

CHAPTER 4

Dealing with Uncertainty in Resources: Simple Rules for Human Foraging

Introduction

The adaptive problem of finding resources is crucial for all animals. Animals in heterogeneous environments, where resources are distributed in patches, are required not only to make decisions on where to forage, but also on *how long* they should forage in a particular patch (i.e. patch-time allocation). Animals need to decide when it is better to continue foraging in the current patch and at what point it is better to leave and travel to a new one. Consider a parasitoid insect searching for caterpillars on cabbage plants. If the parasitoid has visited nearly all the caterpillars on a plant, staying longer on that plant is wasteful because it would take a long time to find the next unvisited caterpillar: it is better to move to another plant where the initial rate of encounter is higher. Conversely it is wasteful to leave too early, because of the travel costs of finding another plant. What the parasitoid needs is a decision rule timing the moment of departure from the patch based on its previous success on that patch and others.

A patch can be defined as a “local area with relatively high probability of resource encounter surrounded by areas where the probability of resource encounter is at or near zero” (Bell, 1991, p. 11). This means that the travel distances within a patch are smaller than the distances between patches and illustrates why the costs (e.g., energy use or increased predation risk) of travel between patches are usually incorporated into models of patch-time allocation. Patches are usually conceptualized to differ in quality. Rich patches provide a higher initial return per time unit (i.e., capture rate) than poor patches. Foragers upon entering a patch utilize its resources, resulting in depletion over time, and must search for its contents — typically, search for exhaustible and cryptic resources.

Classical optimal foraging theory addresses the patch-time allocation that would ultimately maximize an individual’s fitness by referring to Charnov’s seminal work on the

marginal value theorem (MVT; Charnov, 1976). The theorem states that the *optimal* strategy for each animal is to leave a patch when the instantaneous rate of return (e.g., of food) from the current patch falls below the mean return rate from the environment when following the optimal policy.

When an animal first enters a rich patch, resource gains from exploiting it are high, because there is lots of food present and it is easy to find. As time passes, however, food resources will be depleted and it takes longer and longer to find a food item. Hence, more time is spent searching and less is spent eating. This declining rate of energy gain can be represented by a graph of diminishing returns, because the “marginal value” of the patch decreases and the slope of the graph levels off (see Figure 4.1). When the travel time between patches is taken into account, then the line that gives the maximum long-term rate of energy gain is the line from point *A* that touches the gain curve at a tangent.

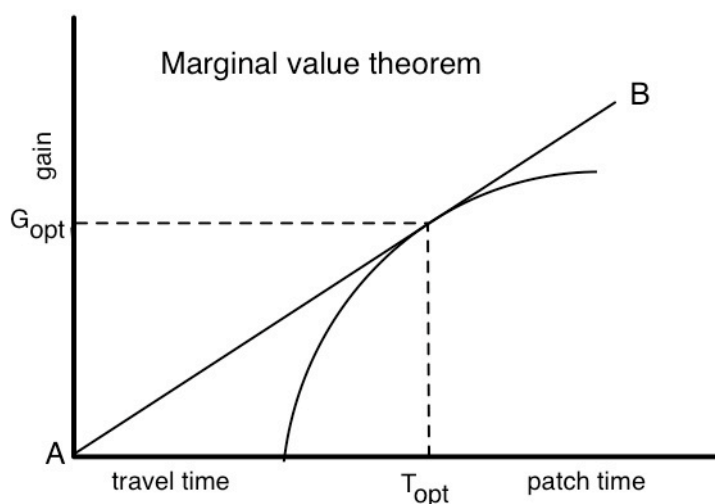


Figure 4.1 The marginal value theorem. The shape of the gain curve arises from resource exploitation; the osculation point of the tangent (*AB*) defines the optimal patch residence time T_{opt} ; derived from Charnov (1976).

Whereas the MVT predicts general phenomena in optimal foraging for which quantitative and qualitative experimental verifications exist, the assumptions about the information constraints that foragers face are often unrealistic. First, animals do not necessarily have complete knowledge of the abundance and distribution of resources in the habitat. To fulfill a crucial assumption of the MVT, animals would need to know the mean net return rate under the optimal policy from the environment. But the problem is, how does the animal acquire that information (or a good estimate of it)? Animals entering a new environment have only incomplete knowledge about this feature, although they might start to estimate it from their

foraging success. This means that an “animal must use a behavioral rule which both learns the parameters and optimally exploits what it has learnt” simultaneously (McNamara & Houston, 1985, p. 231) — a circularity that the MVT does not attend to.

Second, the MVT assumes a continuous and monotonically decreasing rate of energy return. For example, spiders eat their prey by injecting poison into their body and then suck out the juice from their bodies. Along with resource depletion the sucking of juice becomes harder and harder and the spider can estimate how the resource return rate drops. However, for many animals foraging is a succession of *discrete* events. In this case, resources (e.g., food items in a patch) are encountered stochastically and return rates cannot be defined by continuous functions (McNamara, 1982).

Third, the MVT does not link its functional optimality predictions with proximate mechanisms that a forager can use. In continuous foraging the MVT suggests a mechanism that relies on current intake rate as the only cue. However, in the stochastic case, where future return rate is difficult to calculate because the current return rate offers only an inaccurate estimate, the MVT offers no mechanistic solution. What informational cues could an animal obtain while foraging to adjust its patch residence time, and what rules for integrating these cues would perform efficiently? The problem seems complex, but some researchers have proposed simple decision mechanisms, so-called rules of thumb, to model animal patch departure (Bell, 1991; Livoreil & Giraldeau, 1997; Waage, 1979; Wajnberg, Fauvegue, & Pons, 2000) and it has been calculated in what kind of environments each works well (Iwasa, Higashi, & Yamamura, 1981).

Here we propose to look at the same problem for humans: identify and analyze the simple heuristics that people use to decide when to give up on one patch (or task) and move to another. Specifically, we will test whether the heuristic rules that have been proposed as guiding animals in deciding when to leave a patch of food may also underlie human decision making when foraging for physical objects or information (e.g., in memory).

This chapter is organized as follows: In the remainder of this introductory section, we will first provide an overview of some classic papers in the animal literature on simple patch-leaving rules and connect these rules to particular kinds of foraging environments. We will then investigate if (and how) work in anthropology and psychology has addressed the questions of foraging behavior and patch choice in humans. We will conclude the Introduction by outlining our empirical approach to studying human patch-leaving decisions. The second and third sections of this chapter will then each report the design and methodology of a computerized human foraging experiment and the results obtained. The final section will discuss these results.

Simple Rules for Animals in Discrete Foraging Environments

Waage (1979) described a model for how long insect parasitoids decide to remain on a particular patch. Female insect parasitoids, in this case the wasp *Venturia canescens*, look for hosts into which to lay their eggs. The adaptive problem is that the desired hosts, typically other insects, are not evenly dispersed over the habitat, but rather come in patches, in groups of variable size. Since there is a direct link between number of successful ovipositions (i.e., laying of eggs) and fitness, we expect selection for an efficient behavioral mechanism to determine the timing of patch leaving. A constraint is that these parasitoid wasps are very short lived and start reproducing soon after birth, which keeps them from learning the geography of their environment or the profitability of different areas (van Alphen, Bernstein, & Driessen, 2003). Waage (1979) showed how a simple mechanism could model the patch-leaving task (see Figure 4.2a) and fit the experimental data.

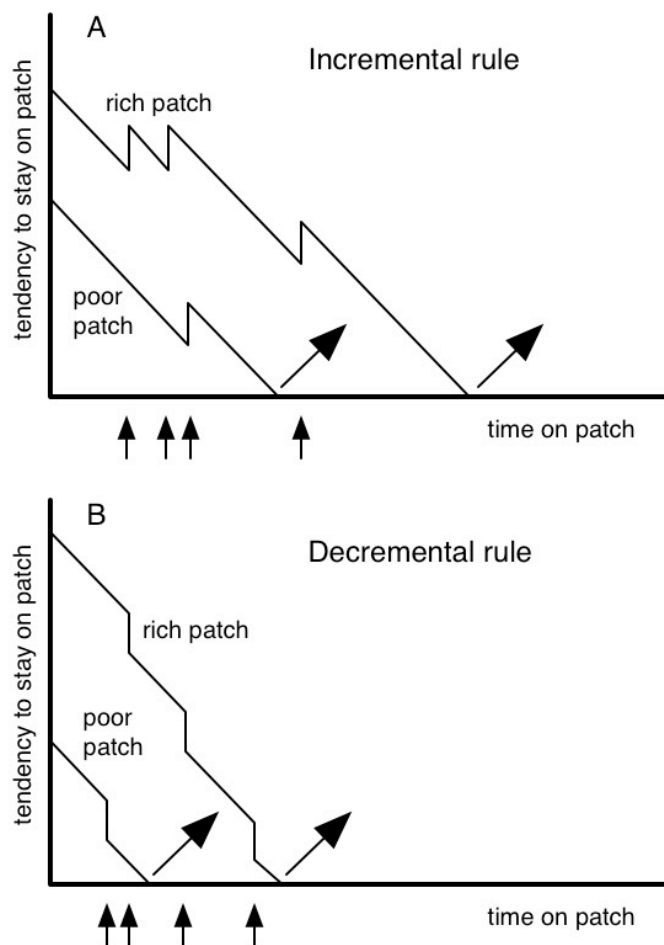


Figure 4.2 A parasitoid is using an incremental mechanism for decision making when each oviposition (indicated by small arrows) increases the probability of staying in a patch (above) and a decremental mechanism when each oviposition reduces the probability of staying (below); adapted from van Alphen et al. (2003, p. 83).

In Waage's (1979) model, an initial "responsiveness" (i.e., tendency to stay in the patch) is set by intensity of kairomone (smell) concentration, which is a good indicator of size of patch and host density. Responsiveness decreases linearly with time spent at a patch, but each successful oviposition alters the waning of this response by adding an increment to the current level. When the level of responsiveness has dropped below a critical threshold, the parasitoid leaves the patch and looks for a new one. Think of clockwork that is wound up a little each time a free host is encountered—when the clock timer eventually expires, the animal leaves the patch. Waage (1979) called this mechanism an *incremental mechanism*.

In some species, however, such as the family of Trichogrammatidae wasps, it has been shown that an oviposition leads to the exact opposite: each successful oviposition of an egg in a host decreases the initial responsiveness (Wajnberg, Gonsard, Tabone, Curty, Lezcano, & Colazza, 2003; see van Alphen et al., 2003 for review). These puzzlingly different results for two closely related parasitoid species can be explained by adaptation to the environment. If there is large variability in patch quality in the environment, then an incremental mechanism for patch departure is most adaptive (see Figure 4.2a). On the other hand, if the number of hosts is rather evenly distributed across the patches (or the parasitoid is well informed about patch quality), as is true for the Trichogrammatidae wasps, then a *decremental mechanism* performs best (see 4.2b): If you know (roughly) how many items there are, then all you have to do is count down each time you find an item and leave as soon as the count falls below a threshold. Thus, the distribution of hosts determines the optimal mechanism (Iwasa et al., 1981; Driessen & Bernstein, 1999; Wajnberg et al., 2000).

In other work on patch-leaving rules, Krebs, Ryan, and Charnov (1974) claimed that the black-capped chickadee's (*Parus atricapillus*) search for mealworms on artificial pinecones could be modeled with a *giving-up-time rule*, (i.e., the tendency to stay in a patch declines with unsuccessful search, and it is reset to maximum with each resource item found; see Figure 4.3). Interestingly, the birds' giving-up time was nearly constant for all patch types although the amount of food varied among patches.

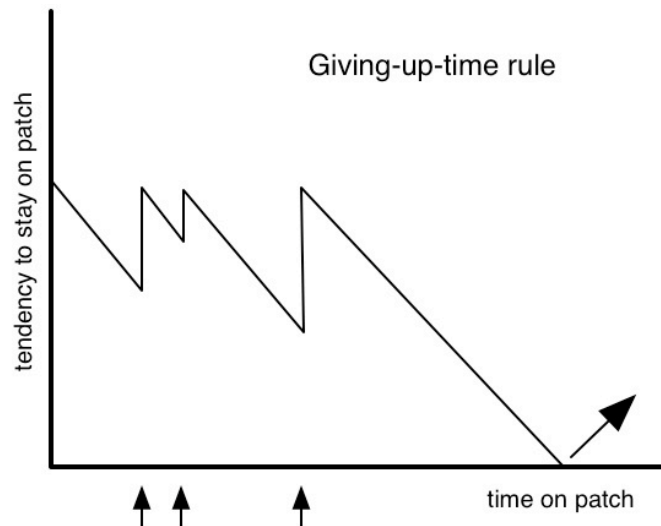


Figure 4.3 The giving-up-time rule. The tendency to stay in patch declines with unsuccessful search, and it is reset to a maximum with each resource item found (indicated by small arrows); adapted from Stephens & Krebs (1987, p. 175).

Along these lines, Iwasa and colleagues (1981) analyzed different possible prey distributions in the environment and investigated their match to particular patch-leaving rules. They compared the giving-up-time rule to two other rules, the *fixed-time rule* (i.e., the forager searches for a fixed period of time in each patch and leaves the patch independent of the number of catches; see Figure 4.4) and the *fixed-number rule* (i.e., the forager leaves the patch when a fixed number of food items has been captured; see Figure 4.4). These rules can be understood as being adapted to different points along an environmental continuum: If there is maximum certainty in the environment (e.g., patches always consist of three items), then a “take- n -items-and-leave-patch rule” cannot be outperformed by any other rule. On the other hand, if the environment follows a Poisson distribution, nothing works better than a fixed-time rule.

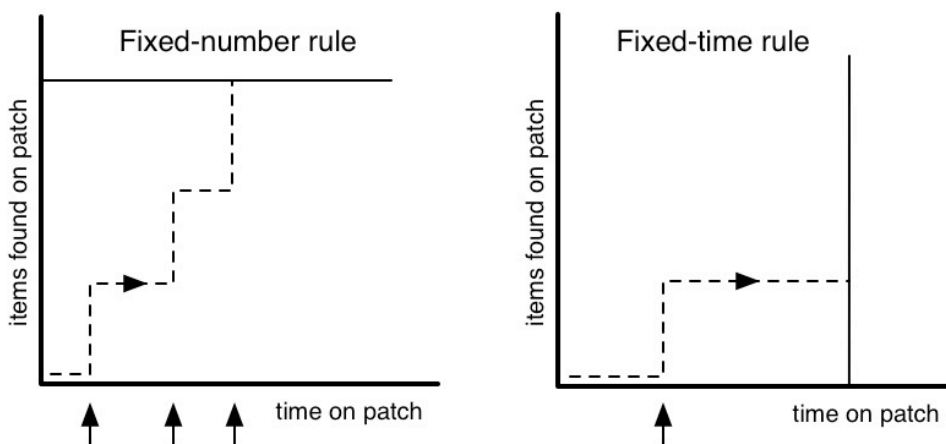


Figure 4.4 An organism is using a fixed-number rule when a patch is left after a fixed number of items have been found (left) and a fixed-time rule when a patch is searched for a fixed time and then left independent of the number of catches (right); adapted from Iwasa et al. (1981, p. 718).

What this explains is that the final performance of these strategies depends on the prey distributions between patches: If variance in the number of prey per patch is high, then the giving-up-time rule and the incremental rule perform well, but if variance is sufficiently low, then the decremental rule or the fixed-number rule outperform them (Iwasa et al., 1981; Stephens & Krebs, 1987). Patches vary in quality and we work on the assumption here that this quality cannot be recognized upon entering a patch. Thus, the information value provided by a prey capture depends on the overall distribution of patch qualities. Stephens and Krebs (1987) explain how:

With a fixed number of prey per patch, each capture tells the forager that the patch is getting worse; with a high-variance distribution, a capture tells the forager that it may have hit the jackpot and it should stick around; and with a Poisson distribution, a capture gives no information about relative patch quality. (p. 174)

Table 4.1 presents an overview of the various patch-leaving rules discussed.

Table 4.1 Patch-leaving rules

Proximate mechanism	Environmental structure to which adapted
<p>Decremental rule Set initial tendency to stay in patch upon entering; tendency decreases steadily with time (e.g., linearly); each successful catch subtracts a decrement from the current level; leave patch when threshold is met</p>	Environments with evenly dispersed distributions (i.e. low variability of patches)
<p>Incremental rule Same as decremental rule, but each successful catch adds an increment to the current level; leave patch when threshold is met</p>	Environments with aggregated distributions (i.e. high variability of patches)
<p>Giving-up-time rule Leave patch if time since last catch exceeds threshold</p>	Environments with aggregated distributions
<p>Fixed-number rule Leave patch when fixed number of items has been captured</p>	Environments with constant numbers of items per patch
<p>Fixed-time rule Search patch for a fixed period of time and leave patch independent of number of catches</p>	Environments with Poisson distributions of items per patch

Note. Patch-leaving rules taken from Krebs et al. (1974), Iwasa et al. (1981), and van Alphen et al. (2003).

The ways in which nature can cause such rules, or mechanisms, to be implemented from an organisms' cognitive and behavioral repertoire are manifold, but a particularly neat way of accomplishing this is provided by the following example. The ladybug (*Coccinella septempunctata*) forages for aphids and determines patch departure indirectly by a simple

regulation of motor activity. Whenever the beetle stumbles upon an aphid, which is an indication that a patch with more aphids might have been hit, it reduces its locomotor rate and increases its turning rate. Doing so, the beetle changes the probability of contacting more aphids. Smaller and more circular movements are taken, resulting in denser search patterns and making the ladybug less likely to leave the current patch. Unless more aphids are found soon, these changed movement measures slowly decay over a period of 30–40 s back to the prefeeding values, bringing the beetle back to a straighter emigration path (Carter & Dixon, 1982).

Human Foraging Behavior in Anthropology and Psychology

Overall, anthropology provides a rich body of findings on foraging decisions among hunter-gatherers (Kelly, 1995; Smith, 1991; Winterhalder & Smith, 1981). However, most of the work deals with environmental variables and how they systematically relate to foragers' diets (e.g., "effective temperature" or "primary production" as predictors for the dependence on gathered vs. hunted foods; e.g. Binford, 1990) or how foragers arrive at subsistence decisions given the available choice of resources. Typical optimal foraging models aiming to explain resource choices include *diet-breadth models* (should a resource, including its search and handling cost, be taken by a forager when he or she encounters it?) and *patch-choice models*. Patch-choice models assume clumpy, random, and sequentially encountered arrangements of resources in the environment and stress what kind of resource patches should be included in the foray. Kelly (1995) suggested that these models are similar to a diet-breadth model in that patches can be ranked in terms of their energetic return, but they differ in that they include the time spent searching a patch for resources to come up with the overall patch return rate. Reasoning according to patch-choice models leads to different patch-harvesting rates and a sequence of behaviors that can be predicted by the MVT, similar to what we saw in the animal literature reviewed above: (1) A forager enters a patch when the net resource-harvest rate is high; (2) resources are then gathered and game is hunted, which means resources decrease; when the point of diminishing returns is reached the forager (or the foraging community) does best by (3) moving on to a new patch (Charnov, 1976).

Some anthropological research has investigated such decisions by emphasizing different types of hunting (Smith, 1991) or by defining *individual resources* as patches (Hawkes, Hill, & O'Connell, 1982). A behavior well documented from observations among the Ache in Paraguay (Hill, Kaplan, Hawkes, & Hurtado, 1987; Hill & Hurtado, 1996) is that exhibited when a particular individual resource is sought (e.g., a peccary) but a different one is encountered

during foraging (e.g., honey or palm larvae). Intuitively, a forager should decide to switch to the resource encountered if it offers higher energetic intake than the one that was originally looked for and this is what was found in the Ache. Although these foraging decisions are related to the problems raised in this chapter, anthropological research on the topic has not addressed patch leaving in terms of actual decision mechanisms.

In contrast to anthropology, psychology offers only a scarce literature on human foraging decisions. Although there is some work on aspects of *information foraging* (e.g. Pirolli & Card, 1999) and perceptual search using visual foraging paradigms (e.g. Gilchrist, North, & Hood, 2001; New, 2001), little research deals with the questions or experimental tasks that we have in mind.

Our species has been called *informavores*, stressing the mass of information humans daily seek and consume (Dennett, 1991). Not surprisingly, researchers have begun to speak of *information foraging* when it comes to humans dealing with a vast quantity of information in everyday life (Pirolli & Card, 1997, 1999). Some have investigated how people's strategies and technologies for information search and consumption are co-adapted with their personal information environments (e.g., work places, desktops, etc.) and the software applications that they use (Pirolli, 2005). In classical food foraging in heterogeneous environments, we find the need to time optimal patch leaving; information foragers' environments can be understood in the same way: Information a forager is looking for comes in variable quantities hidden in different piles of papers, file drawers, bookshelves, libraries or in online data collections all differing in the rate at which they provide information (Pirolli & Card, 1999). Just think of how Internet content tends to come in a patchy structure, in which clusters of some Webpages will be localized (e.g., navigating from one departmental Webpage to the next), but going from one cluster to another one may require more effort (e.g., finding a specific department on the Internet; see also Pirolli, 2005). The problem, time allocation to differing clumps of resources, is identical: Optimal information foragers should maximize the rate of valuable information gained per unit cost, given the constraints of the task environments (e.g., profitabilities of different sources and costs of finding and accessing them). Pirolli and Card (1997) suggested using an evolutionary ecological perspective on information-gathering strategies, "treating adaptations to the flux of information in the cultural environment in much the same manner as biologists study adaptations to the flux of energy in the physical environment" (p. 643).

Recently, two psychologists from Indiana University, Robert Goldstone and Benjamin Ashpole, investigated distributions of groups of human foragers in real-time virtual environments, when the optimal foraging strategy for an individual is not only a function of the

resource distribution and the individual's own movement, but also dependent on the strategies used by others (Goldstone & Ashpole, 2003, 2004). Their work is motivated by a model in biology that explains phenomena of population-level foraging behavior (i.e., the ideal free distribution model; Fretwell & Lucas, 1970), such as groups of animals distributing themselves in a nearly optimal manner, with their distribution matching the distribution of resources (e.g., Godin & Keenleyside, 1984). Goldstone and Ashpole found empirical deviations from the optimal distribution such as that participants underutilized the richer of two resource patches. However, Goldstone and Ashpole's results would have to be analyzed at an individual level to tell us something about the mechanisms involved in assessing patch quality and deciding when to leave one patch for another. Additionally, it is a different problem from ours, because the resources are renewing.

Investigating Simple Foraging Rules in Humans

Researchers at the Center for Adaptive Behavior and Cognition (ABC) have demonstrated that simple heuristics can be very effective, in terms of both frugality and performance, when used to make many kinds of decisions (Gigerenzer & Goldstein, 1996; Gigerenzer, Todd, & the ABC Research Group, 1999; Gigerenzer, 2000), and they have specified the environments in which these heuristics work well (Todd, Fiddick, & Krauss, 2000; Gigerenzer et al., 1999). As we discussed earlier, behavioral ecologists have done similar work on rules of thumb in animals (for a review see Hutchinson & Gigerenzer, 2005). The similarity in these two lines of inquiry should encourage the breaking down of boundaries between disciplines, here biology and psychology, in an approach that can often inform researchers in both fields (e.g., Hertwig & Ortmann, 2001). Therefore, we will take such an approach here as well.

Our focus in this chapter is on the information-processing mechanisms that underlie foraging behavior. More precisely, we are interested in investigating how humans solve the problem of patch departure in environments with variable but discrete resource distributions. We think that humans, like the animals in the studies provided above, can solve the problem of patch leaving by relying on simple mechanisms. We posed this set of general questions:

- (1) What kinds of simple rules do humans use to achieve good foraging efficiency in patchy environments?
- (2) Whereas most animals tend to be specialists and have rules that are adapted to how food naturally occurs in their particular environment, humans are generalists, which means

that we may have evolved to feed on some foods that are evenly dispersed across patches and on some that are aggregated in a few but better patches. Are humans sensitive to this environmental variation and can they adapt their patch-leaving heuristics to the types of environments they face?

- (3) Are the decision rules that people use in spatial search also applied in other search domains? (e.g., as heuristic rules in information search)?

To answer these questions we ran two experiments that differed in whether search was external (e.g., for physical objects) or internal (e.g., for information in memory), but whose environmental parameters (e.g., travel times, mean reward rates) were closely matched.

In the first experiment, our *fishing task*, participants were presented with a virtual landscape on a computer screen allowing them to “forage” at a pond (i.e., a patch). If they stayed they would catch fish at stochastic intervals depending on the number of fish left in that pond; if they chose to leave it would take time to walk to the next pond.

In the second experiment, foraging for fish was replaced by searching for solutions to a *word puzzle*. In a modified anagram search task, people had to generate meaningful words out of random letter sequences. In both tasks, we investigated whether people used simple patch leaving rules of the sort described earlier and whether the rules used differed in environments with differing resource distributions.

Searching the External Environment: The Fishing Task

In the earlier sections we investigated what kinds of proximate mechanisms can model animal patch-leaving decisions (Green, 1984; van Alphen et al., 2003) and how well they work in various types of environments with different prey distributions (Iwasa et al., 1981; Roitberg & Prokopy, 1984). To uncover what decision mechanisms are used by humans in the patch-leaving problem in (discrete) foraging environments, we programmed a behavioral experiment: the fishing task. Therewith, we analyzed participants’ patch-leaving decisions and looked for evidence of the use of the simple rules that have been proposed for animals in analogous environments.

Method

Participants were presented with a virtual landscape in which they foraged for fish in a sequence of ponds and decided on how long to stay at each pond. All ponds appeared to be the same, but

the number of fish in each varied. There was a constant travel time of 25 s between patches (and no other cost). Each participant experienced an evenly dispersed, a Poisson, or an aggregated (i.e., negative binominal) distribution of fish per patch. Thus, different types of leaving rules would perform best in each environment (see Table 4.1 above). We investigated how well the patch-leaving rules participants used in our task matched the ecologically rational patch-leaving rules. Figure 4.5 shows plots of the resource distributions that we used:

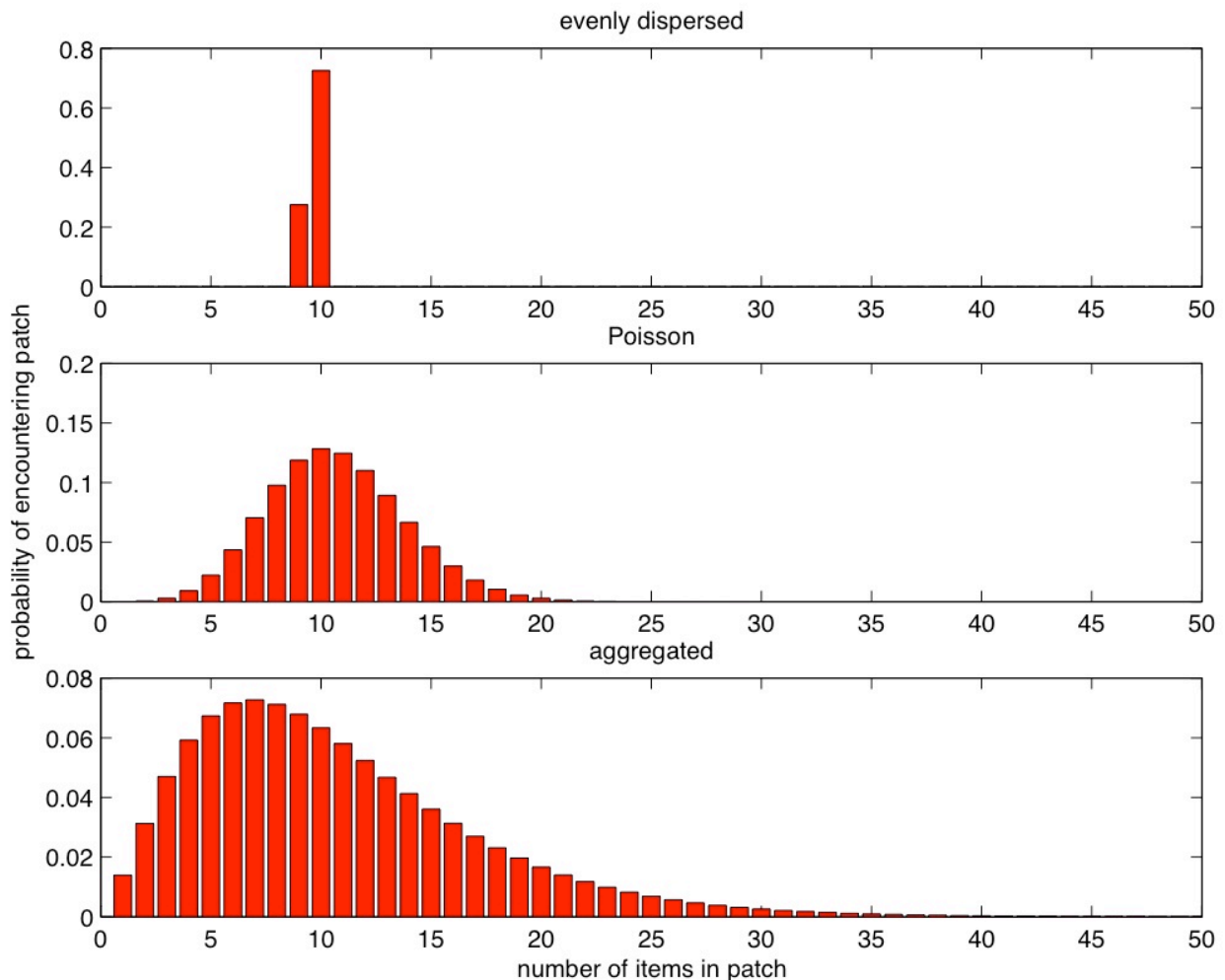


Figure 4.5 Resource distributions for the fishing task. The mean number of items is constant (9.7), but environments differ in their variance (from top to bottom: 0.21, 9.71, and 41.89).

To test whether people adapt to another feature of the environment, we created a fourth environment in which we modified the travel time between patches. In general across environments, participants should leave sooner when travel time between patches is decreased and we tested this by generating a second “aggregated” environment identical to the first in distribution of fish but in which we decreased the travel time from 25 s to 15 s.

In addition to the qualitative process predictions (i.e., which rules would be employed in which environment), we also made quantitative predictions. Specifically, we determined the optimal parameters that each rule should have so that we could compare this against human behavior (see also Hutchinson & Gigerenzer, 2005). For this reason, we calculated the optimal policy in each resource environment with dynamic programming (Houston & McNamara, 1999). These predictions will be given at the beginning of the Results section.

Participants

Participants for the pilot and the main study were recruited using the ABC subject database. All testing took place at the facilities of the MPI. The 100 participants (64 women, 36 men) for the main study were randomly assigned into four experimental conditions of 25 subjects. Each of these experimental conditions reflected one environment. The average age for women was 25 years ($SD = 3$) and for men 27 years ($SD = 3$). Participants were paid at the end of the experiment according to their overall foraging success (i.e., number of fish caught).

Materials

The complete task, including the instructions and a training session, were presented on a computer screen using a specially written computer program (Czienskowski, 2005a). The program recorded the foraging success (e.g., number of captures and misses), the number of visited patches, and the time participants spent at each patch (details about the experiment are given in the next section). The main instructions, identical in all four experimental conditions, informed participants about two main features.

The first feature concerned the appearance of fish within a pond and how participants' foraging success would affect this. Instructions were given that the number of fish in each pond could be variable, that only one fish could appear at a time, and that there was no replenishment: If a fish was caught, it was removed from the total number left in the pond, but if a fish was missed, then the number would stay the same. Additionally, participants were told that the rate at which fish appeared was solely dependent on the number of fish that were left in the pond, but that the exact times when they showed up on the surface were random.

The second feature had to do with moving from one pond to the next. Instructions were given that there were an infinite number of potential ponds to visit, but that participants would not be able to go back to an earlier pond. Participants learned that their one key task—besides capturing fish—was to determine when to switch from one pond to the next. The only clues we gave participants about a good strategy were given by the following text:

The final payout that you will receive depends on the total number of fish that you caught. You will achieve a better outcome (i.e., higher payout) if you avoid two extreme ways of playing: One would be to switch too early; the other would be to stay too long at each pond. For instance, in the former, you would miss a good overall performance due to the costs of the time delay that goes along with clicking the switch pond button.

Procedure

Upon arrival, participants were seated in front of a laboratory computer. The experimenter selected the software's stochastic resource environment, requested participants to turn in their watches and cell phones (so that they would have no access to an external time source), and then left. Participants read through the onscreen instructions at their own speed. They received instructions on how to use the mouse to catch fish and leave patches. Additionally, participants conducted an unpaid training session of 4 minutes to familiarize themselves with the software. This training session was completely identical to the later main experiment (i.e., participants experienced the same resource distribution of fish at these ponds).

At the start of the experimental session, a cartoon-like character with a fishing rod walked into the image on the screen and stopped at the pond. The fishing rod was hauled out and the mouse cursor changed into the shape of a float, indicating that the fisherman was now ready to capture fish (see Figure 4.6).

Participants needed to monitor the pond and forage for fish, which only appeared for a short time interval of 2 s. The rate with which fish appeared was $0.005 \times \text{number of fish s}^{-1}$. Upon clicking a fish with the mouse cursor, it would be caught and automatically moved to the bucket (an animation of 2 s). During this transfer no other fish would appear and no other action could be performed with the mouse. Thereafter, the mouse cursor reappeared at the center of the pond and the algorithm that controls the appearance of fish continued. With each successful catch, a picture of a fish was added to the resource stack (Figure 4.6, right edge). This resource stack, initially empty, was an indicator of the number of fish that had been caught so far in that patch and was the only (visual) feedback participants received about their foraging success. Note that the total number of fish caught at all ponds was used to calculate overall foraging success (and thus the final payout), but that the fish caught at earlier ponds were not shown in the resource stack that built up at each subsequent pond. Each fish was worth € 0.20.



Figure 4.6 Search in the external environment: The fishing task (Czienskowski, 2005a). Screenshot shows the fisherman moving the cursor toward a fish on the surface (top of pond). The resource stack (right side) shows the current foraging success and a switching button (lower right) allows switching to a new pond.

To encourage participants to imagine that they were encountering a series of different ponds, we randomly rotated the pond border and placed some tussocks randomly around it. Other than that, all ponds were the same. Fish had the same size, but their coloring and texture were variable within specific graphical parameters to allow them to be somewhat camouflaged in the color of the background (i.e., the pond surface). This was included so that catching fish would not be too easy and participants would have to remain attentive throughout the task.

To switch a pond, participants had to click a red “switch pond” button (see Figure 4.6, lower right side of screenshot). This would cause the fisherman to leave the screen, followed by a 21 s time delay in which a bouncing-ball animation with a “Please wait!” sign was shown. Another round started with the fisherman marching into the screen, stopping at the fresh pond, and hauling out the fishing rod. The animations for the fisherman walking into and out of the screen each took 2 s so that the total travel time between ponds was 25 s (15 s in the environment with shorter travel time).

After the main experiment, participants filled out two questionnaires. The first was an onscreen questionnaire that was aimed at assessing participants’ experiences with the fishing task and the kinds of information they might have used in the task. Here, we asked them whether they came up with a particular strategy to determine their patch leaving and, if yes, how they would describe it. An additional set of questions appearing on a later screen asked about their

usage of three cues (i.e., number of fish captured, time spent at a patch, and time interval since last capture). All judgments were made on a 4-point scale ranging from 1 (did not use that information at all) to 4 (used that information very often). See Appendix E for details.

The second questionnaire was a short paper-and-pencil instrument assessing clinical depression. Nesse and Keller (2003) had presented their subjects with a virtual foraging task quite similar to our fishing task in which subjects moved a figure on a computer screen among different resource patches. Staying time at these patches did vary along with variation in the rate of depletion of resources and participants got feedback on how many resources they obtained per unit of time. Unlike our research aims—focused on individual foraging performance and the patch-leaving decisions participants make—Nesse and Keller (2003) were interested in giving-up times in general and linked them to the regulation of goal pursuit (e.g., allocating effort among different social goals requiring large investments in the future) since the latter is known to tie in with mental disorders such as depression (see Nesse, in press). Their results indicated that longer staying times in patches went with increased scores on clinical instruments measuring depressive mood, prompting us to give the depression questionnaire (Beck's Depression Inventory; Beck & Steer, 1987) to our laboratory participants and to collect this data as well. In the future, we plan to compare our results with those obtained from a sample of patients suffering from clinical depression; none of these results are included in this chapter.

The duration of the fishing task was about 60 minutes, which included time to work through the instructions, the training session, and the post-experimental questionnaires. The experimental part lasted 45 minutes. However, participants were neither informed about this exact experimental time nor given the time spent at their current patch since relying solely on an “internal clock” should more closely reflect natural foraging situations.

Results

Although some participants occasionally failed to capture fish that appeared, most participants captured all of them. Since the average number of fish that each person missed per patch was smaller than 1 ($M = 0.14$, $SD = 0.39$), we excluded these “miss” events from further analyses.

The upper plot of Figure 4.7 shows the optimal policies for each of the four resource environments. The figure depicts a state space of food items caught and the time spent on the patch. On entering the patch, the forager is always at the origin and moves rightward and sometimes up. When crossing the line defining the policy, the forager should go on to a new patch. In the Poisson environment the optimal policy is an almost vertical line (i.e., stay in each

patch for about 100 s regardless of the foraging success), whereas in the aggregated environment each additional resource capture should increase patch-staying time (see stepwise shape of the solid lines). Note that the line for the Poisson distribution would be vertical were it not for a short time delay after each fish appears when another will not appear (see description of experiment). Although 15 s seems much shorter than 25 s, the difference in optimal policy is slight (24 s and 30 s, respectively). In contrast, the patch-staying time should not be relevant to a forager who is in an evenly dispersed environment. In this case, one does best by leaving after two items have been found.

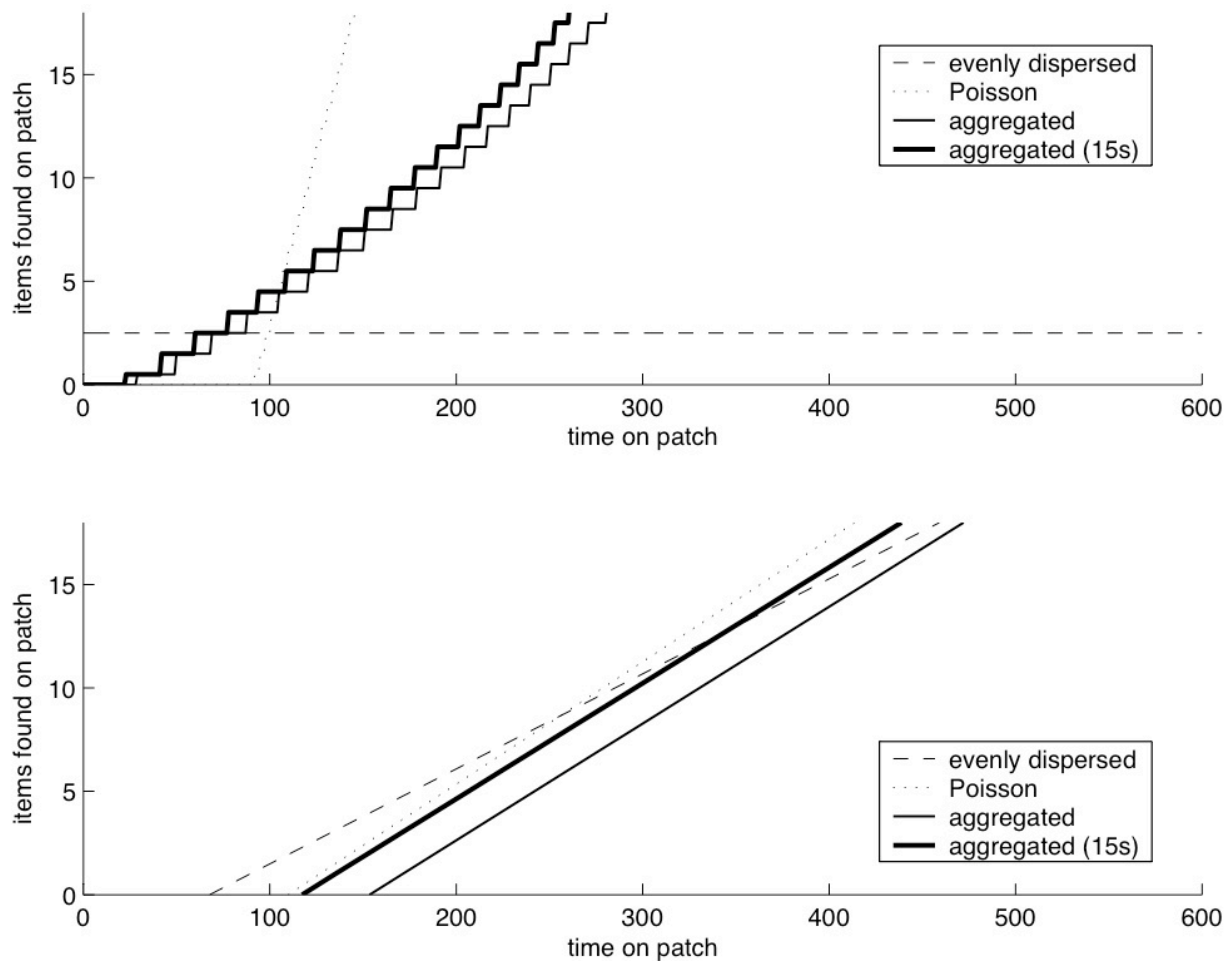


Figure 4.7 Optimal policy (above) and observed outcomes (below) within each environment of the fishing task.

Exploratory Graphs

As a first step in the data analysis we wanted to visualize each individual's policy. Therefore we produced separate plots for each participant and then grouped all the individuals in the same environment into larger exploratory graphs. These display the three cues that previous models suggested might be used to decide when to leave: The number of items, n , captured at a patch,

the time, t , spent at a patch, and the *time-interval* since the previous capture. For our exploratory plots, we paired these cues in all three combinations.

A useful feature of these plots is that they directly translate participants' foraging behavior into the way that we depicted the decision rules in the earlier sections of this chapter. For instance, Figure 4.8 shows samples of the n - t plots.

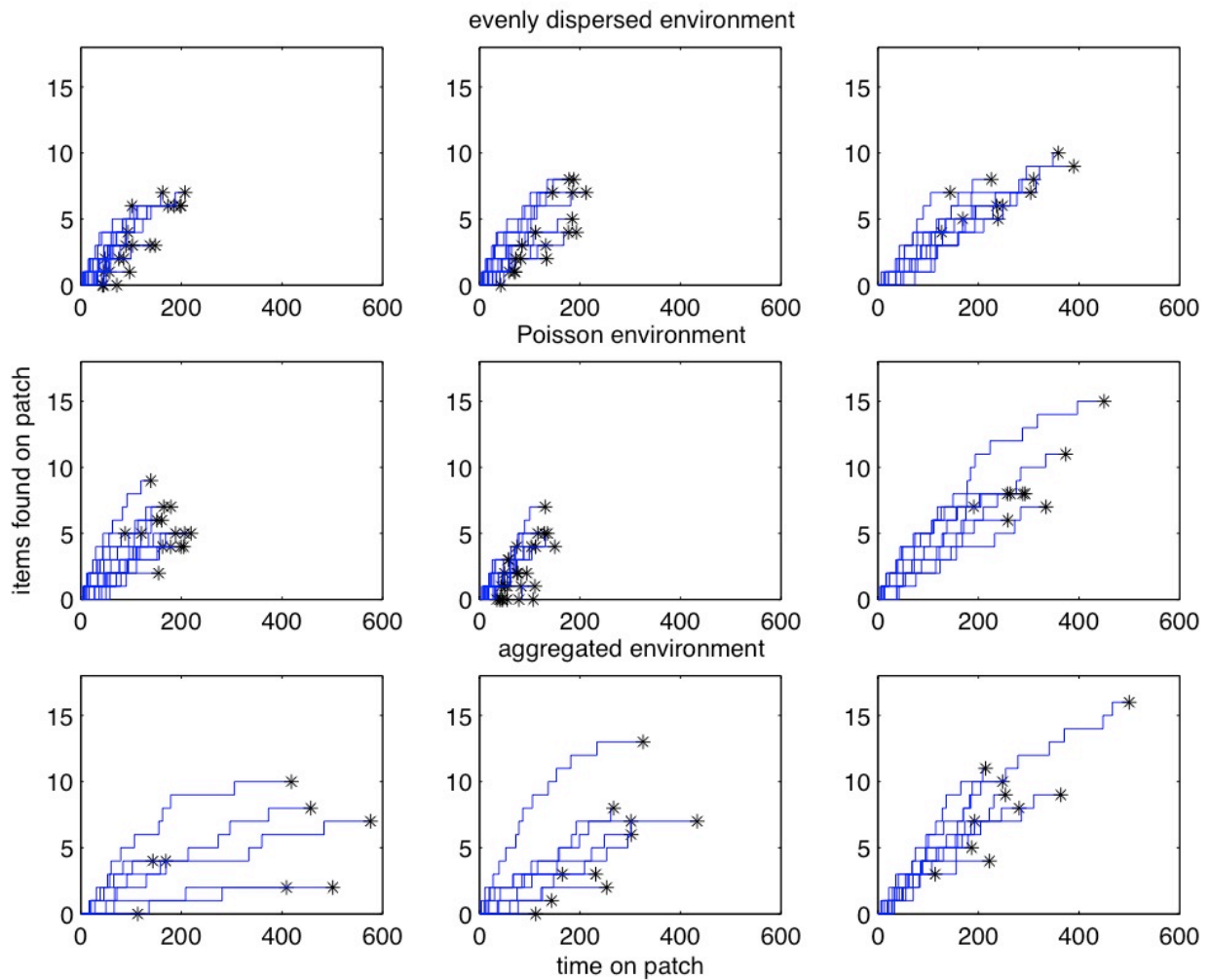


Figure 4.8 Plots of number of catches n against the patch-staying times t . Each row shows three randomly chosen participants for each of the three resource environments; each line corresponds to a separate patch and asterisks indicate switching events.

In Figure 4.8, a line depicts one visited patch and the steps in these lines the times at which participants successfully captured an additional fish. The asterisks mark when participants decided to hit the switch patch button. For example, in the bottom left plot, the topmost line shows a patch where this participant switched after catching 10 fish in about 400 s.

A first inspection of this graph (and the other n - t plots not shown here) suggests that a good explanation of when switching occurs is a combination of the time spent at a patch and the

number of items found. If one fits a line through the switching points it is roughly straight with a positive slope: If people caught a lot of fish in a patch, they tended to stay longer in that patch. The slope is steeper than the rate at which fish accumulated with time at the patches. This trend seems to hold not only in the aggregated environment (where such a relationship was predicted), but also in the other two environments. We will investigate this finding in the next subsection by fitting regression lines.

The giving-up-time rule (see Figure 4.3) utilizes the time interval since last capture. We can inspect if people used this information by plotting each participants' time spent at a patch against the time intervals since previous capture (Figure 4.9).

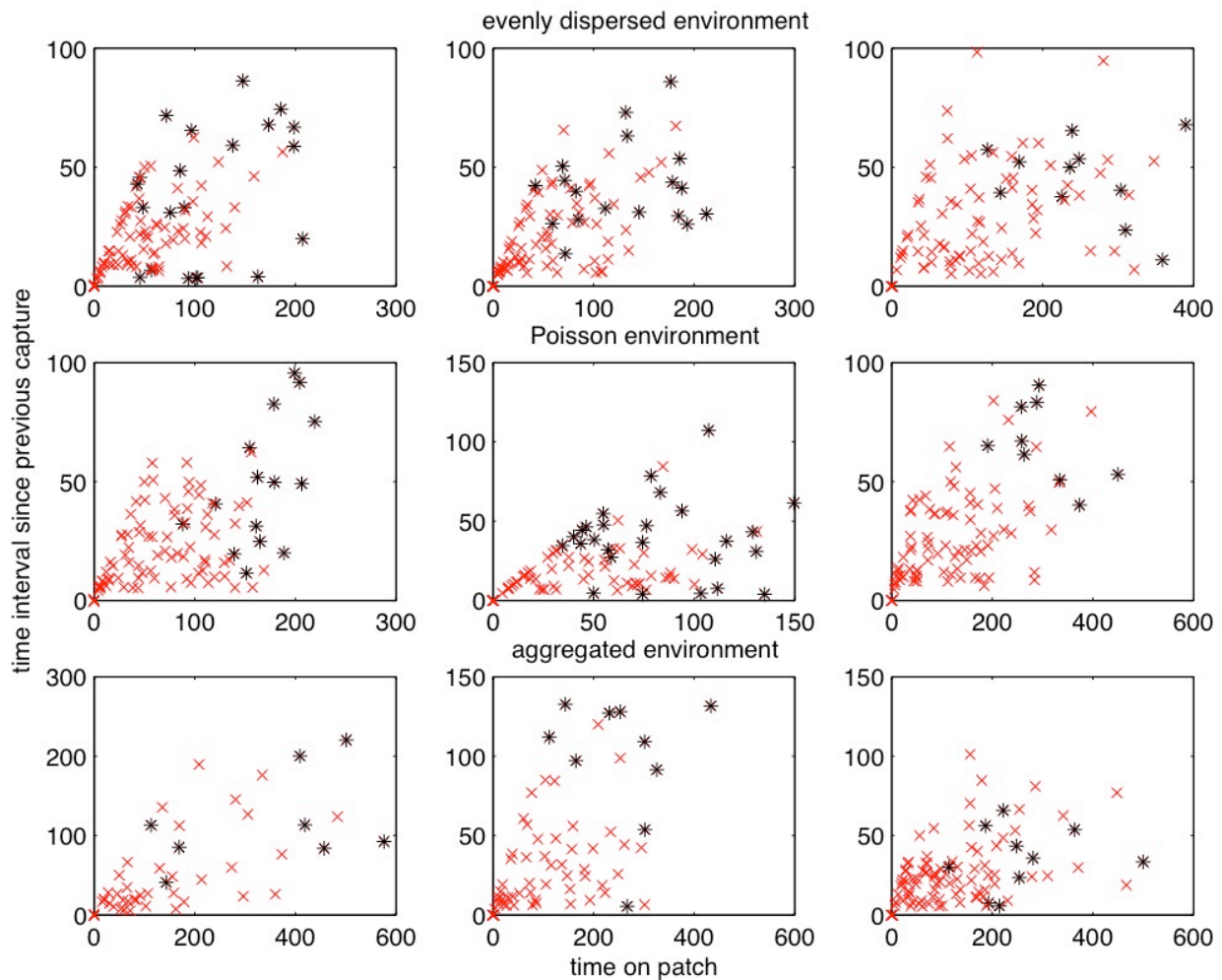


Figure 4.9 Plots of *time intervals* since previous capture against the patch staying times t . Each row shows the same participants as in Figure 4.8 for each of the three resource environments; crosses show time intervals between two subsequent captures and asterisks indicate switching events (i.e. the giving-up time).

The crosses in Figure 4.9 indicate time intervals between two consecutive catches and the asterisks show the time between the last capture and the switch to the next pond (i.e., the giving-up time). Note that the scales of the axes vary between plots. If people were using a giving-up-time rule, we would expect that (1) all the asterisks would be more or less on one horizontal line parallel to the t -axis and (2) they should be consistently above the other symbols that show time intervals between captures. However, neither appears to be the case. Although the giving-up times do often appear in the upper areas of each plot (e.g., middle rightmost plot), they are quite scattered within the plots and are not on the same level. Even worse, in some instances the earlier intervals between captures are larger than the final giving-up times (e.g., see lower rightmost plot).

Regression of t on n

Visual inspection of the n - t plots suggests that the points when an individual leaves might fit close to a straight line (see Figure 4.8). On a t versus n plot the *intercepts* of each line refer to how long a person stayed at a patch if no fish appeared and the *slopes* of these lines to how much additional time a person stayed at a patch after catching another fish. For this reason, we analyzed these prospective straight-line relationships using regression with the dependent variable being the time spent on each patch. Because we wanted participants to have enough time to learn about the underlying statistical regularities of each resource distribution, we analyzed only the second half of the patches they visited. A three-way analysis of variance (ANOVA; see Table 4.2) examined the influence of the factors subject, number of captures at the current patch, and environment on participants' patch-staying times.

Table 4.2 Analysis of variance for the time spent at a patch across all environments of the fishing task

Source	<i>df</i>	Adjusted MS	<i>F</i>	<i>p</i> -value
Environment	3	24,271	4.92	0.003
Subject (Environment)	96	8,574	4.03	<0.001
Number of captures	1	951,744	447.15	<0.001
Environment * Number of captures	3	5,741	2.70	0.045
Subject * Number of captures (Environment)	96	5,693	2.67	<0.001
Error	513	(2,128)		

Notes. Adjusted sum of squares used for significance tests; brackets indicate nesting, asterisks an interaction term.

The significant effect for environment shows that the intercept of an individuals' regression line systematically varies with environment. Table 4.3 summarizes these average

values, which equal the length of time a person stayed at a patch when no fish occurred (Figure 4.7 compares the predictions and observations graphically). However, only participants in the Poisson environment had initial staying times close to the optimal prediction (i.e., to stay about 100 s before moving on). Participants' observed staying time is shortest in the evenly dispersed environment and longest in the two aggregated environments. As predicted, a reduction in travel time led to earlier patch switching. This can be observed from the change in mean intercept values for the two aggregated environments (intercepts drop from 154 s to 117 s when travel time is reduced to 15 s). Nevertheless, the average observed staying time in both aggregated environments was much longer than predicted by the optimal policy and the relative difference due to the change in travel time was much greater than expected.

Table 4.3 Predicted and observed average initial patch-staying time (intercepts) and average time increments after captures (slopes) across environments

Environment	Predicted		Observed	
	Intercept (seconds)	Slope (seconds per item)	Intercept (seconds)	Slope (seconds per item)
Evenly dispersed	—	0 ^a	67.71 ^a	21.75 ^a
Poisson	93	2.43 ^a	109.85 ^a	16.88 ^a
Strongly aggregated	30	14.78 ^a	153.54 ^a	17.70 ^a
Strongly aggregated (15s)	24	13.41 ^a	117.32 ^a	17.86 ^a

Note. ^a values are computed from straight-line regressions.

Table 4.2 indicates a significant interaction between environment and the number of captures. This interaction tells us that the slopes of the regression lines (i.e., the additional time a participant spent at a patch after a successful capture) differ across environments (see rightmost column of Table 4.3). However, a plot of the slopes suggested considerable skewness, so we also compared between environments using a nonparametric Kruskal–Wallis test. The difference for the intercepts remained significant, $H(3) = 11.06$, $p = .011$, but not for the slopes, $H(3) = 3.90$, $p = .272$. Closer inspection reveals that the difference between slopes is mainly due to the value from the evenly dispersed environment differing from the other values. However, this slope changes in the opposite direction to that predicted. The slopes are all significantly above 0, indicating an incremental rule.

These results are based on fitting straight-line relationships, which probably oversimplify the true relationship and could lead to artifacts. So we also tried fitting more complex models. We added the number of previous patch visits as well as the “time since last capture” into the model. We also allowed curvilinear relationships by adding quadratic terms, and also

interactions between variables and environment and subject. The model resulting from a stepwise multiple regression analysis is shown in Table 4.4.

Table 4.4 Analysis of variance for the time spent at a patch across all environments of the fishing task when adding participants giving-up-time, a quadratic term for the number of captures and the number of previous patch visits

Source	<i>df</i>	Adjusted MS	<i>F</i>	<i>p</i> -value
Subject	99	2,945	2.12	<0.001
Number of captures	1	250,806	180.71	<0.001
Subject * Number of captures	99	3,752	2.70	<0.001
Number of captures * Number of captures	1	19,130	13.78	<0.001
Giving-up time	1	2,419	1.74	0.187
Subject * Giving-up time	99	2,184	1.57	0.001
Error	412	(1,388)		

Note. Adjusted sum of squares used for significance tests; asterisks indicate interaction term.

Note that now there is no significant effect for environment. Adding the giving-up time increased the fit only a little, although it was statistically significant. Overall, there remains a strong incremental effect of the number of captures on participants' tendency to stay at a patch. In all four of our environments, people behaved as if foraging in a strongly aggregated environment: Finding a lot in a patch is associated with staying longer.

Cox Proportional Hazard Model

We performed an alternative analysis that would allow us to test for the effects of multiple factors in one statistical model and model the error in a statistically more valid way. Whereas the premise of the previous model was a deterministic decision rule (i.e., to leave the patch or not) this new analysis assumes stochastic decision rules (i.e., various factors that increase or decrease the probability of patch leaving).

The Cox proportional hazard model is a mathematical model developed for analyzing survival data (Cox, 1972; Lee & Wang, 2003), data that occur when an outcome of interest is the time to an event (e.g., predicting when car engines break down, kids drop out of high school, or parasitoid wasps leave patches). The Cox model is the most general of the survival regression models, because it makes no assumptions about how survival probability depends on time. Other variables are assumed to have a consistent multiplicative effect on the instantaneous rate of death.

As an illustration, we consider an example from the behavioral ecology literature, where such methodology is often used to model animals' patch departure (Haccou & Hemerik, 1985;

Wajnberg et al., 2000; Alphen, et al., 2003; Boivin, Fauvergue, & Wajnberg, 2004). Outreman, Ralec, Wajnberg, and Pierre (2005) presented a study addressing how an insect parasitoid, the wasp *Aphidius rhopalosiphi*, makes patch-departure decisions from various types of host patches and how previous patch experience in the environment modifies this decision-making process. In these experiments, wasps were observed foraging in an environment containing several patches of various host densities and behavioral records were taken. Outreman and colleagues (2005) formulated a patch-leaving model in terms of a hazard rate, which represents the “probability per unit of time that a parasitic wasp leaves the visited patch, given that it is still on it” (p. 210). In this case, the Cox proportional hazard model assumes that the patch-leaving tendency is the product of a more basic tendency to leave (i.e., the baseline hazard) and a factor representing the joint effect of all the explanatory variables:

$$h(t; z) = h_0(t) \exp \left\{ \sum_{i=1}^p \beta_i z_i(t) \right\}$$

In this equation, $h(t; z)$ is the hazard rate, $h_0(t)$ the baseline hazard, t the time that passed since the wasp entered the patch, and β_i the regression coefficients that give the relative contribution of the p covariates $z_i(t)$. A quantitative measure of the effect of any particular covariate is then given by the expression $\exp \{ \sum \beta_i z_i \}$, the hazard ratio. If this latter term is larger than 1, then the patch-leaving tendency of the wasp is increased (i.e., the parasitoid would leave the patch earlier), while hazard ratios lower than 1 would indicate that the patch-leaving tendency is decreased (i.e., the parasitoid stays longer at that patch). Using this model, Outreman and colleagues (2005) demonstrated two things: First, wasps indeed used local cues such as the number of successful ovipositions or cues about patch quality to adapt their patch-staying times. Second, wasps were sensitive to information acquired at previous patches such as the quality of the last visited patch. If the previous patch was rich in resources, they were more likely to stay longer on the current patch.

To analyze our data with a Cox hazard model, we generated a list of covariates that might affect participants' patch-leaving tendency. The first covariates selected were two cues discussed throughout this chapter: the number of captures (i.e., the number of fish caught at the current patch) and the time since last capture. These were both time-dependent covariates (i.e., their values changed during the course of the patch visit; see Kleinbaum, 1997). Following Outreman et al. (2005) we also included covariates that would assess if people incorporated

experience from previously visited patches into their patch-leaving rules. Thus, we included covariates such as the total number of fish caught since the beginning of the experiment and the number of patches already visited. Table 4.5 gives an overview of all the covariates considered:

Table 4.5 Covariates tested for their effect on subjects' patch-leaving tendency in the fishing task

Covariates relevant to the within-patch experience

Number of fish caught at the current patch^a

Time interval since last capture^a

Covariates relevant to the experience on the previously visited patches

Number of previous patch visits

Number of fish caught at previous patch

Giving-up time in previous patch

Density of the previous patch

Number of fish caught since start of the experiment

Note. ^a indicates a time-dependent covariate

We entered all of the participants' patch visits from the second half of the experimental session into a step-forward likelihood-ratio Cox regression analysis. In addition to all covariates given in Table 4.5, subject and environment were included as categorical variables and environment was crossed with all covariates. The categorical variable subject was necessary because we were interested in the variation between environments; therefore, given our between-subjects design, we also needed to include the variation between subjects in the analysis. Ideally, one would aim for a nested design in such a case (i.e., subject nested within environment), but this was not possible with the statistical software available. All continuous covariates were separately tested for the linearity of their effect; with the number of captures we consequently used a square root transformation. Table 4.6 shows the results of the final model after the stepwise procedure:

Table 4.6 Estimated regression coefficient (β), standard error (SE), Wald statistics, and hazard ratios [$\exp(\beta)$] for covariates that had a significant effect on the patch-leaving tendency across all environments in the fishing task

	β	SE	Wald	df	p-value	$\exp(\beta)$
Subject	n/a	n/a	555.80	99	<0.001	n/a
Number of fish caught at the current patch	-0.524	0.051	105.27	1	<0.001	0.592
Environment * Number of fish caught at current patch	n/a	n/a	10.72	3	0.013	n/a
Giving-up time	0.010	0.002	42.15	1	<0.001	1.010
Number of fish caught at previous patch	0.031	0.012	6.46	1	0.011	1.031

Notes. The overall significance of the fitting model: $\chi^2 = 849$, $df = 105$, $p < .001$; asterisk indicates interaction term.

The Cox hazard model enables us to look at the relative contribution of particular covariates. Here, the crucial statistic is the Wald statistic, which tells us whether the predictor makes a significant contribution. By far the largest effect was found for subject as suggested in our exploratory graphs. However, what is of most interest are the cues that people use to time their patch leaving. Two of the covariates relevant for the within-patch experience turn out to be significant: One is the number of fish captured at a pond (Wald = 105.27); the other is the time since last capture (Wald = 42.15). Hence, consistent with the regression results from the previous section, the number of captures within a patch plays the major role. In addition, participants seemed to take information from previously visited patches into account, because the number of fish caught at the previous patch is also significant (Wald = 6.46).

Every capture in a given pond increased participants' tendency to stay in a patch. Both the time since last capture and the number of fish caught at the *previous* patch decreased the tendency to stay (see hazard ratios in last column of Table 4.6). The latter could mean that participants who have experienced high-quality patches earlier judge future patches to be likely to be high quality; consequently for a given perceived quality of the present patch, they are likely to leave earlier than if future patches had been judged of poorer quality.

To test the differences between environments in a statistically more valid way (comparing against individual variation because of the between-subjects design), we reran the Cox regression removing the environment term but including an interaction term between subject and the number of captures. We then compared the individual coefficients for this interaction (i.e., how the number of captures increased the probability of leaving for each subject) between environments (Figure 4.10).

To test the differences between environments statistically we first used Tukey's honestly significant difference (HSD) test to compare the means of the three environments sharing the same travel time: The increase in tendency to leave after a fish capture was significantly greater in the aggregated environment than in the evenly dispersed ($q = 4.71, p < .005$) and the Poisson environment ($q = 3.42, p < .05$). Second, we carried out an orthogonal a priori comparison between the two aggregated environments to check for the effect of differences in travel time: Time increments after a successful capture were significantly longer with 25 s of travel time than with 15 s, $t(96) = 2.18, p = 0.032$.

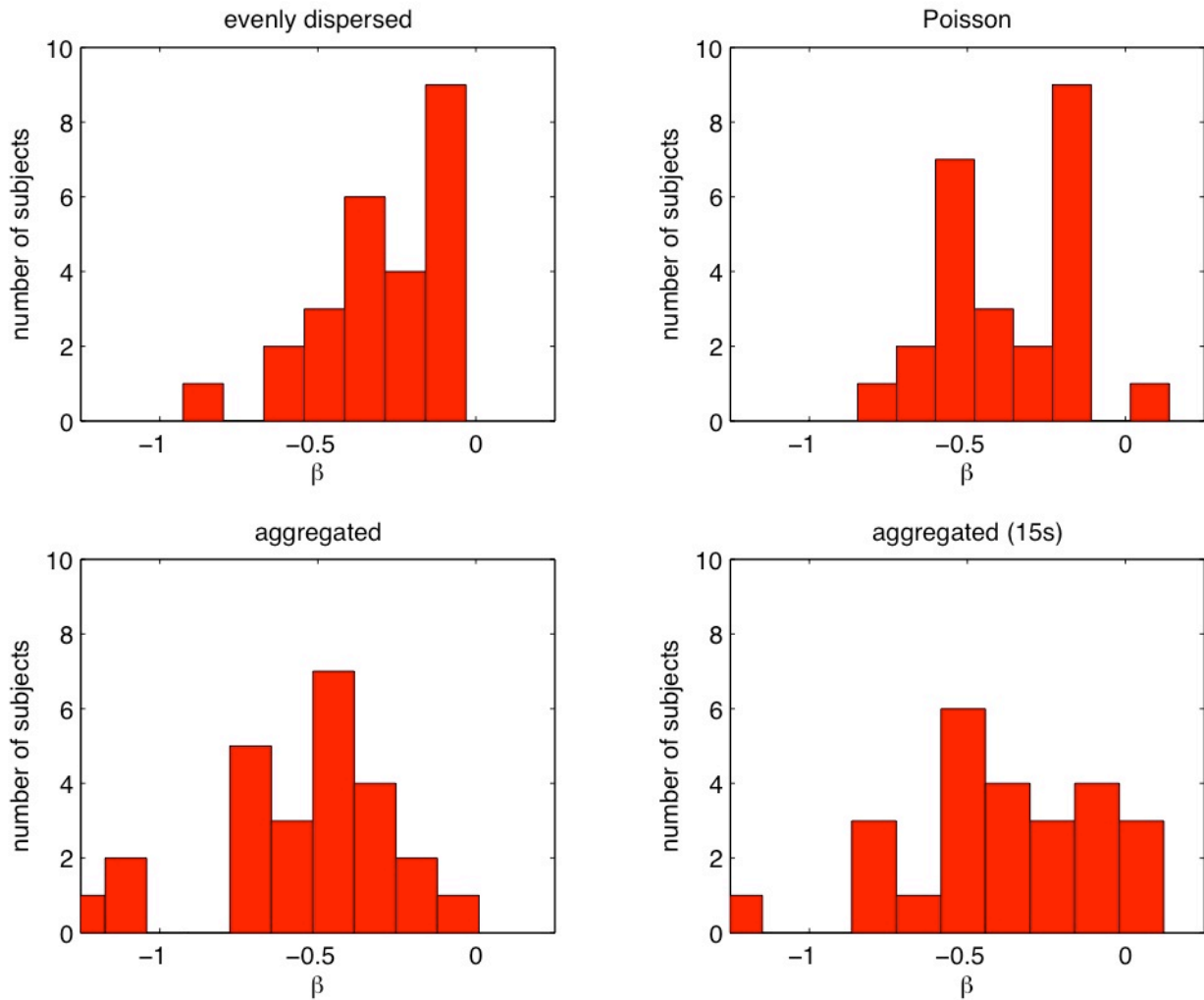


Figure 4.10 Histograms showing the effect of a resource capture on the tendency to stay for different subjects; although the zero point of the scale is arbitrary, more negative numbers indicate a larger increase in patch-staying tendency when an item is captured.

Questionnaires

The last part of this section analyzes the responses to the questions we posed to participants at the end of the experiment. Participants rated to what extent they utilized specific informational cues and reported on any patch-leaving strategies developed over the course of the experiment.

Each person made three forced judgments on a 4-point rating scale. Participants were asked (1) how important for their patch-leaving they would rate the number of captures they had made at the current patch, (2) how important the time spent at the patch was to them, and (3) if they paid attention to the time since the last capture. Across all three environments, only very few people reported that they were not using these cues at all. The majority reported making use of these cues “often” or even “very often.” We found no significant differences between environments, so we pooled the data across the three environments. In total, the time since last

capture was the cue that people reported utilizing most. The responses on each question can be seen in Table 4.7.

Table 4.7 Qualitative responses summed across the three environments of the fishing task

Cue	Cue usage				Times mentioned in reports
	not at all	rarely	often	very often	
Number of fish caught at the current patch	4	22	29	20	8
Time spent at patch	4	21	37	13	4
Time since last capture	1	6	26	42	30

Notes. Questionnaire responses were forced-choice questions from 1 (did not use that information at all) to 4 (used that information very often); written reports were coded by two independent raters.

Among the participants, 83% also gave written reports about the potential strategies they used. Two independent raters read these reports and assigned the texts to four distinct categories. Whereas three of these categories were identical to the ecologically valid cues, each pinning into one of the specific resource environments, a fourth category subsumed the remaining statements that were not clearly assignable; missing responses were also coded into this category. If more than one cue was mentioned simultaneously, raters were instructed to extract the most important one. The following text extracts illustrate the written responses and how they were coded:

I always set the specific goal of capturing eight fish per pond and never switched before that (first category: number of captures)

I waited for a specific (yet subjective) time and then switched (second category: time spent at patch)

If it took too long until the next fish would appear, then I switched to the next pond (third category: time since last capture)

The rightmost column of Table 4.7 shows how often participants mentioned these particular cues in their written responses. Numbers are given for cases in which both raters agreed on the final coding (inter-rater reliability of 74%). Consistent with participants' responses on cue usage, the large majority of written responses were coded in favor of a strategy that used the time since last capture.

Discussion

We found that capturing a lot of items is associated with longer staying times. Although this effect of adding a time increment after a successful capture could principally result from two of the patch-leaving rules that we studied—the giving-up-time rule and the incremental rule—we demonstrated that our results favor the latter. Including the “time since the last capture” improved the model fit of both the standard regression analyses and the Cox hazard analysis, but the largest contribution was always achieved with the “number of captures” within each patch. This pattern was also consistent with the exploratory graphs that we studied, but not with the qualitative responses that participants gave in our post-experimental questionnaire. Here, the majority of participants mentioned the use of strategies that incorporate time intervals since last capture as the most important cue.

As predicted, participants applied an incremental decision rule in the aggregated environments, but they did this also in the evenly dispersed and the Poisson environment. Although participants’ average initial staying times somewhat differed between environments, the time increments after successful item captures were almost identical. Switching behavior after a fixed number of items (as predicted for the evenly dispersed environment) or switching after a fixed time (as predicted for the Poisson environment) was not observed. On the contrary, participants behaved as if foraging in an aggregated environment is their default. Our additional test of the effect of changing travel time between two otherwise completely identical environments resulted in the predicted outcome that shorter travel time leads to earlier switching.

Searching the Internal Environment: The Word Puzzle Task

Patch departure decisions in biology are not limited to food foraging. One reason to leave could be resource depletion; other reasons differ from mere depletion, such as when prey is disturbed by a predator and becomes less vulnerable (Bell, 1991). As indicated earlier, some researchers have generalized this problem further to other domains by emphasizing that the situation of diminishing returns at patches is similar to when people forage for external information, such as facts contained in Websites—hence, the term *information foraging* (Pirolli & Card, 1997, 1999; Pirolli, 2005).

In our second task we again addressed the question of how and with what kinds of mechanisms people deal with diminishing returns in foraging situations—this time by taking a cognitive information-foraging perspective, but foraging in memory (i.e., searching in the

internal environment), rather than in an external cultural source, such as the Web. How people search for information in the internal or external environment has always been mentioned as a central feature of the study of heuristics (Gigerenzer, Todd, & the ABC Research Group, 1999), but only few studies have actually investigated decision strategies that are accompanied by information search in memory (e.g. Bröder & Schiffer, 2003). We created a computerized information-foraging task that we call the *word puzzle* to investigate this.

Method

In our computerized task, we presented subjects with a modified anagram puzzle in which they searched for words from their memory-lexicon. Participants were presented with meaningless sequenced of letters (e.g., LGIRNAHEM) and asked to generate meaningful German words out of each sequence. They could use all or only some of the letters provided for each solution as long as they used each letter only once for each solution. For instance, for the sequence mentioned above participants could come up with the words GEHIRN and LAGER, but also other shorter words using fewer letters such as RING or GARN, whereas words such as GEHIRNE (two Es) or RINDE (a D) would be violations of our task.

Participants could generate words out of this letter sequence—could “forage” within this patch—for as long as they wanted and were paid for each meaningful word found. Some valid solutions were more difficult to spot than others, and there was only a finite number of solutions for each letter sequence, so participants needed to decide at what point they wanted to switch to a new sequence due to the diminishing returns with the current sequence (i.e. patch). Switching sequences was—keeping the animal foraging literature in mind—made costly by including a constant time delay (i.e. the travel time) between sequences.

Since this task was designed in analogy to the fishing task, we aimed at testing the same hypotheses as before and checked whether rules used in an external resource search may also generalize to internal information search. However, the environment used here was a completely different one (i.e. language material) and it was impossible to create resource distributions that mirrored those in the fishing task, because we did not have control of when solutions appeared. The best we could do was to manipulate the degree of aggregation in sequence quality. First, we generated sequences at random and then gave those sequences to an initial round of participants. Second, based on their responses and the number of solutions they found, we would rank sequences by their quality. By selecting from the ranking we could construct two resource distributions, which we labeled “dispersed” and “aggregated”. Finally, a second round of

participants experienced either the dispersed or the aggregated environment in our main experiment.

An important aspect was how to generate sequences varying in “quality”. One way would be to have sequences differing in *length*, in terms of numbers of letters, where participants are unaware of how long (or short) the next sequence will be. For instance, the mean length of sequences could be nine letters, but sequences might vary by up to three letters. However, in this case, it becomes problematic to tell which of these sequences are then actually more difficult (e.g. longer sequences provide a higher number of permutations but are more cognitively demanding). Additionally, people could start using additional cues to determine patch quality (e.g. length of sequence) resulting in more complex and thus harder to analyze patch-leaving rules. Another alternative, the approach that we chose, was to keep the length of the sequences constant but to vary the *difficulty* of these sequences themselves, in terms of how many possible words each could yield. The dispersed environment was limited to sequences of medium difficulty level, whereas the aggregated environment used a mixture of very easy and very difficult sequences. Details are given below.

A final aspect concerned what kind of word solutions we would instruct participants to search for. All the resource environments that we considered so far—both in the animal literature as well as in our fishing task—assumed that the successful capture of one item was independent from finding another item. Given the peculiarity of the language material this assumption was violated. For example, finding a specific word in memory (e.g. RING) would instantly prompt participants to find many more words that are closely associated forms of this original word. Such solutions could, for instance, be the plural of the word (e.g. RINGE) or different cases (e.g. the genitive RINGES). In this way, people could discover subclusters of solutions that would bias our results, because we wanted a consistent decline in the rate of finding solutions (rather than a series of steps). We decided to instruct participants to look only for singular nouns in the nominative case and thereby aimed to make finding word solutions fairly independent from one another. Furthermore, we set the minimum length of an acceptable word solution to be at least four letters so that participants would not come up with the same (easy) solutions for different sequences and then switch to the next sequence before trying to find more sophisticated words.

Sequence and Wordlist Generation

The length of the letter sequences was fixed to nine letters, with a constant ratio of six consonants and three vowels so that the difficulty across sequences *appeared* similar in this

regard (even if it actually differed). Within each sequence a letter could appear only once. Letters with the lowest letter frequencies in the German language were excluded since this information could readily be utilized as a cue for the difficulty of a sequence. Specifically, the letters J, Q, X, and Y (letter frequency of 0.27, 0.02, 0.04 and 0.08 percent, respectively) were excluded from the sequence generation (Bauer, 2000). We generated a list of 70 letter sequences following the above criteria and ensured that each sequence was not just a reordering of another (Czienskowski, 2005b). Note that no German umlauts occurred within these sequences.

Next, a wordlist was compiled that contained all the possible meaningful word solutions from our set of sequences. For this purpose, we initially merged two professional linguistic lists. One of the lists contained approximately 55,000 nouns and was provided by the online dictionary team at the Technical University of Chemnitz. The second noun list was obtained from the Center for Automatic Language Processing, Department of Informatics at the University of Leipzig and consisted of more than 182,000 words. This merged list was shortened by taking out doubles, words with duplicate letters, words that were not four to nine letters, words that held German umlauts, and words that contained the letters J, Q, X, or Y. Subsequently, this shortened list was used as a filter on all the possible letter combinations created by each of our 70 sequences. The respective intersections—letter combinations from a sequence that were also found in our shortened word list—were kept and put into an unchecked word solution list. This unchecked word solution list was then given to German native-speaking student helpers for final checking and correction. Whereas the unchecked word solution list still contained around 10,000 words, the final checked list of meaningful solutions had 1,511 entries. Note that there were two reasons for this large difference between the unchecked and the checked solution list. One is that the second (and larger) of our linguistic raw lists was derived from a bigger list of all German words by letting an algorithm search for nouns. Such a procedure is fast yet unreliable in terms of the errors it produces (e.g. filtering out verb infinitives). A second reason is that we had additional criteria for what words were valid solutions; details will be given in the Materials section.

Participants

Participants for pilot studies, sequence selection, and the main study were recruited using the ABC subject database. All testing took place at the facilities of the MPI. Participants were German native speakers who self-reported not suffering from any form of dyslexia. To collect the data on sequence quality (see details below), 26 participants (13 women, 13 men) were each

randomly assigned to five blocks of 12 sequences each (10 sequences were kept aside for the training session of the main experiment). Sequences within each block were randomly shuffled and the order of blocks varied systematically. This procedure was chosen to allow for a semi-random order of sequence presentation while ensuring that each sequence was seen by a similar number of participants. Participants could work through as many blocks as they could finish within 45 minutes.

For the main study, 60 participants (31 women, 29 men) were randomly assigned to two experimental conditions of 30 participants. One experimental condition consisted of sequences that all had medium difficulty (i.e. the dispersed resource environment); the other consisted of sequences of low and high difficulty (i.e. the aggregated resource environment). Here, the average age for women was 26 years ($SD = 4$) and for men 25 years ($SD = 3$). Participants were paid at the end of the experiment by their overall foraging success (i.e. number of valid solutions generated). The duration of the experimental phase in the main study was 60 minutes.

Materials

Consistent with the fishing task, the full experiment including the instructions and the training session was presented on a computer screen using a specially written computer program (Czienskowski, 2005c). The program recorded all the words that participants entered, the success participants had while foraging at the letter sequences (e.g., the numbers of correct and false words), the number of visited sequences and the time participants spent at each sequence (details about the experiment are given in the next section). Instructions were the same in both experimental conditions and informed participants about the composition of the letter sequences, what kind of words they were supposed to look for, and how they could move from one sequence to the next. Participants also learned about the exact length and the vowel-to-consonant ratio of sequences, that each letter would only appear once per sequence, that no German umlauts would occur and that spelling out words with umlauts by using two vowels was forbidden (e.g., using AE for Ä). In addition, they were informed that four very rare letters of the alphabet were excluded.

Instructions were given that participants should only seek singular nouns in the nominative case, that all words had to be German, and that no names of persons, geographical places, or brand names would be accepted. Exceptional cases such as the ambiguity of verb infinitives (e.g. “gehen” into “das Gehen”) or adjectives changed into substantives (e.g. “alt” into “der Alte”) were mentioned, but excluded as well. As a comprehension check, participants worked through a 25-item quiz on these grammatical rules. Each quiz item was an example of

potential solution and participants had to judge if it would be allowed. There was no penalty for making mistakes on this quiz, but participants had to correct their mistakes before they could continue with the experiment.

Participants were told that they could see an unlimited number of letter sequences yielding a variable number of solutions, but that there was no going back to an earlier sequence. As in the fishing task before, we instructed participants that the timing of when to switch from one sequence to the next would crucially influence their final payout and that they should avoid two extreme ways of playing: switching too early or to staying too long at each sequence.

Procedure

Participants came to the laboratory and were seated at a computer. The experimenter either assigned them to a specific block order of sequences (these participants were part of the sequence selection study) or selected one of the two resource environments (these participants were part of the main experiment). Participants had to turn in their watches and cell phones for the duration of the experiment. Each person worked through the onscreen instructions and the training quiz at his or her own pace. The technical screen setup and how to control the mouse and keyboard during the experiment were explained. Furthermore, participants conducted a 4-minute training session, which was completely identical to the main experiment. The order of sequences was identical in the training session but randomly varied in the experimental part. Upon start of the experiment, participants were presented with a letter sequence at the center of the screen and could start typing solutions into an empty entry mask located right underneath the sequence (Figure 4.11).

If participants typed in a solution that was found in the word list, they received visual feedback in the form of a green circle along with a “Correct!” sign and the entry mask was automatically cleared for a new entry. Alternatively, a red circle indicated that the word was incorrect (or that it was not found in our word list) and participants received specific feedback about the kind of error they had made. These specific error reports were given when a word was entered that was shorter than four letters, when an entry used a letter that was not available in the current sequence, when letters were used multiple times, when participants tried spelling out umlauts or when the word was a repetition of a word the participant had already found in this sequence. In all other cases the entered word was reported to be not in our word list. Incorrect entries remained in the mask and had to be removed via the delete key. Participants were instructed about potential shortcomings of the word list (i.e. false rejections of valid words) but were told that they should continue with the experiment in such cases.



Figure 4.11 Search in the internal environment: Training screen of the word puzzle (Czienskowski, 2005c). Screenshot shows the letter sequence (upper middle) and the entry mask in which participants typed in their solutions (middle). Participants received feedback on their solutions: If correct, a green circle lit up (left), if incorrect, a red circle lit up (right). A word stack (right side) showed current foraging success. A switching button (lower right) allowed participants to switch to a new sequence.

Each correct word that a participant found appeared in the word stack (Figure 4.11, right side). Analogously to the fishing task, this stack was emptied every time a new sequence was presented. The total number of correct words found in all sequences was used to calculate the final payout for the experiment. Each word was worth € 0.20.

At any time participants could decide to switch to a new sequence by clicking the red “switch sequence” button (Figure 4.11, lower right). Upon clicking the button, a bouncing ball animation with a “Please wait!” sign appeared on an empty screen and participants had to wait for 25 s. Another round started with the experimental screen showing a new letter sequence that was randomly drawn without replacement from the pool of available sequences of that resource environment (or block if this was the sequence selection study).

Participants in the main study filled out two supplementary questionnaires and performed an additional estimation task. The first questionnaire was equivalent to the questionnaire used in the fishing task and requested participants to give feedback on the kinds of information they might have used in the task. We asked them to report if they came up with a particular strategy to determine their patch leaving and, if possible, to tell us about it. Again, three further questions asked about the usage of three cues (i.e. the number of correct words

found, time spent at a sequence, and the time-interval since last capture). Here, judgments were made on a 4-point Likert scale.

The second questionnaire was a brief paper-and-pencil form assessing participants' verbal proficiency. We used a standardized multiple choice vocabulary test as a valid and short measure of verbal intelligence (i.e. Mehrfachwahl-Wortschatz-Intelligenztest MWT-B; Lehrl, 1999).

For the estimation task, each participant was randomly presented with one half of the letter sequences from the other experimental condition (see section on sequence selection below). The task was to quickly estimate the number of correct word solutions a participant could find from each of the 13 letter sequences. Sequences were presented in random order and appeared sequentially. There was no time restriction for participants' answers, but sequences were masked after a presentation time of 10 s since we were interested in the accuracy of participants' initial sequence quality assessment.

Quality of the Wordlist and Sequence Selection

To examine the quality of our wordlist, we looked at the amount and the kinds of errors participants made in the sequence selection study. Across all participants, 64.8% ($SD = 13.7$) of their word entries were correct and 35.2% ($SD = 13.7$) incorrect. All of these incorrect word entries were analyzed and coded for five different error groups. These groups were (1) syntax errors (e.g., using letters that were not part of a sequence, using duplicates, etc), (2) word criteria errors (e.g., forming words that were meaningful but violated our criteria, such as plurals, non-nominative cases, etc.), (3) repetition errors, (4) nonsense errors (i.e., forming words that did not exist), and (5) so-called false positive errors (i.e., forming words that should have been allowed but were flagged as errors because the wordlist did not recognize them). Whereas errors resulting from violating our defined word criteria or typing nonsense words were quite common (48 and 31%, respectively), syntax errors occurred less often (17%). Word repetitions almost never occurred (1%). Fortunately, only a few words were rejected because of missing words in our wordlist (3%). This low false-positive rate is important, because it prevents participants from becoming frustrated by shortcomings of the wordlist. We collected all these wrongly-rejected words and included them into the wordlist for the main experiment.

We produced plots for the sequences to investigate how variable different participants were in the number of solutions they generated for the same sequence (Figure 4.12). Because of our structured block design, each sequence was seen by at least five participants.

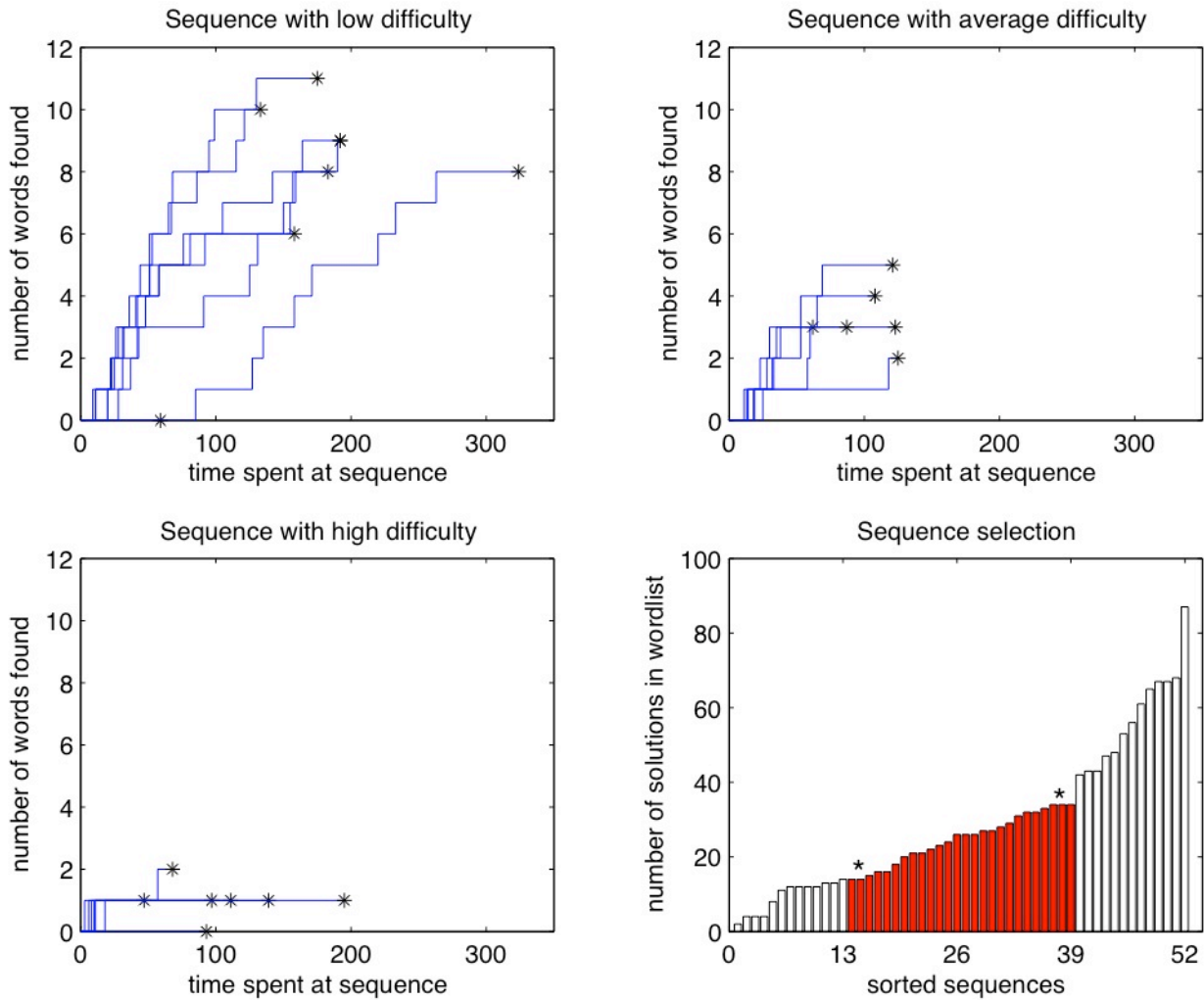


Figure 4.12 Examples of sequences of differing quality (upper left, upper right, and lower left subplot); each subplot shows all the participants who saw this sequence. Sequences for the aggregated (white bars) and dispersed (grey bars) environment were each chosen by selecting two quartiles of the sequences that were sorted by the number of solutions in the wordlist (lower right subplot); asterisks indicate difficulty level of two placed sequences (see text for details).

Each line in a plot shows the foraging success of one participant seeing a specific sequence and the time when he or she left that sequence. Difficulty of each sequence was determined based on the mean number of solutions participants found for each. For instance, Figure 4.12 shows example sequences of low (mean solutions $M = 7.6$, upper left plot), average ($M = 3.3$, upper right), and high difficulty ($M = 1$, lower left). We computed the average number of solutions participants found for each of the 60 sequences and correlated this with the actual number of solutions each sequence had according to our wordlist. Although participants found on average only about 15% of the possible solutions at each sequence, the number of solutions a sequence had in our wordlist is a good predictor of the actual number that participants found ($r = .80, p < .001$).

We further analyzed participants' responses to the sequences by fitting a function relating the rate of finding solutions to how many solutions remained to be discovered. Across sequences, a high number of potential solutions for a sequence was associated with a high estimated rate of finding solutions. To strengthen this relationship (so that, as with the fishing task, rate of "capture" indicated the number of solutions remaining) we excluded 8 sequences with high residuals. We then selected sequences for the two environments of the main experiment. All remaining 52 sequences were ordered by their number of solutions in the wordlist since we wanted to order sequences by how good they were potentially and not by how many words participants could find before switching (Figure 4.12, lower right). Sequences in the lower and upper quartile were used for the aggregated environment, and the two middle quartiles were merged to form the dispersed environment.

To facilitate the comparison of participants in the two experimental conditions, we ensured that all participants saw two particular sequences that were placed into the otherwise random ordering of letter sequences. One sequence was ranked in difficulty at the top of the lower quartile and the other at the bottom of the upper quartile, so the sequences were not untypical of either the dispersed or the aggregated environment (Figure 4.12, lower right). These sequences appeared after about 25 minutes of main experimental time, but their deliberate placement among the other sequences was unnoticed by participants. Both sequences were the same in both experimental conditions and appeared in a fixed order: first the high difficulty sequence and then the low difficulty sequence.

Results

Exploratory Graphs

As in the fishing task before, our initial data analysis was driven by the need to visualize individual participants' foraging behavior and to link that behavior to the decision rules we discussed earlier. We produced plots for each participant that related the number of correct words n found at a sequence, the time t spent at a sequence and the *time interval* since finding the last correct word. Figure 4.13 shows samples of the n - t subplots for the two environments of the word puzzle:

In all these plots, a line depicts one letter sequence, the steps in these lines the times at which participants found a correct word and the asterisks when participants switched sequences. In comparison to the n - t plots of the fishing task, there is now larger variation between

participants in the same resource environment. To clarify the within-participant patterns we re-plotted the same graphs with axes scaled to individual performance (Figure 4.14).

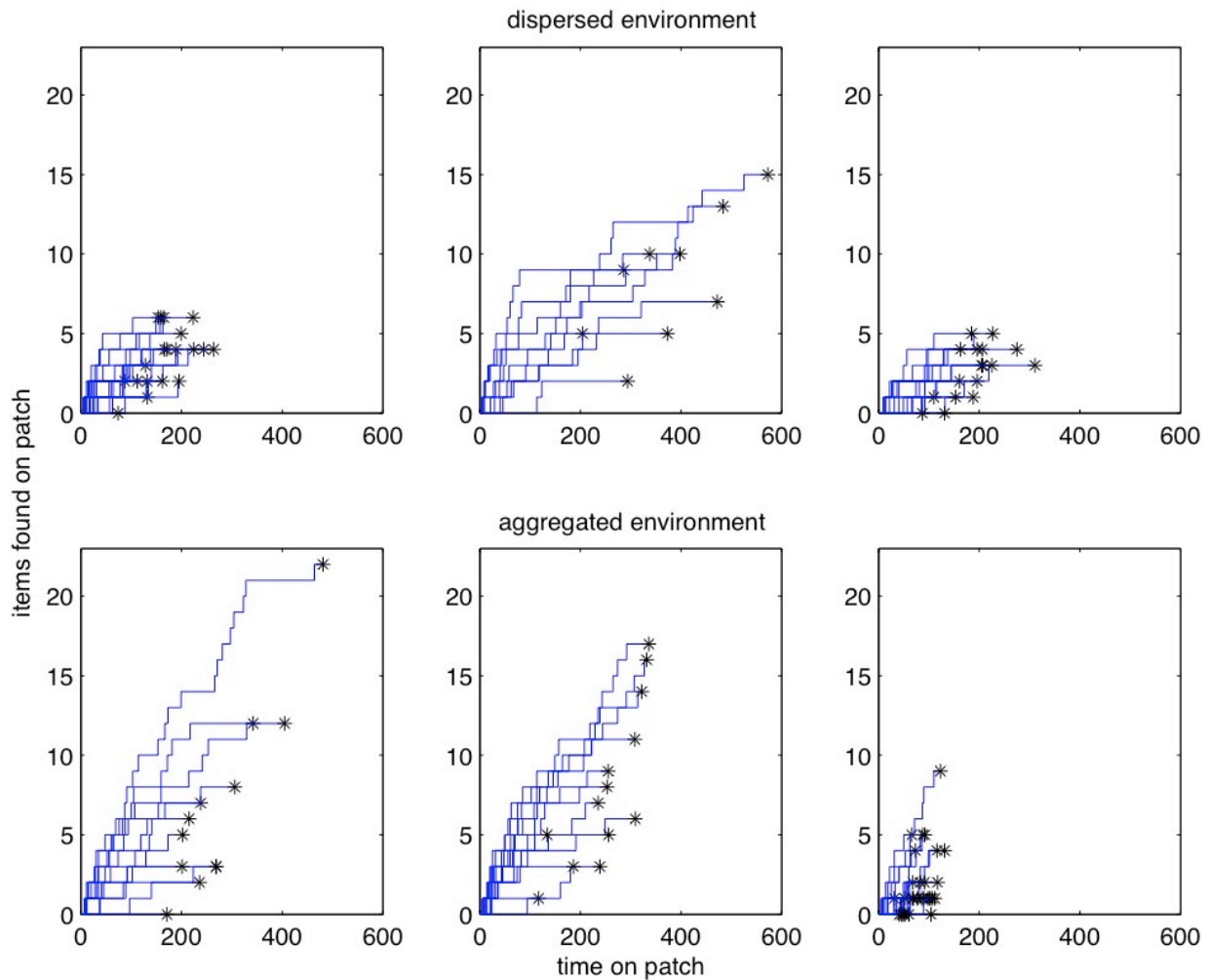


Figure 4.13 Plots of number of correct words n against the patch staying-times t . Each row shows three randomly chosen participants for each resource environment; each line corresponds to a separate sequence and asterisks indicate switching events.

As with the fishing task, in both environments a straight line with a positive slope is a good fit to the switching points. This means that participants stayed longer at patches when they found a lot of words. Such behavior is compatible with what we would expect in an environment that is more aggregated than Poisson. Because we do not know whether our dispersed environment is more or less aggregated than Poisson, we are interested mainly in the difference in slope between environments. We will investigate this further in the next section.

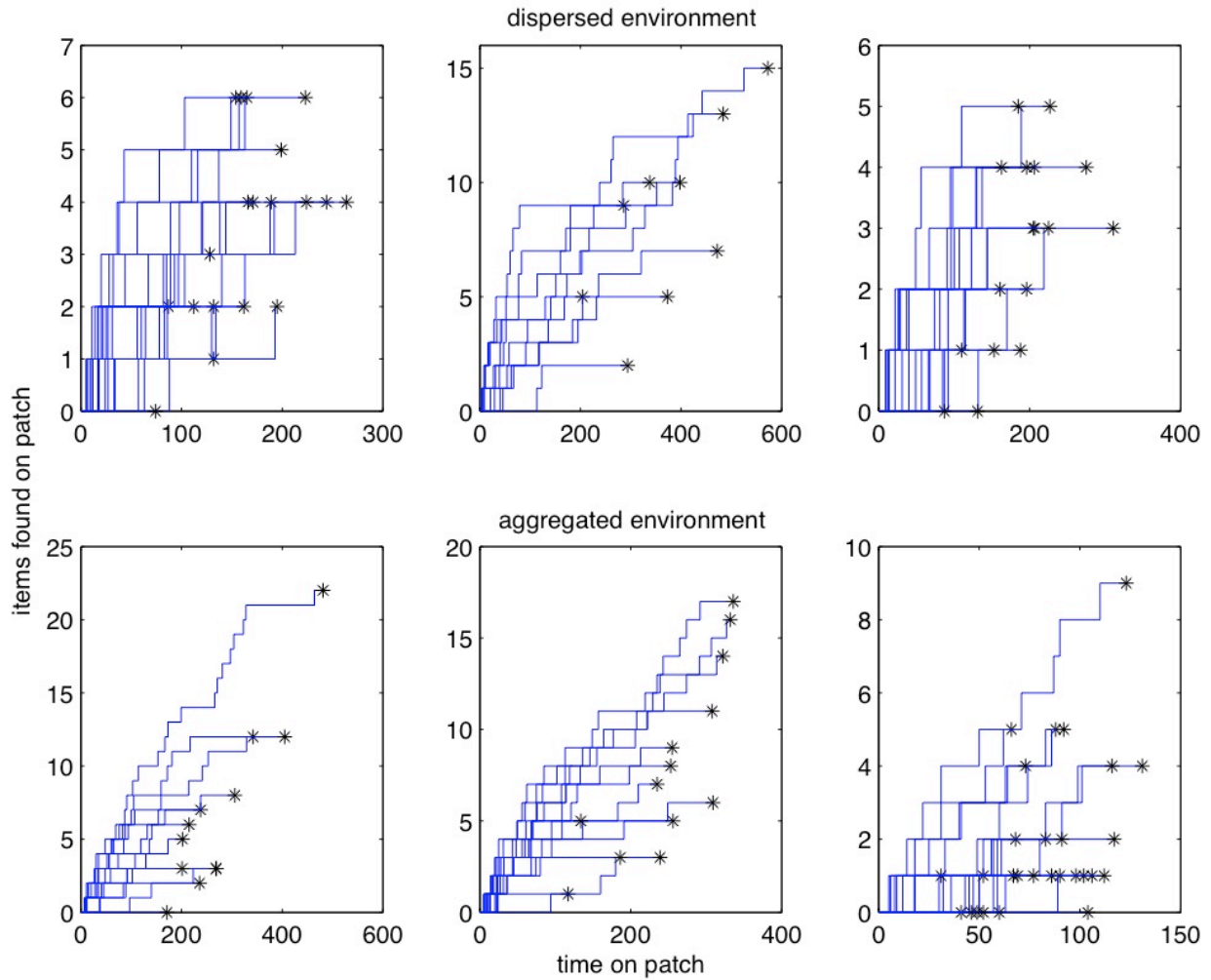


Figure 4.14 Plots of number of correct words n against the patch staying-times t . Each row shows the same three participants as in Figure 4.13 for each resource environment, but data is plotted on unequal axes; each line corresponds to a separate sequence and asterisks indicate switching events.

To inspect if participants used the giving-up-time rule, we plotted each participant's time at a patch against the time intervals between successful word findings (see Figure 4.15). However, participants do not seem to use a giving-up-time rule since neither are all asterisks on one horizontal line parallel to the t -axis nor are they consistently above the symbols that indicate time intervals between word findings.

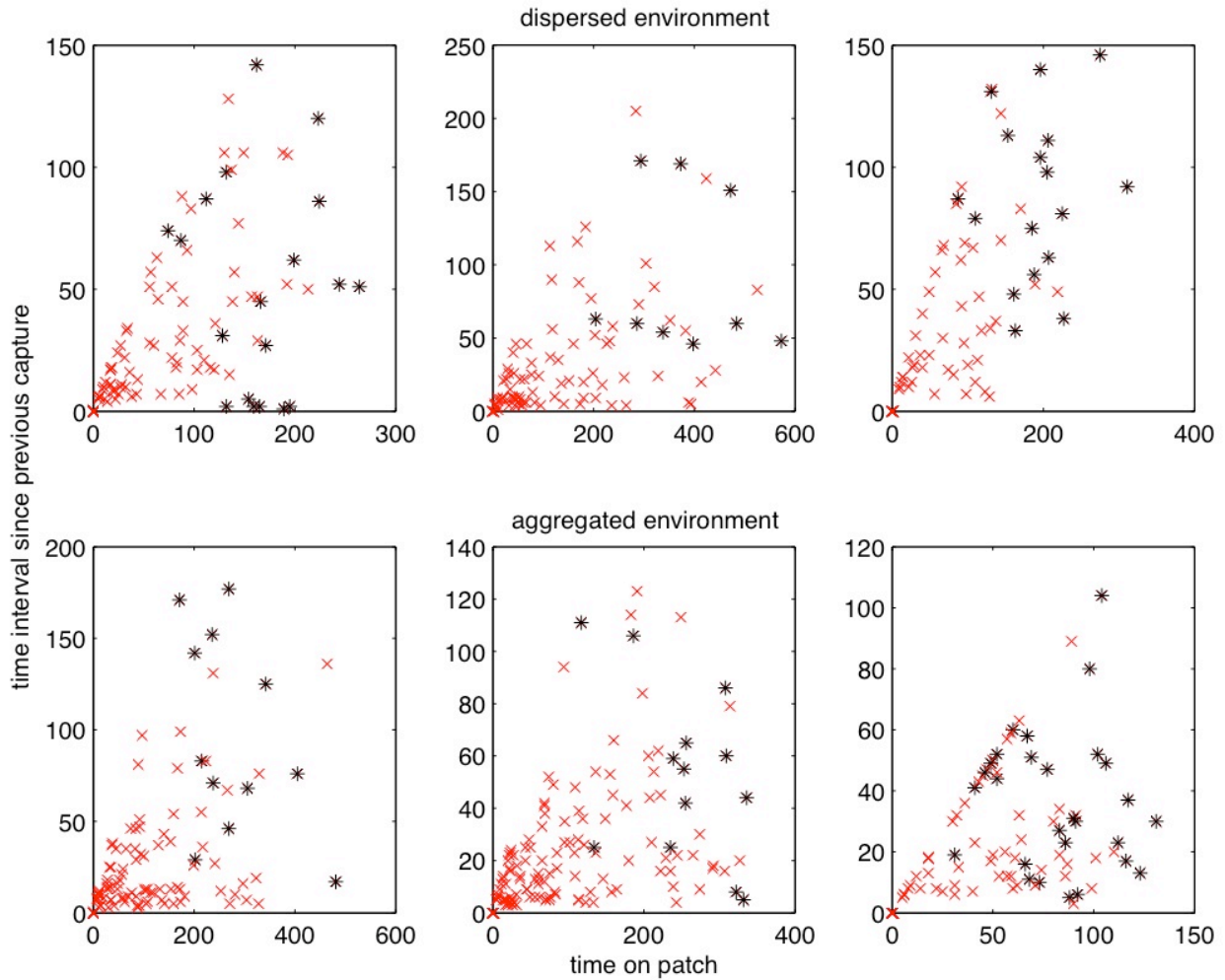


Figure 4.15 Plots of *time intervals* since previous capture against patch-staying times t . Each row shows the same three participants for each resource environment; crosses show time intervals between 2 subsequent words and asterisks indicate switching events (i.e. the giving-up-time).

Regression of t on n

When regressing t against n , the intercepts of each line estimated the time that a participant would stay at a sequence if he or she did not find a word, and the slopes of these lines indicate how much longer a participant stayed after finding each word. As for the fishing task, we analyzed only a subset of all the patches that participants visited, so as to allow participants time to learn about the underlying statistical regularities of each resource distribution. Thus, only those sequences that were visited after the scheduled appearance of the two fixed sequences were put into the analysis.

An ANOVA examined the influence of the factors subject, number of correct words found at the current patch and environment on participants' patch-staying times (Table 4.8).

Table 4.8 Analysis of variance for the time spent at a patch in the two environments of the word puzzle

Source	<i>df</i>	Adjusted MS	<i>F</i>	<i>p</i> -value
Environment	1	20,934	23.37	<0.001
Subject (Environment)	57	5,286	5.90	<0.001
Number of words found	1	277,538	309.90	<0.001
Environment * Number of words found	1	201	0.22	0.636
Subject * Number of words found (Environment)	57	3,383	3.78	<0.001
Error	406	(896)		

Notes. Adjusted sum of squares used for significance tests; asterisks indicate interaction term; one subject was excluded for looking at only one sequence within the analyzed data set.

The intercept of a participants' regression line systematically varied between the two resource distributions as indicated by the significant effect for environment. Whereas participants in the dispersed environment would stay 119 s before giving up if they found no solution, participants in the aggregated environment would stay only 90 s. Note that the interaction term between environment and the number of correct words is not significant: Although, as predicted, the slope is slightly less positive in the aggregated environment, the time increments after a successful word finding are very similar in each environment (11 s and 12 s, respectively).

The distributions of intercepts and slopes had considerable skew. Non-parametric Kruskal–Wallis tests confirmed that there is no difference in the slopes [$H(1) = 0.06, p = .808$], but now the significant effect for the intercepts disappeared [$H(1) = 1.03, p = .310$].

As in the analysis of the fishing task, we also tried fitting more complex models and added to the model the time since the last found word, the time since the start of the experiment, the number of previous patch visits, and a quadratic term for the number of words found. In addition, we allowed for interactions between these variables and environment and subject. Table 4.9 shows the results of this further stepwise regression analysis.

Overall, the impact of the number of correct words found on participants' tendency to stay at a patch remained the most influential factor while the giving-up time added only little. Note that despite analyzing only the second half of the data, there is a significant effect of the time since the start of the experiment. This could be an indication of either experience with or tiredness during the task.

Table 4.9 Analysis of variance for the time spent at a patch in the two environments of the word puzzle when including participants' giving-up time, a quadratic term for the number of words found, and the time since start of the experiment

Source	<i>df</i>	Adj MS	<i>F</i>	<i>p</i> -value
Environment	1	15,441	10.10	0.002
Subject (Environment)	57	2,191	3.07	<0.001
Number of words found	1	159,690	223.54	<0.001
Environment * Number of words found	1	532	0.75	0.389
Subject * Number of words found (Environment)	57	3,737	5.23	<0.001
Number of words found * Number of words found	1	23,316	32.64	<0.001
Giving-up time	1	36,420	50.98	<0.001
Time since start of the experiment	1	16,321	22.85	<0.001
Error	403	(714)		

Notes. Adjusted sum of squares used for significance tests; brackets indicate nesting, asterisks an interaction term; one subject was excluded for looking at only one sequence within the analyzed data set.

Placed Sequences

We analyzed data on the placed sequences in an analogous way to the t vs. n regression above, except that with only two points it is straightforward to fit the best fitting straight line between them. Whereas the intercepts did not differ between environments [$H(1) = 3.25, p = .072$], the slopes were marginally statistically different [$H(1) = 3.85, p = .050$]. This means that, as one would predict, participants increased their staying time more with each solution found in the aggregated environment. As an additional test, we looked whether the sequence yielding more solutions had a shorter or longer staying time: Whereas there was no systematic difference in the dispersed environment (23 shorter and 25 longer), participants in the aggregated environment more often showed the positive relationship expected of an environment more aggregated than Poisson (10 shorter and 40 longer). This difference was significant (Fisher's exact test, $p = .005$). Note that we ran these analyses with additional participants from an earlier data collection (with shorter experimental time), but in which these two sequences were placed in the same way.

Cox Proportional Hazard Model

We investigated the same list of covariates as for the fishing task for their potential effect on participants' patch-leaving tendency. However, in addition to the covariates that assess participants' experience at the current patch (e.g., the number of correct words found) or the experience gained at previously visited patches (e.g., density of the previous patch), we also included other performance-independent indicators of the quality of the sequences (see Table 4.10). We hypothesized that participants might utilize such information about the sequence (e.g.,

letter frequency of specific letters) to adjust their patch-staying times. Such a situation would be comparable to insect species that regulate their initial patch-staying times by the intensity of a single pheromone cue [see description of Waage's (1979) model in the Introduction of this chapter].

Table 4.10 List of the covariates tested for their effect on subjects' patch-leaving tendency in the word puzzle

Covariates relevant to the within-patch experience
Number of found words on the current patch ^a
Giving-up-time (i.e. time between last found word and switch) ^a
Covariates relevant to the experience on the previously visited patches
Number of previous patch visits
Number of found words at previous patch
Giving-up time in previous patch
Density of the previous patch (i.e. number of solutions in wordlist)
Number of found words since start of the experiment
Covariates relevant to the quality of the sequences
Total letter frequency of sequence
Average estimate for the number of solutions in that sequence
Sum of available word-frequency information

Note. ^a indicates a time-dependent covariate

Two of the sequence-quality covariates were the mean responses from the sequence solution estimation task and the total letter frequency of each sequence (i.e., the sum of all the percent frequencies of the nine individual letters). The latter was included because spotting high-frequency letters might be a good cue for the number of available solutions to that sequence. However, there might have been also more complex cues that participants used based on recognizing combinations of letters making up familiar words or syllables. Rather than considering too many possibilities, we added a single sophisticated metric that should accurately capture this possibility. This third sequence-quality covariate was computed using word-frequency information for all German 1-2 syllable words of length 2-8 letters (obtained from the Department of General and Neurocognitive Psychology at the Free University of Berlin). For each letter sequence, we gathered the word frequency information for all of its possible word solutions and entered the sum of these frequencies as a covariate. Table 4.11 shows the high correlations between the number of solutions in our word list and the sequence-quality covariates that we created.

All participants' patch visits after the placed sequences were entered into a step-forward likelihood-ratio Cox regression analysis. As in the fishing task, two of our covariates were time dependent, subject and environment were included as categorical variables and all continuous

covariates were tested for linearity of their effect; for the time since the last capture we used a logarithmic transformation. Table 4.12 shows the results of the final model.

Table 4.11 Intercorrelations between the number of solutions in wordlist and the sequence quality covariates

Covariate	1	2	3	4
1. Number of solutions for that sequence in the wordlist	—	.42	.44	.42
2. Total letter frequency of sequence	.82	—	.64	-.01
3. Estimate for the number of solutions in that sequence	.55	.77	—	.08
4. Sum of available word-frequency information for that sequence	.92	.77	.47	—

Notes. Correlations for the aggregated environment (white area) and dispersed environment (shaded area) are each based on a sample size of 26 sequences. Bold numbers indicate correlation is significant at the .05 level (two-tailed).

The largest effect was again found for subject. Participants utilized information, both from their within-patch experience and from their experience of previously visited patches: The time since the last capture (Wald = 91.65), the number of words found at the previous patch (Wald = 8.38) and the total number of previous patch visits (Wald = 40.07) are highly significant covariates. All of these three covariates decrease the tendency to stay at a sequence. In contrast to the results obtained from the standard regression, there was no significant effect for the number of words found at the present patch. However, when computing the analysis for each environment separately, the number of words found did reach statistical significance in the aggregated environment ($p = .002$), but not in the dispersed environment ($p = .261$).

Table 4.12 Estimated regression coefficient (β), standard error (SE), Wald statistic, and hazard ratio [exp (β)] for covariates that had a significant effect on the patch-leaving tendency in the two environments of the word puzzle

	β	SE	Wald	df	p-value	exp (β)
Subject	n/a	n/a	549.97	59	<0.001	n/a
Giving-up time	0.552	0.064	73.53	1	<0.001	1.737
Total letter frequency of sequence	-0.015	0.010	2.33	1	0.127	0.985
Environment * Total letter frequency of sequence	n/a	n/a	15.58	1	<0.001	n/a
Number of previous patch visits	0.098	0.015	40.13	1	<0.001	1.103
Number of found words at previous patch	0.007	0.003	8.11	1	0.004	1.007

Notes. The overall significance of the fitting model: $\chi^2 = 905$, $df = 64$, $p < .001$; asterisk indicates interaction term.

There was an interaction term between environment and one of our sequence-quality covariates—letter frequency. To test these differences between environments more correctly (i.e., compared to the variation between subjects), we reran the Cox regression removing the environment term, but included an interaction term between subject and letter frequency.

Unfortunately, here, the coefficients did not converge and we could not further statistically test these differences between environments with the software available to us.

Questionnaires

In both environments, the majority of participants reported using the number of correct words found in a sequence, the time they spent so far at that sequence and the time interval since finding the previous correct word as cues to determine their patch leaving from a given letter sequence. Because there were no significant differences in the answers between environments, we pooled the data for the two environments. As in the fishing task, the time since last word found was the cue that people reported utilizing most often. Table 4.13 summarizes the total responses on each question.

Table 4.13 Qualitative responses summed across the two environments of the word puzzle

Cue	Cue usage				Times mentioned in reports
	not at all	rarely	often	very often	
Number of words at the current patch	3	23	29	5	1
Time spent at patch	1	19	32	8	2
Time since last word find	1	13	27	19	6

Notes. Questionnaire responses were forced-choice questions from 1 (did not use that information at all) to 4 (used that information very often).

Two independent raters coded the responses that 65% of the participants gave in written reports about their potential strategy use. The commonest category of responses was strategies that used the time since last solution (see rightmost column of Table 4.13; inter-rater reliability of 77%), but a large fraction of participants now also reported strategies that had only little to do with the three ecologically rational cues, focusing instead on the linguistic aspects of our stimulus material. The following text excerpts give examples of these written responses:

I switched almost immediately when there was no ‘I’ or ‘E’ in the letter sequence.

I tried coming up with words that sounded similar or rhymed with the solutions that I had found at this sequence. The moment that I could not think of more combinations, I switched sequences.

Since I could not think of that many words containing the vowels ‘U’ and ‘O’, I gave up earlier on these sequences.

Discussion

Our current results suggest that people use patch-leaving rules that are ecologically rational in an aggregated environment. However, different parts of our results support different patch-leaving rules. While the exploratory graphs and the standard regression analysis suggest a simple straight-line relationship (i.e., finding a lot of items is associated with longer staying times) and therefore the use of an incremental rule, the results of the Cox hazard model indicate the use of giving-up times—thus, supporting the giving-up-time rule. In addition, results from the Cox hazard model and the written questionnaire responses demonstrate that participants used cues that were predictive of the quality of our letter sequences. Here, the total letter frequency, but also the frequency of specific letters seem to have been utilized.

We found only small differences in the way participants adapted their patch-leaving rules to the two environments we created. The analysis of placed sequences did not support the hypothesis that in the more aggregated environment finding a solution has a greater incremental effect on tendency to stay, but this finding was not convincingly duplicated in either the *t* vs. *n* or Cox regression. Overall, participants behaved as if foraging in an aggregated environment is their default.

General Discussion

In a series of two computerized foraging experiments, we investigated if the heuristic rules that have been proposed as guiding animals in deciding when to leave a patch of food may also underlie human decision-making when foraging for resources. One of our tasks investigated how people search for resources in the external world, while the other task explored whether people apply similar rules in an internal information search from memory.

In both experiments, people applied patch-leaving rules that are ecologically rational in an aggregated environment. One of these rules, the incremental rule, exploits the statistical pattern of such aggregated environments by adding a time increment for each successful resource capture to an organisms' patch-staying tendency. The other rule, the giving-up-time rule, adjusts the tendency to stay in a patch by utilizing the time since last capture. Participants in both tasks did not adapt parameters of their patch-leaving rules much, if at all, to the types of environments they faced. Switching behavior expected from other decision rules was not observed. On the contrary, participants used the same two patch-leaving rules that fit aggregated environments in the other types of environments (dispersed and Poisson) that we generated as well. Why was this the case?

Most species of plants and animals rarely, if ever, distribute themselves in a purely random manner in their natural environment, because individual organisms are not independent from one another: Whereas mutual attraction leads to aggregation for some species, mutual repulsion leads to regularity (dispersed environments) in other species (Taylor, 1961). Most often, however, these deviations from randomness are in the direction of aggregation since aggregation offers considerable ecological benefits (Waters, 1959; Krause & Ruxton, 2002). Such advantages can be the (1) responses to physical environments (e.g., resource availability, light or temperature), (2) reproductive behavior (e.g., clumped arrangements of eggs or offspring being in close parental contact), (3) mutual attraction with other individuals of the same species (e.g., mating behavior), (4) interactions with other species (e.g., parasites or predator avoidance) or (5) benefits in foraging behavior (e.g., to capture prey types that would be too large, too agile or too dangerous for a single individual). Since humans have been hunters and gatherers for about 99% of their human history (Tooby & DeVore, 1987), it could well be that our (evolved) psychology is adapted to assume such aggregated resource distributions as our default, because it would have offered a selective advantage under ancestral conditions.

Additional studies using our fishing task experiment should further explore why participants did not adapt well to the non-aggregated resource environments. It could be that foraging for 45 minutes was simply not long enough to learn the underlying environmental regularities of these resource distributions and we could prolong the duration of the experimental phase to investigate this. More research could address whether participants react to changes in other environmental parameters besides the shortening of travel time we introduced as one condition of our fishing task (e.g., more/less variable resource return rates, fewer fish initially in each pond, or travel times that change during the course of the experiment). For instance, reducing the number of fish per pond might make it easier to detect evenly dispersed resource distributions and could therefore facilitate the use of a decremental- or a fixed-number rule.

Our cognitive information foraging task, the word puzzle, could also be extended. Here, creating larger stimuli sets (to generate more different resource environments) could more readily test for differences in the strategies with which participants determine their patch leaving. Varying the quality of letter sequences by other means than mere difficulty might be another thing to try. Do participants still rely on decision rules appropriate in aggregated environments when the quality of the sequence is varied by its length or the vowel-to-consonant ratio? What sequence-quality cues would people then start using?

Research with both tasks can (and should) also address the general question whether participants are sensitive to environmental variation by introducing within-subject designs. Here, it would be interesting to see to what extent participants adhere to previous decision rules when faced with a different environment that calls for other ecologically rational patch-leaving rules. Or are people better able to learn these environmental regularities when they change during the course of the experiment? Such an approach might be amended by letting participants actually do both tasks, foraging in the external world and foraging in the internal world, because this could facilitate participants' insight of which rules to apply in which environment.

Finally, as an idea for future directions of this foraging research in general, we might also think of investigating real-world environments. Many tasks in a variety domains have the same foraging-patch structure as outlined here and it could be profitable to look at some of these for evidence of patch-leaving decision mechanisms that people naturally use. Looking at operational research, how the military designs search patterns (e.g., searching for mines or boats), how shoppers look for particular goods in a store, or how cab drivers decide on the best place to pick up passengers could provide such data. Real world environments could even include field experiments with "classical foraging" tasks such as people screening the forest ground for mushrooms or digging out potatoes.