata et al., 2009), but closer to optimal in memory search (Hills et al., 2012). Hills and his colleagues used cross-modal priming to show that external search patterns can be transferred to internal search patterns, suggesting that there is a central executive control process monitoring both internal and external search behavior. Therefore, the difference of patch-departure behavior in internal and external search task might be due to the fact that foragers have more knowledge about the gain function of a patch in the internal search task than the external search task. Similarly, in the condition of mixed uptake functions, results showed that people were farther away from the optimal (i.e., late departure) in the mixed easy, mixed hard puzzles than the easy and hard puzzles respectively suggesting that the knowledge of a patch might be important to determine the optimal departure in the task.

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