Risky Hybrid Foraging: The Impact of Risk, Reward Value, and Prevalence on Foraging Behavior in Hybrid Visual Search

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Abstract

In hybrid foraging, foragers search for multiple targets in multiple patches throughout the foraging session, mimicking a range of real-world scenarios. This research examines outcome uncertainty, the prevalence of different target types, and the reward value of targets in human hybrid foraging. Our empirical findings show a consistent tendency towards risk-averse behavior in hybrid foraging. That is, people display a preference for certainty and actively avoid taking risks. While altering the prevalence or reward value of the risky targets does influence people's aversion to risk, the overall effect of risk remains dominant. Additionally, simulation results suggest that the observed risk-averse strategy is suboptimal in the sense that it prevents foragers from maximizing their overall returns. These results underscore the crucial role of outcome uncertainty in shaping hybrid foraging behavior, and shed light on potential theoretical developments bridging theories in decision-making and hybrid foraging.

Keywords: hybrid foraging, risk-sensitivity, decision-making

Public Significance Statement. Hybrid foraging characterizes a wide range of real-world searching scenarios where people search for multiple potential items across multiple patches. However, in the real world, rewards are often uncertain. The current study highlights the important role of risk sensitivity in shaping hybrid foraging behavior when potential items vary in prevalence, reward, and outcome uncertainty. Our findings reveal that being cautious about taking risks can lead people to miss out on opportunities to maximize their overall gains in hybrid foraging.

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Imagine that you are in the woods and hunting for various types of mushrooms (e.g., shiitake, oyster, portabella, etc.). A common strategy would be to search in one region for the different types of mushrooms, and then, at some point, to move on to a new region in search of more mushrooms. This is an illustration of “hybrid foraging” (Wolfe et al., 2016), where people search multiple patches (here, regions of the woods) for multiple instances of multiple possible types of targets (different types of mushrooms).

Hybrid foraging combines the characteristics of hybrid search (i.e., searching for a single instance of any of several target types in the presence of distractors; e.g., Schneider and Shiffrin, 1977; Wolfe, 2012) and foraging (i.e., searching for multiple instances of a single target type; e.g., Bond, 1981; Cain et al., 2012; Stephens and Krebs, 1986; Wolfe, 2013). It is an essential process in various cognitive domains (see Hills et al., 2015 for a broad review), such as memory search (Hills et al., 2012; Lundin et al., 2023) and social learning (Kharratzadeh et al., 2017; Wisdom et al., 2013). The current study probes hybrid foraging using visual displays where participants search for multiple instances of several target types. Hybrid foraging is characteristic of a wide range of real-world scenarios, from looking for keys and cards in pockets, to surfing the internet for a literature review (Pirolli, 2007), to potential life-or-death situations, such as screening medical images for potential signs of cancer (Trueblood et al., 2021; Williams and Drew, 2019; Wolfe et al., 2016, 2021). Understanding hybrid foraging can help us comprehend the key factors that influence behavior in these common but complex real-world search scenarios.

The prevalence of different target types plays a significant role in shaping hybrid foraging behavior (e.g., Wolfe et al., 2016, 2018). A commonly occurring target is usually preferred over a rare target, if both targets have the same value, which can result in elevated miss errors at low prevalence (i.e., the prevalence effect). The value of targets also shapes hybrid foraging behavior. A high-value target is usually preferred over a low-value target, even in cases where locating high-value targets requires more effort (Tagu and Kristjánsson, 2022; Wolfe et al., 2018).

Moreover, the effects of prevalence and value can interact with each other. Wolfe et al. (2018) found that high-value but rare targets were preferred over low-value but prevalent targets, indicating that the preference for high value can override an aversion to rarity.

To date, the existing literature on hybrid foraging (e.g., Tagu and Kristjánsson, 2022; Wiegand and Wolfe, 2021; Wolfe et al., 2018) has primarily focused on situations where selection of a target type guarantees an associated amount of reward (i.e., sure targets). However, in the real world, rewards are often uncertain, and the uncertainty of outcomes impacts human cognitive and neural processing (Monosov, 2020). For example, imagine that you prefer gathering shiitakes, but only one in ten of that variety were of edible quality. In such a situation, an individual must consider multiple factors (reward probability, reward value, and prevalence) to maximize foraging outcomes. In particular, outcome uncertainty is likely to play a significant role in shaping hybrid-foraging behavior. The goal of this paper is to examine how outcome uncertainty affects foraging behavior and how the effect of this risk interacts with the effects of reward value and prevalence within the hybrid foraging paradigm.

Outcome uncertainty has been consistently shown to affect the behavior of animals in food foraging (Bateson, 2002; Kacelnik and Bateson, 1996), and in various decision-making paradigms with humans (Weber et al., 2004). When foraging for food, animals often encounter choices between options differing in reward variance. For example, bumblebees and monarch butterflies usually have to decide whether they should forage from the flower species providing constant nectar volumes (i.e., sure targets) or the flower species providing varying nectar volumes (i.e., risky targets). Studies (e.g., Cartar and Dill, 1990; Rodrigues et al., 2010; Waddington et al., 1981) find that, in most cases, these nectar-collecting foragers prefer the constant reward over the variable reward, reflecting a risk-averse foraging strategy. On the other hand, animal foraging behavior can change depending on the context (see review in Bateson, 2002). For instance, Caraco and colleagues (1981, 1990) showed that juncos tended to be risk-averse when they expected to obtain sufficient daily energy above their survival threshold. That is, when juncos had ample intakes or the ambient temperature was comfortable, they visited the station providing a fixed amount of millet seeds more frequently than the station providing variable seed amounts. But when their survival was in danger, juncos became risk-seeking and visited the risky station more often than the sure station.

Human risk preferences also demonstrate sensitivity to context. As captured by Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), when choosing between a sure gain, such as a token for $100, and a risky gain with a low probability of winning, such as a gamble yielding $1000 with a 10% chance and $0 with a 90% chance, people tend to be risk-seeking and prefer the risky option over the sure option, although the expected value of both options are equal. On the other hand, when choosing between a sure gain ($100 with certainty) and a risky gain with a high probability ($125 with an 80% chance and $0 with a 20% chance), people tend to be risk-averse and prefer the sure target option over the risky option. Furthermore, when people learn the option information (e.g., the reward probability and the mean reward value) from experiential sampling, as opposed to description, their risk preferences can change such that they tend to be risk-averse when encountering risky gains with a low probability and risk-seeking when encountering risky gains with a high probability (e.g., Barron and Erev, 2003; Hertwig and Erev, 2009; Hertwig et al., 2004; Weber et al., 2004).

In this paper, we examine the impacts of outcome uncertainty, the prevalence of different target types, and the expected value of targets in hybrid foraging. In a 15-minute hybrid foraging session, participants collect reward points by searching for target letters in “patches” (i.e., screens full of letters). They can travel to a new patch at any time during the task (non-exhaustive foraging, Á. Kristjánsson, Ólafsdóttir, and Kristjánsson, 2020). Different target letters are associated with different numbers of reward points with different probabilities. In addition, the prevalence of different target letters varies in some conditions. To maximize overall return from the task, foragers have to balance the likelihood of receiving a reward, the possible reward values, and the ease of locating targets in a dynamic visual display. Performing well at the task involves the interaction between cognitive components of both decision-making and visual search.

We quantify the degree of outcome risk across targets using the coefficient of variation

(CV). Compared to other risk measurements, such as the outcome variance, the CV has been shown to be a better predictor of risk preferences in meta-analyses of both animal foraging behavior (Kacelnik and Bateson, 1996) and human risky choice (Weber et al., 2004). Specifically, the CV measures the outcome variability in relation to the mean value of an alternative, as it is a ratio of the standard deviation of outcomes (SD) to the expected value (EV). For instance, if a target yields a 20-point reward with a 20% chance and 0 points with an 80% chance, then the $CV = \frac{SD}{EV} = \frac{\sqrt{64}}{4} = 2$. Intuitively, the CV reflects the degree of risk per unit return. A high value of CV indicates that acquiring the target involves a large amount of risk (i.e., a risky target), while a zero-valued CV indicates a target providing a sure reward. Additionally, we manipulate the prevalence of targets by varying the display proportion of different targets at the onset of patches, following the convention in standard hybrid foraging tasks (e.g., Wolfe et al., 2016, 2018).

We first investigate the effects of risk and prevalence on hybrid-foraging behavior by holding the expected value of targets constant (Experiment 1: equal EV). We manipulated the association between risk and prevalence across four conditions. In the equal-prevalence, unequal-risk condition, the difference among targets is solely in CV, and we assess the main effect of risk on foraging behavior in this condition. In the unequal-prevalence, equal-risk condition, we assess the main effect of prevalence on foraging behavior by having all the targets be sure targets (i.e., CV = 0). In the next two conditions, we are interested in the interaction between risk and prevalence on foraging behavior. In the common risk condition, the risky target has the highest prevalence; while in the common sure condition, the sure target has the highest prevalence. Our results suggest a robust preference for the sure target over the risky target, even in the situation where the risky target is much more prevalent. This finding highlights a strong risk-aversion tendency in human hybrid foraging behavior.

Would an increase in the reward value of the risky targets reduce risk aversion in hybrid foraging? We investigate this question in a follow-up experiment (Experiment 2: unequal EV) in which we assign a higher expected value to the risky targets. Our results suggest that an increase in the reward value of risky targets reduced risk-averse foraging behavior, especially when the risky targets were highly prevalent, but not to an extent to eliminate risk aversion altogether. Finally, we developed a model based on optimal foraging strategies for both in-patch searching and patch-leaving behavior in our task. We compare our empirical findings to the simulations from this optimal model to further explore how risk causes human foragers to deviate from the optimal foraging strategies.

All of the experiments were conducted under IRB #210989 approved by the institutional review board of Vanderbilt University.

Experiment 1: Targets with Equal Expected Value

In Experiment 1, we examine the effects of risk and prevalence on the foraging preferences in hybrid risky foraging tasks. The expected value (EV) of payoffs was held constant across targets.

Method

Participants

In order to have 50 participants in each of four conditions (Table 1), we targeted a sample size of 200 participants. Participants were recruited online from Amazon Mechanical Turk (MTurk) using the CloudResearch platform according to the following criteria to ensure data quality: (1) they must be at least 18 years old; (2) they must reside in the United States; (3) they must have an approval rate of at least 95% for completed human intelligence tasks on MTurk. A total of 201 participants (102 women, 99 men; age: M = 40.86 , SD = 12.61) completed the study online. The sample size was determined prior to data collection, and the data was analyzed only after all data had been collected.

All participants who completed the 15-minute experiment were paid a $1 base rate and a performance-based bonus ranging from $0 to $1 to incentivize effort. The amount of the bonus was determined by the average points participants earned per second: $0.20 for 2-3 points per second, $0.50 for 3-4 points per second, $1 for above 4 points per second, and $0 for below 2 points per second. The average bonus payment participants received was \$0.37.

Participants who had low performance (i.e., either their rate of earning points was less than 1.5 points per second or they committed more than 20% false positive errors) were excluded from the data analyses. The exclusion criteria were pre-registered. In total, 22.38% of participants (N = 45) were excluded. After the exclusions, we had 38 participants in Condition 1a, 34 in Condition 1b, and 42 in Condition 1c, and 42 in Condition 1d.

Materials

We programmed the hybrid foraging task in JavaScript. At the beginning of a hybrid foraging session, eight letters were randomly selected from the English alphabet. Four of the letters were assigned to represent targets (i.e., T1, T2, T3, and T4), and the other four were assigned to represent distractors. A click on a letter removed the letter from the screen. Clicking on a distractor resulted in zero reward. Selecting a target letter yielded a certain amount of reward points with a certain probability (Table 1). Specifically, a selection of T1 (i.e., the sure target) would always yield 4 reward points. T2, T3, and T4 were designated as risky targets, with the potential to yield 5, 8, and 20 points respectively, upon selection, with a probability of 80%, 50%, and 20% respectively. The order of risk (as reflected in the CV values) among targets was T1 $<$ T2 $<$ T3 $<$ T4, with T4 being the riskiest target.

The prevalence rate of a target Ti was determined by the number of instances of that target divided by the total number of instances of all targets at the onset of patches (t_0): $Prevalence\ of\ Ti = \frac{Number\ of\ Ti\ at\ t_0}{\sum_{i=1}^{4} Number\ of\ Ti\ at\ t_0} = \frac{Ni,t_0}{\sum_{i=1}^{4} N_{i,t_0}}$. In order to prevent participants from adopting a counting strategy, we pseudo-randomized the initial number of Ti in a patch (i.e., N_{i,t_0}). Let $\overline{N}_{i,t_0}$ notate the mean number of Ti at t_0. The actual number of Ti at t_0 was then set to be $\overline{N}_{i,t_0}$ with 0.6 probability, $\overline{N}_{i,t_0} - 1$ with 0.2 probability, and $\overline{N}_{i,t_0} + 1$ with 0.2 probability. In the equal-prevalence condition, the average number of each target at the onset of patches (i.e., $\overline{N}_{i,t_0}$) was 8. In the unequal-prevalence conditions, the average number of each target varied between 2, 4, 9, or 17. On average, a foraging patch had 32 targets, and the average prevalence of target Ti at the onset of patches was $\overline{N}_{i,t_0}/32$. The number of distractors was equivalent to the number of targets on average in each patch. Thus, participants saw an average of 64 items on the screen at the start of a patch.

The association between CV and prevalence was manipulated across four between-subject conditions (a, b, c and d; Table 1). In Condition a (unequal prevalence, equal risk), targets had equal prevalence but varied in risk (i.e., CV). In Condition b (common risk), the value of CV positively correlated with prevalence so that riskier targets were more prevalent. In Condition c (common sure), the value of CV was negatively correlated with prevalence, resulting in the sure target having the highest prevalence. In Condition d (unequal prevalence, all sure targets), targets varied solely in prevalence and the value of CV was held at zero (i.e., sure targets).

Table 1

Manipulated variables in different conditions of Experiments 1 and 2. Note that values shown in the Prevalence column are the mean relative display proportions for targets when a new patch begins.

Experiment	Condition	Target	Prevalence	Reward Points	Probability	Expected Value	Coefficient of Variation
Experiment 1 Equal Expected Value	a Equal Prevalence Unequal Risk	T1	8/32	4	1	4	0
		T2	8/32	5	0.8	4	0.5
		T3	8/32	8	0.5	4	1
		T4	8/32	20	0.2	4	2
	b Common Risk	T1	2/32	4	1	4	0
		T2	4/32	5	0.8	4	0.5
		T3	9/32	8	0.5	4	1
		T4	17/32	20	0.2	4	2
	c Common Sure	T1	17/32	4	1	4	0
		T2	9/32	5	0.8	4	0.5
		T3	4/32	8	0.5	4	1
		T4	2/32	20	0.2	4	2
	d Unequal Prevalence All Sure Targets	T1	2/32	4	1	4	0
		T2	4/32	4	1	4	0
		T3	9/32	4	1	4	0
		T4	17/32	4	1	4	0
Experiment 2 Unequal Expected Value	a Equal Prevalence Unequal Risk	T1	8/32	2	1	2	0
		T2	8/32	5	0.8	4	0.5
		T3	8/32	16	0.5	8	1
		T4	8/32	60	0.2	12	2
	b Common Risk	T1	2/32	2	1	2	0
		T2	4/32	5	0.8	4	0.5
		T3	9/32	16	0.5	8	1
		T4	17/32	60	0.2	12	2
	c Common Sure	T1	17/32	2	1	2	0
		T2	9/32	5	0.8	4	0.5
		T3	4/32	16	0.5	8	1
		T4	2/32	60	0.2	12	2

To prevent participants from adopting a “reading strategy” where, for example, participants might start at the upper left and “read” to the lower right (Wolfe et al., 2016), all of the letters (i.e., items for foraging) were constantly moving on the screen at a rate of 20 pixels per second. The total screen size of a patch was set to be 650 pixels × 650 pixels. Participants could proceed to a new patch at any time during the foraging session by clicking on a button. The location of patches on the screen remained fixed throughout the entire session (see Figure 1).

Procedures

After consenting to participation, participants were randomly assigned to one of four between-subject conditions (Table 1). At the beginning of the experiment, participants were informed that their task was to collect as many points as possible for 15 minutes by foraging for target letters across multiple patches. They were also informed that the amount of a bonus payment would be determined by their performance, as measured by the number of points they earned per second. After they read through the payment schedule, participants were informed about the identity of the four target letters and about the reward points, the winning probabilities, and the prevalence of each target type. The description of each target type followed the scheme: “Letter O has a X percent chance of giving you Y points. Approximately, Z% of the targets will be this kind”. When participants were ready, they proceeded to a short practice phase where they were required to collect 100 points before they started the 15-minute main hybrid foraging task. Participants were informed that their performance in the practice phase would not affect their bonus amount.

During the main hybrid-foraging task, participants selected a letter by moving a blue cursor on top of it and clicking on it. Once a letter was selected, it disappeared from the current patch. If the selected letter yielded a reward, the cursor would turn green for 100 milliseconds with a coin-dropping sound. Distinct coin-dropping sounds were assigned for different numbers of reward points. If a selection resulted in zero points, the cursor would turn red for 100 milliseconds with a negative feedback sound.

Participants did not need to hold the target letters in memory, as they were constantly displayed at the top of the screen (see Figure 1a). The number of points participants earned per second was displayed on the top-left of the screen, and the total number of points participants accumulated within a patch was presented on the top-right of the screen. The 15-minute main foraging task was divided into three 5-minute blocks to allow participants to take a short break in between. The remaining time for a block and the total points earned by participants throughout the main task were displayed on the right side of the screen for participants.

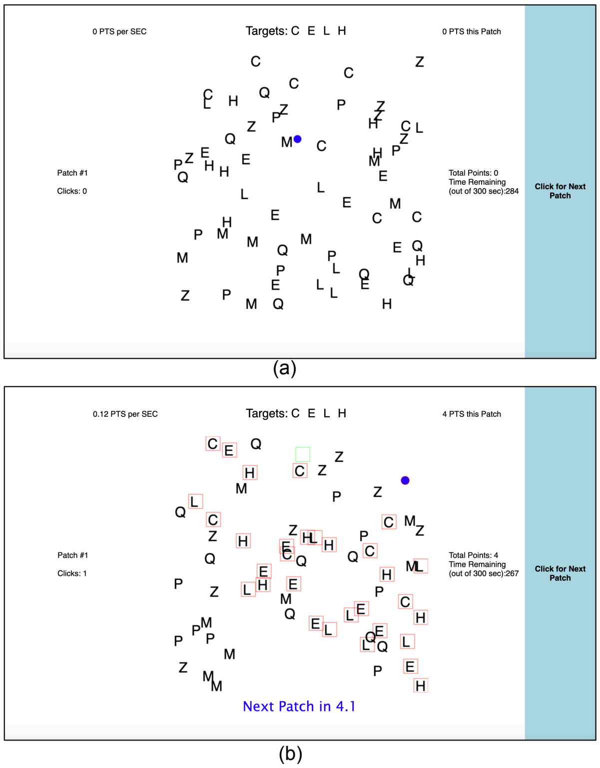


Figure 1

Example screenshots from the hybrid foraging task. Panel (a): a screenshot during the foraging task. Panel (b): a screenshot during the travel time between patches. During the 15-minute foraging session, participants accumulated reward points by collecting moving target letters of four different types in patches. They could move to a new patch at any time by clicking on a blue vertical bar on the right side of the screen, with a cost of a 5-second transition time. Target types varied in outcome probability, expected reward value, and prevalence. Full description of target information was provided to participants before the start of the foraging session.

Participants could move to a new patch by clicking on a blue vertical bar located on the right side of the screen at any time, with a cost of a 5-second transition time between patches.

During the transition time (Figure 1b), movements of letters ceased. Green boxes were displayed at the locations of targets that had been selected, while red boxes were displayed at the locations of uncollected targets on the screen. Meanwhile, a countdown for the transition time was displayed at the bottom of the screen. Even if participants selected all of the target items in a patch, they needed to click on the blue vertical bar to move to a new patch and incurred the travel time. After completing the 15-minute hybrid-foraging task, participants were informed about the amount of bonus they earned and were asked to fill out a demographic questionnaire (see Supplementary Materials for details).

Transparency and Openness

The pre-registrations for all of the experiments, the data, and the code for the optimal model simulation are available on the Open Science Framework at: https://osf.io/bf9st/.

Results

Our main analyses investigate the effects of risk and prevalence on hybrid-foraging behavior by examining within-patch foraging behavior and patch-leaving behavior for each condition. The main results are shown in Figure 2. Before presenting the results of these analyses, we compared several overall performance measures across conditions (Table 2). Results from Welch's ANOVAs showed that the number of patches participants viewed ($F(3,79.5) = 0.057,\ p = 0.989,\ \omega^2 = -0.008$), the number of clicks participants made within patches ($F(3,79.2) = 2.367,\ p = 0.77,\ \omega^2 = 0.026$), the average amount of time participants spent in-between clicks ($F(3,79.2) = 2.732,\ p = 0.49,\ \omega^2 = 0.032$), and the total number points participants earned ($F(3,82.4) = 1.720,\ p = 0.169,\ \omega^2 = 0.014$) did not differ significantly across conditions in Experiment 1. In addition, the error rate as measured by the average proportion of clicks on non-target items was below 5% in each condition. In total, participants made over 650 clicks on average throughout the main foraging task.

Table 2

Overall foraging performance in Experiments 1 and 2 throughout the hybrid foraging session.

		Number of Patch Clicks		Number of Viewed Patches		Inter-click Time (second)		Total Points	
Experiment	Condition	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Experiment 1 Equal EV	a: Equal Prevalence	26.777	4.923	26.868	7.231	1.099	0.355	2787.974	820.634
	b: Common Risk	26.701	5.854	27.177	13.899	1.229	0.467	2587.206	887.447
	c: Common Sure	28.621	4.096	27.333	7.814	1.027	0.413	2965.524	828.455
	d: Unequal Prevalence	28.772	3.155	26.714	6.232	0.989	0.251	2976.095	732.532
Experiment 2 Unequal EV	a: Equal Prevalence	29.350	3.124	22.909	6.339	1.219	0.504	4104.636	1284.761
	b: Common Risk	27.524	5.225	24.311	7.751	1.351	0.704	5884.578	2117.735
	c: Common Sure	27.897	5.886	25.750	7.484	1.135	0.400	2728.682	854.512

Within Patch Foraging Behavior

We evaluated within-patch foraging preferences by assessing the extent to which the selection of targets deviated from random selection. Specifically, we compared the relative proportion of a target being selected (termed the “selection proportion") to the relative proportion of that target on display (termed the “display proportion") at each click . We estimated the difference between these two proportions for each target from the first to the 30th click within patches. Fewer than 37% of patches received over 30 clicks.

The display proportion (the top row in Figure 2) quantifies the proportion of a specific target on display in relation to the total number of targets on display at the n^{th} patch click. The pattern of display proportions reflects the change in prevalence among targets as they are selected (and thus depleted) in a patch. For example, if there were 8 instances of each target at the beginning of a patch, and a participant selected T1 as their first choice, then the display proportion for T1 is $\frac{8}{32}$ at the 1st click and $\frac{7}{31}$ at the 2nd click. The display proportion for the other targets (i.e., T2, T3, and T4) are $\frac{8}{32}$ at the 1st patch click and $\frac{8}{31}$ at the 2nd patch click.

The second row in Figure 2 shows the selection proportion of each type of target. The selection proportions are calculated by dividing the number of selections made on a specific target at the n^{th} patch click by the total number of selections made on all targets at the n^{th} patch click. For instance, imagine a participant who sees a total of 25 patches during the main task. In 22 of these 25 patches, their first click was on a target and in the remaining 3 patches, their first click was on a distractor. Out of these 22 first clicks on targets, the participant selected T1 for 13 times, T2 for 6 times, T3 for 2 times, and T4 for 1 time. In this case, the participant's selection proportion for T1, T2, T3, and T4 at the first click would be $\frac{13}{22}$, $\frac{6}{22}$, $\frac{2}{22}$, and $\frac{1}{22}$, respectively. Thus, the four values at each click will add to 1.

Differences between selection and display proportions reflect the foraging preferences for each target after accounting for the variation in prevalence among targets (the third row in Figure 2). Random selection would be indicated by a zero difference between selection and display proportions. A positive difference indicates over-picking a target compared to what chance would predict; whereas a negative difference reflects under-picking a target. We estimated proportion differences of each target for each participant, and then performed analyses using those individual-level estimates.

Below, we first present the results from Condition 1a (equal prevalence) and 1d (unequal prevalence) to demonstrate the main effects of risk and prevalence on foraging behavior, and then present the results from Conditions 1b (common risk) and 1c (common sure) to illustrate the interaction between effects of risk and prevalence on foraging behavior in hybrid foraging tasks.

Unequal Risk, Equal Prevalence, Equal EV (Condition 1a). In this condition where all of the targets had the same expected value and were distributed evenly at the start of a new patch (i.e., the prevalence of targets was equal), differences between selection and display proportions varied by the riskiness of the targets (see the first column of Figure 2). The difference between selection and display proportions for T1 was above zero and exceeded that of the other targets at the start of patches, reflecting a strong initial preference for the sure target in the early stage of patch foraging. As T1 became increasingly harder to locate as instances of T1 decreased, participants began to select the next low-risk target (T2). Nevertheless, T1 was still over-picked compared to chance, as indicated by the positive proportion differences. In contrast, the proportion differences of risky targets, T3 and T4, were below zero at the beginning of patch foraging, suggesting that participants selected risky targets less often than predicted by chance. Moreover, with the depletion of targets over time, the riskiest target (T4) remained under-picked, reflecting that participants were averse to risk when they foraged for multiple targets with equal expected value. Eventually, selections among targets converged to random selection towards the end of patch foraging (see the bottom row in Figure 2). The observed behavioral patterns were supported by the results of robust regression (Huber, 2004) with robust standard errors (see Table 3; estimated coefficients are summarized in Table 1 in the Supplementary Materials). As compared to ordinary least square, robust regression employs alternative methods for residual minimization in order to reduce the influence of outliers. We modeled the difference between selection and display proportions as a linear function of the main and interaction effects of target type and patch click, after accounting for heteroscedasticity in the observed data (Hampel et al., 1986; Li, 1985; see Figure 1 in the Supplementary Materials). In sum, participants demonstrated a preference for certainty and an aversion to risk in Condition 1a.

Table 3

Results of Type III ANOVA omnibus tests for effects in the robust regression models with robust standard errors: Proportion Difference $= 1 +$ *Target Type* $*$ *Patch Click for each condition in Experiment 1. Estimated coefficients are summarized in Table 1 in the Supplementary Materials.*

Condition	Term	Df	F	P-value
1a Equal Prevalence	Intercept	1	102.894	< 0.001
	Target Type	3	88.547	< 0.001
	Patch Click	1	64.378	< 0.001
	Target Type × Patch Click	3	49.309	< 0.001
1b Common Risk	Intercept	1	30.710	< 0.001
	Target Type	3	12.775	< 0.001
	Patch Click	1	53.523	< 0.001
	Target Type × Patch Click	3	23.471	< 0.001
1c Common Sure	Intercept	1	109.936	< 0.001
	Target Type	3	73.923	< 0.001
	Patch Click	1	10.226	0.001
	Target Type × Patch Click	3	14.318	< 0.001
1d Unequal Prevalence	Intercept	1	18.604	< 0.001
	Target Type	3	39.672	< 0.001
	Patch Click	1	10.796	0.001
	Target Type × Patch Click	3	9.519	< 0.001

Equal Risk, Unequal Prevalence, Equal EV (Condition 1d). Condition 1d was a baseline hybrid foraging condition where all the targets yielded an identical and sure number of reward points. The sole variation among targets was in terms of prevalence. Observed proportion differences (the last column in Figure 2) indicate that participants consistently selected the most common target (T4) at a rate that was higher than predicted by chance, while they under-picked less common targets (T1 and T2) throughout the course of patch foraging. The results from robust regression (Table 3; estimated coefficients are summarized in Table 1 in the Supplementary Materials) corroborated these observations. Note that this represents an active preference for the common items; not just the passive effect of relative prevalence. These patterns indicate a standard prevalence effect on participants' foraging behavior; that is, the common targets were preferred over the rare targets. This is consistent with the findings in the existing literature on hybrid foraging (e.g., Wolfe et al., 2018).

Common Risk, Equal EV (Condition 1b). In Condition 1b, risk was positively correlated with prevalence. The riskier targets were more prevalent at the onset of patches. Despite this advantage in prevalence, participants still avoided selecting the risky targets. Similar to what was observed in the equal-prevalence condition (Condition 1a), participants over-picked the sure target (T1) and under-picked the risky target (T4) in the early stage of patch foraging (second column in Figure 2), despite the fact that risky targets were easier to locate at the onset of patches.

As targets were depleted over time, the difference between selection and display proportions for the riskiest target (T4) increased from a negative to a marginally positive value. This suggests that in the later stage of patch foraging, the advantage in prevalence of the riskiest target eventually led participants to select it more frequently, but not to an extent that was significantly greater than random selection. Meanwhile, the selection of the other targets (T1, T2, and T3) also converged to a pattern of random selection. The results of robust regression (Table 3; estimated coefficients are summarized in Table 1 in the Supplementary Materials) confirmed these observations.

As compared to what was observed in the equal-prevalence condition (Condition 1a), the overall difference between selection and display proportions for the riskiest target (T4) in Condition 1b was less negative, Welch's t-test: $t(2088) = 8.51,\ p < 0.001,$ Cohen's d $= 0.368$.

This suggests that an increase in the prevalence of risky targets led to less pronounced risk aversion. However, risk still played a dominated role in shaping foraging behavior. The most prevalent target (T4) in the common-risk condition (Condition 1b) was selected less often than in the baseline hybrid foraging task (Condition 1d), Welch's t-test: $t(1903) = -9.02,\ p < 0.001,$ Cohen's d $= 0.385$, because the most prevalent target was also highly risky in Condition 1b but not in Condition 1d.

Common Sure, Equal EV (Condition 1c). A clear preference for certainty and an aversion to risk were also observed in the common-sure condition (Condition 1c), where risk was inversely associated with prevalence. Throughout the course of patch foraging, the differences between selection and display proportions for the sure target (T1) were consistently above zero (the third column in Figure 2), indicating that participants persistently over-picked the sure target. The next low-risk target (T2) was under-picked in the early stage of patch foraging, but then it was selected more often than predicted by chance as sure target (T1) was depleted. In contrast, risky targets (T3 and T4) were under-picked throughout patch foraging. The observed patterns were supported by results of robust regression (Table 3; estimated coefficients are summarized in Table 1 in the Supplementary Materials). Furthermore, the proportion difference of the sure target (T1) deviated more positively from zero in the common-sure condition (Condition 1c) than in the equal-prevalence condition (Condition 1a), Welch's t-test: $t(2342) = 4.97,\ p < 0.001,$ Cohen's d $= 0.203$, reflecting that participants were more eager to collect the sure target when it was easier to locate. In other words, the preference for certainty was amplified by prevalence.

Patch-leaving Behavior

Next we examined the proportions of different targets that were left behind in relation to the initial number of instances for each target. For example, if a patch started with eight instances of T1 and two of those instances were not selected when a participant left the patch, then the left-behind proportion of T1 is $\frac{2}{8}$. The observed left-behind proportions for targets are illustrated in Figure 3.

We performed a two-way mixed ANOVA analysis (Murrar and Brauer, 2018), using the Greenhouse-Geisser correction for sphericity on degrees of freedom, to examine whether the left-behind proportions were significantly different across targets (within-subject factor) and across conditions (between-subject factor). Results showed a significant difference in left-behind proportion across targets, $F(1.69, 256.92) = 7.20,\ p < 0.001, \eta^2 = 0.019$, and an interaction between targets and conditions, $F(5.07, 256.92) = 5.86,\ p < 0.001, \eta^2 = 0.046$. However, there was no significant main effect of condition on left-behind proportions, $F(3.00, 152.00) = 0.58,\ p = 0.63,\ \eta^2 = 0.007$.

As shown in Figure 3, the patterns observed in Conditions 1a and 1d show the effects of risk (Condition 1a) and prevalence (Condition 1d) on overall foraging preferences. When targets varied solely in the degree of risk (Condition 1a), the left-behind proportions for targets were related to the degree of risk. The left-behind proportions were larger for riskier targets. On average, participants left more than 22% of the riskiest target (T4) while less than 10% of the sure target (T1) when they moved on to new patches. When targets varied solely in prevalence (Condition 1d), the pattern of left-behind proportions were related to the prevalence of targets. Participants left a smaller proportion of the most prevalent target (8.97%) as compared to the rarest target (16.93%), reflecting a standard prevalence effect.

When risky targets were highly prevalent (Condition 1b), the left-behind proportions of risky targets (T3 and T4) were only slightly smaller than those in the equal-prevalence condition (Condition 1a), Welch's t-test: $t(125) = 1.69, p = 0.094, \text{Cohen's d} = 0.278$. In addition, the left-behind proportions of the risky targets in Condition 1b were not significantly lower than the safe targets in the same condition, $F(3, 73.1) = 0.340,\ p = 0.797,\ \omega^2 = -0.015$. This suggests that the advantage in prevalence for the risky targets was not enough to override people's preference for certainty.

In addition, we observed that the left-behind proportions in the common-risk condition (Condition 1b) also differed from what was observed in the baseline foraging condition

(Condition 1d), even though prevalence was manipulated similarly in these two conditions. The left-behind proportion of T4 was higher, $t(49.1) = 2.17,\ p = 0.035,$ Cohen's d $= 0.514$, in Condition 1b than in Condition 1d. This suggests that a common target is less appealing to foragers if it is highly risky.

When the sure target was highly prevalent (Condition 1c), we observed a similar pattern of left-behind proportions as in the equal-prevalence condition (Condition 1a). In both conditions, the left-behind proportions of risky targets (T3 and T4) were much higher than the left-behind proportions of safer targets (T1 and T2), suggesting an overall preference for certainty and aversion to risk (Welch's t-test: $t(101) = -3.23,\ p = 0.002,$ Cohen's d $= -0.523$ for Condition 1a; $t(128) = -3.61,\ p < 0.001,$ Cohen's d $= -0.558$ for Condition 1c).

Experiment 1 Conclusions

In Experiment 1, we examined the effects of risk and prevalence on hybrid foraging behavior. The patterns of within-patch selections revealed a primary effect of risk on foraging behavior. Participants showed a strong preference for certainty and an aversion to risk in all conditions that varied the riskiness of targets. A secondary finding is that the effects of risk and prevalence interacted with each other and shaped foraging behavior together. When risky targets were prevalent, participants showed less risk aversion, but not to the extent that this aversion was eliminated.

Experiment 2: Targets with Unequal Expected Value

As shown in the existing literature (e.g., Wolfe et al., 2018), the expected value (EV) of targets can also play an essential role in shaping foraging behavior. In Experiment 2, we examine the effect of expected value in conjunction with the effects of risk and prevalence on foraging behavior. We are particularly interested in probing whether an increase in the expected value of risky targets would encourage individuals to seek out these targets. To achieve this, we manipulated expected values to be positively associated with CV values across targets. That is, the riskier targets yielded higher expected outcomes. Experiment 2 consisted of three conditions, paralleling the first three conditions of Experiment 1 (Condition a-c).

Method

Participants

150 participants (86 women, 62 men, 1 non-binary, 1 agender; age: M = 41.91 , SD = 12.85) recruited from MTurk using CloudResearch completed the study. Participants were recruited subject to the same criteria used in Experiment 1 to ensure data quality. The sample size was determined prior to starting the data collection, and the data were analyzed only after all data had been collected. The payment schedule was identical to Experiment 1. The average bonus payment participants received was $0.66.

11.33% of the participants (N = 17) were removed due to poor performance before the data analyses. The exclusion criteria were identical to Experiment 1. After the exclusions, we had 44 participants in Condition 2a, 45 in Condition 2b, and 44 in Condition 2c.

Materials

The materials used in Experiment 2 were identical to those used in Experiment 1, except that EV was positively associated with CV across targets in all of the conditions (Table 1). In Condition 2a (equal prevalence), all the targets had the same prevalence, but varied in both expected value and risk. In Condition 2b (common risk), the high-EV, riskier targets were more prevalent. In Condition 2c (common sure), the low-EV, sure target was the most prevalent. Note that the differences in EV were quite dramatic. The sure target had an EV of 2 points while the riskiest target had an EV of 12 points.

Procedures

The procedures were identical to Experiment 1.

Results

We first compared overall performance measures across conditions (see Table 2). Results from Welch's ANOVAs suggested that the number of patches participants viewed ($F(2,86.1) = 1.84,\ p = 0.164,\ \omega^2 = 0.037$), the number of clicks participants made within patches ($F(2,80) = 2.48,\ p = 0.090,\ \omega^2 = 0.062$), and the average time participants spent in-between clicks ($F(2,83.3) = 1.64, p = 0.199,\ \omega^2 = 0.028$) did not differ significantly across conditions. The error rate, as measured by the average proportion of clicks on non-target items, was below 5% in each condition. In total, participants made over 650 clicks on average throughout the foraging session. These are similar to what we observed in Experiment 1.

Comparing prevalence-CV conditions (i.e., Conditions a, b, and c) between Experiments 1 and 2, we find that the number of clicks participants made within patches in Experiment 2 (M = 28.3 clicks / patch) was similar to that in Experiment 1 (M = 27.4 clicks / patch), Welch's t-test: $t(238) = -1.29,\ p = 0.197,$ Cohen's d $= -0.165$. However, participants in Experiment 2 on average viewed fewer patches (M = 24.3) as compared to those in Experiment 1 (M = 27.1), Welch's t-test: $t(206) = 2.53,\ p = 0.012,$ Cohen's d $= 0.325$. This is likely because, on average, it took participants longer to make a click in Experiment 2 (M = 1.236 seconds) than in Experiment 1 (M = 1.111 seconds), Welch's t-test: $t(241) = -2.01,\ p = 0.045,$ Cohen's d $= -0.254$.

Unlike Experiment 1, we observed a significant difference in the total number of points participants earned across conditions in Experiment 2, $F(2,78.8) = 50.68, p < 0.001,\ \omega^2 = 0.429$. Participants earned more points in the common-risk condition than in other conditions. This is because the risky targets now had higher expected values. As a result, the condition with more risky targets (i.e., Condition 2b) had higher expected value for the entire task.

Below, we examine the foraging behavior across time in a patch, as illustrated in Figure 4, for the different conditions of Experiment 2. We also compare forging behavior in Experiment 2 to the corresponding conditions in Experiment 1 (e.g., Condition 1a vs Condition 2a). We assess both within-patch foraging behavior and patch-leaving performance to investigate the effects of expected value, risk, and prevalence on hybrid foraging behavior.

Within Patch Foraging Behavior

Unequal Risk, Equal Prevalence, Unequal EV (Condition 2a). When the targets were equally prevalent, participants showed a preference for certainty in their patch foraging behavior, even though the riskier targets had higher EVs. Differences between selection and display proportions (the first column in Figure 4), showed that the low-EV, sure target (T1) was over-picked, while the high-EV, risky targets (T3, T4) were under-picked at the start of patch foraging. With the depletion of targets, target selection converged to random selection. However, as compared to Condition 1a in Experiment 1 where all the targets had the same EV, the sure target T1 was picked less often, while the riskiest target T4 was picked more often in Condition 2a. This suggests that a higher expected value for the risky targets made participants more willing to search for and select these targets. This shows that participants were sensitive to EV, even if it did not fully overcome their risk aversion.

To statistically assess the effect of variations in EV on the proportion differences, we compared condition 1a where targets had equal EV to condition 2a where targets had unequal EV. For this analysis, we used the robust regression model from Experiment 1, but included an extra categorical independent variable “EV” with two levels, namely equal-EV (condition 1a) and unequal-EV (condition 2a). The results (see Table 4; estimated coefficients are summarized in Table 2 in the Supplementary Materials) supported the aforementioned observation that the presence of risky targets with higher EV encouraged individuals to select those targets more often as compared to the situation where all targets had equal EV.

Common Risk, Unequal EV (Condition 2b). When the high EV, risky targets were highly prevalent in patches, participants still under-picked the risky targets and over-picked the sure target (see the middle column in Figure 4). However, as instances of the sure target were depleted during the course of forging, the riskiest target (T4) was eventually over-picked compared to the other targets. This suggests that risk-sensitive preferences had an initial impact on patch foraging behavior, but the high expected value and high prevalence of T4 eventually resulted in a bias toward risky choices over time. The observed patterns were confirmed by the results of a robust regression analysis (Table 4) performed on data collected from common-risk conditions in the equal EV experiment (Condition 1b) and unequal EV experiment (Condition 2b). In comparing conditions 1b and 2b, we observed that the proportion differences of T4 increased with patch clicks in both conditions, but started higher in the unequal-EV condition than in the equal-EV condition.

Common Sure, Unequal EV (Condition 2c). We observed similar selection patterns for the sure and the low-risk targets in condition 2c as compared to those in condition 1c. Despite having a relatively low EV, participants over-picked the sure target (T1) throughout patch foraging, and over-picked the second lowest risk target (T2) as patch forging progressed (Figure 4). This suggests that when the sure target was prevalent, the preference for certainty was robust to variations in expected value.

However, unlike condition 1c where the risky targets (T3 and T4) were under-picked throughout the entire course of patch forging, participants in the unequal-EV condition selected the risky targets close to the random chance rate at the beginning of patch foraging. With the depletion of targets over time, they then under-picked the risky targets towards the end of patch foraging. These patterns suggest that the higher expected values of the risky targets in condition 2c encouraged participants to initially select these items more often than in condition 1c.

The results of a robust regression analysis (Table 4), performed on data collected from both common-sure conditions (Conditions 1c and 2c), corroborated these observations. The proportion differences of the risky targets started near zero and decreased with patch clicks in the unequal-EV condition; whereas in the equal-EV condition, the proportion differences of these targets started from a significant negative value and barely changed with patch clicks.

It is worth stressing how strongly participants favor a sure target. As noted above, the riskiest target (T4) in the various conditions of Experiment 2 paid, on average, 12 points compared to 2 points for the sure target T1 that paid off every time it was clicked. Nevertheless, in each condition of Experiment 2, participants continued to favor the sure target at the start of foraging, moving to the risky target only once the instances of the sure target were depleted. In a single gamble, this might make some risk-averse sense. After all, in a single gamble, even if the EV is 12, there is an 80 % chance that you will come away with nothing. However, in a foraging situation like in Condition 2a, for example, if you pick all the eight T4 items, there is only a 16.78% chance of coming up empty-handed. It seems as if participants are playing a foraging game by something like single gamble rules even though that is quite clearly not optimal (see modeling section, below).

Patch-leaving Behavior

Similar to Experiment 1, we assess the effects of risk and prevalence on overall foraging behavior by comparing the left-behind proportions across different prevalence-CV conditions in Experiment 2. We then assess the effect of expected value by comparing left-behind proportions across equal-EV and unequal-EV experiments for each prevalence-CV relationship.

Paralleling our previous findings in Experiment 1, the results of a two-way mixed ANOVA analysis (Murrar and Brauer, 2018) performed on the data collected from Experiment 2 show a significant interaction between targets and conditions on left-behind proportions, $F(3.97, 258.29) = 10.572,\ p < 0.001,\ \eta^2 = 0.056$. However, there was no significant main effect of targets ($F(1.99, 258.29 = 0.849,\ p = 0.428,\ \eta^2 = 0.002$) or conditions ($F(2, 130) = 2.209,\ p = 0.114,\ \eta^2 = 0.021$) on left-behind proportions.

When all targets had equal prevalence but unequal EV (Condition 2a), the left-behind proportions were positively associated with the riskiness of targets (the bottom-left panel in Figure 5). Participants were more likely to leave risky items behind when they moved to the next screen. This is similar to what we observed in the equal-EV condition (Condition 1a; the top-left panel in Figure 5). Consistent with our observations, the results of a two-way mixed ANOVA analysis performed on the data from Conditions 1a and 2a showed a significant difference in left-behind proportions across target types ($F(1.65, 131.67) = 10.221,\ p < 0.001,\ \eta^2 = 0.049$), but not across different EV conditions ($F(1, 80) = 2.569,\ p = 0.113,\ \eta^2 = 0.019$). The interaction between EV conditions and target types was also not significant ($F(1.65, 131.67) = 2.396,\ p = 0.105,\ \eta^2 = 0.012$).

When risky targets were highly prevalent, we observed that participants in the high-EV condition (Condition 2b; the bottom-middle panel in Figure 5) left behind a larger proportion of the sure target (T1) and a smaller proportion of the risky targets as compared to participants in the equal-EV condition (Condition 1b; the top-middle panel of the figure). The results of a two-way mixed ANOVA analysis performed on data from Conditions 1b and Condition 2b supported this observation, suggesting a significant interaction between target types and EV conditions on the left-behind proportions, $F(1.36, 104.55) = 3.661, p = 0.046,\ \eta^2 = 0.019$. The main effects of target types ($F(1.36, 104.55) = 1.841, p = 0.175,\ \eta^2 = 0.01$) and EV conditions ($F(1, 77) = 0.062, p = 0.805, \eta^2 = 0.0005$) were not significant.

When the sure target was highly prevalent, we observed that the overall left-behind proportions in the unequal-EV condition (Condition 2c: M = 0.183; the bottom-right panel in Figure 5) were larger than the equal-EV condition (Condition 1c: M = 0.160; the top middle-right panel in Figure 5), except that the left-behind proportions for the riskiest target (T4) were smaller. The results of a mixed two-way ANOVA analysis performed on data from Conditions 1c and 2c confirmed these observations, showing a significant main effect of target types ($F(2.31, 194.39) = 14.959, p < 0.001,\ \eta^2 = 0.060$) and a significant interaction between target types and EV conditions ($F(2.31, 194.39) = 4.670, p = 0.007,\ \eta^2 = 0.020$) on left-behind proportions. The results found no significant main effect of EV conditions on left-behind proportions, $F(1, 84) = 0.358, p = 0.551,\ \eta^2 = 0.003$.

Experiment 2 Conclusions

In Experiment 2, we examined the effect of expected value in conjunction with the effects of risk and prevalence on hybrid-foraging behavior. The patterns of within-patch selections suggest that participants generally prefer searching for and selecting sure targets. This preference appears to hold even though when EV is 6 times higher in risky targets than in the sure target in Experiment 2. When high prevalence is combined with high EV (condition 2b), participants can be induced to favor the risky targets. These results suggest that participants' risk preferences in hybrid foraging are fairly stable and surprisingly robust. Deviation from a preference for certainty are only observed when risky targets are given multiple advantages (e.g., having both higher EV and being easier/faster to locate).

Optimal Hybrid-Foraging Behavior

During a hybrid foraging session, there are two decisions foragers must constantly make: (1) which target to select, and (2) whether to move to a new patch. In this section, we first investigate if the patch-leaving behavior in our hybrid risky foraging task followed the optimal strategy predicted by the Marginal Value Theorem. Then, we develop a risk-insensitive optimal model to assess how participants' foraging behavior compares to the optimal strategy throughout a foraging session.

Optimal Patch-leaving Rules

Besides deciding what to select during a patch, foragers also have to decide when to move to a new patch. Switching between patches involves a trade-off between exploration and exploitation (Daw et al., 2006; Hills et al., 2015; Sutton and Barto, 2018). Originating from animal studies, the Marginal Value Theorem (MVT, Charnov, 1976) is one of the first optimal models of patch-switching in foraging. It proposes that it is optimal to move to a new patch when the marginal gain from foraging in the current patch drops to the average gain established throughout the foraging session. An example of this would be a mushroom hunter leaving a region when their rate of mushroom acquisition falls below the average acquisition rate established throughout the forest.

The MVT has been found to capture the average patch foraging behavior in a range of cognitive domains (see Daw et al., 2006; Mehlhorn et al., 2015 for review). In human foraging, existing evidence documented both in agreement with (e.g., Wolfe, 2013; Wolfe et al., 2016; Zhang et al., 2015) and deviations from (e.g., Fougnie et al., 2015; Hutchinson et al., 2008; Á. Kristjánsson, Björnsson, and Kristjánsson, 2020; Wolfe, 2013; Zhang et al., 2017) MVT predictions about patch-leaving behavior. This indicates that MVT captures some aspects of human patch-leaving behavior, but may not fully account for all of the variables influencing the dynamics of human foraging (also see Bella-Fernandez et al., 2022 for review). Nevertheless, it is useful to see how well MVT predicts patch leaving behavior in this hybrid foraging setting.

We asked if the patch-leaving behavior in our task followed the optimal strategy as predicted by MVT by comparing the instantaneous rate of return when participants left a patch (i.e., at the last patch click) to their average rate of return estimated throughout the entire foraging session using a paired t-test for each condition (Wolfe et al., 2018). The rate of return (in units of points/second) describes how fast participants earn rewards. It accounts for both the number of points earned at a click, on either a target or a non-target item, and the amount of time spent on making that click. We also assess the rate of clicks (only considering the speed of clicks) and report these results in the Supplementary Materials. The MVT predicts that foragers who adopt an optimal strategy should terminate forging in a patch when their instantaneous rate of return drops to the average rate of return.

The instantaneous return rate was estimated by dividing the number of reward points obtained from an acquisition by the amount of time spent acquiring that gain. For instance, if a participant took 2 seconds to select a target and the selection yielded 4 points, then the instantaneous rate of return is $\frac{4}{2}$ points/sec from this selection. The average return rate was calculated by dividing the total number of reward points by the total duration of the foraging session, including both the time spent on foraging within patches and the time spent on traveling between patches.

For the following analyses, we excluded extremely fast inter-click times (i.e., inter-click time $<$ 300 milliseconds; 4.5% of the data in Experiment 1 and 4.3% of the data in Experiment 2). The foraging duration within a patch is defined as the time from the onset of a patch until the final patch click. To allow for comparisons across conditions (see Wolfe et al., 2018), we normalized return rates by dividing the rate by the expected outcomes from a click, which was 4 points in equal-EV conditions and $(2+4+8+12)/4 = 6.5$ points in unequal-EV conditions. To aggregate instantaneous rate data for MVT analyses, we worked backward from the last click in a patch.

Equal-EV Conditions

When all targets had the same expected value, we observed that the instantaneous return rates decreased to the average return rates at the time when participants decided to leave a patch (Figure 6). This indicates that when it was no longer profitable for participants to continue foraging in a patch, they chose to move on to a new patch, which is consistent with the predictions of MVT. The results of paired t-tests confirmed the observed patterns, showing that the instantaneous return rates at the last patch click (reverse click 1) did not differ significantly from the average return rates in each prevalence-CV condition (Condition 1a: $t(37) = -0.803,\ p = 0.427,\ \text{Cohen's d} = -0.130$; Condition 1b: $t(33) = 0.583,\ p = 0.564,\ \text{Cohen's d} = 0.100$; Condition 1c: $t(41) = -1.54,\ p = 0.132,\ \text{Cohen's d} = -0.237$; Condition 1d: $t(41) = 1.24,\ p = 0.223,\ \text{Cohen's d} = 0.191$).

Unequal-EV Conditions

When riskier targets had higher expected values, return rates also decreased during the course of foraging within a patch, but the rates at the last click (reverse click 1) revealed differences in patch-leaving behavior across conditions (Figure 7). The results of paired-sample t-tests suggest that the marginal return rate at the last click was significantly above the average return rate in the common-risk condition (Condition 2b, $t(44) = 2.79,\ p = 0.008,\ \text{Cohen's d} = 0.415$), but not in the equal-prevalence condition (Condition 2a: $t(43) = 0.933,\ p = 0.356, \text{Cohen's d} = 0.141$) and the common-sure condition (Condition 2c: $t(43) = 1.01,\ p = 0.32, \text{Cohen's d} = 0.152$). This suggests that when riskier targets had higher reward values and prevalence, participants' patch-foraging behavior deviated from the optimal rule — they left patches too early, before maximizing their returns from patch foraging.

In sum, the average patch-leaving behavior revealed that, in most circumstances, participants terminated foraging within patches when their marginal rate of gaining rewards dropped to their average rate of gaining rewards, consistent with the predictions of MVT. However, participants' risk-averse foraging strategy can lead to suboptimal patch-leaving behavior, especially when the risky targets had high EV and were highly prevalent.

Optimal Hybrid-Foraging Strategy

To maximize the overall return from hybrid foraging, foragers must balance the ease of locating a target with the potential reward from selecting that target. When all available targets have the same expected value (as in Experiment 1), the optimal strategy should only consider maximizing foraging speed: selecting targets (regardless of type) as soon as you locate them during patch foraging and leave a patch when your marginal rate of collecting targets drops to your average rate.

When targets have different expected values (as in Experiment 2), then the optimal strategy is affected by the interplay between foraging speed and potential rewards. For instance, if collecting a prevalent but low EV target (EV = 2 points) takes 0.5 seconds, and a rare but high EV target (EV = 12 points) takes 2 seconds, it is optimal to go for the high-value target even it takes longer to find it. This is because the marginal rate of return from collecting the high EV target ($\frac{12}{2} = 6$ pts/sec) is higher than that from the low EV target ($\frac{2}{0.5} = 4$ pts/sec). However, if it takes 4 seconds to locate the high EV target (e.g., it is extremely rare), then the optimal choice is to select the low EV target because the marginal rate of return from the high EV target is too low ($\frac{12}{4} = 3$ pts/sec).

To compare participants behavior to an optimal foraging strategy, we develop a risk-insensitive optimal model. We compare the simulated behavior from the model with the empirical observations to assess how risk-sensitive foraging behavior may deviate from the optimal strategy.

The Optimal Hybrid-Foraging Model

As aforementioned, there are two decisions foragers must constantly make during a hybrid foraging session: (1) which target to select, and (2) whether to move to a new patch. For the first decision, we propose that the optimal strategy is to always select the target yielding a maximum marginal rate of return. For the second decision, we assume that the optimal strategy is to follow the predictions of MVT and leave a patch when the marginal rate of return drops to the average rate of return. Based upon these two assumptions, we developed our optimal model.

As illustrated in Figure 8, during foraging, the model first identifies the target that yields the maximum marginal return rate and then compares it to the average return rate. If the maximum marginal return is larger than the average return, the model selects the target. Otherwise, the model moves on to a new patch, incurring the travel cost. This selection procedure iterates until the elapsed foraging time reaches the time limit. Following Experiments 1 and 2, we set the time limit for a single simulation (i.e., analogous to a participant) to be 15 minutes and the travel time to be 5 seconds. Note that this is a model of an optimal observer who could, in fact, assess the marginal return rate of all items in the display. In practice, observers would not be able to do this and must be basing their click-by-click decisions on assessment of a subset of all items. Thus, one cause for a departure from optimal behavior would be the capacity limitations on the size of the sampled subset.

The average return rate when deciding to select a target is calculated by dividing the accumulated number of reward points by the sum of the elapsed time in the session and the travel time: $\frac{Accumulated\ number\ of\ reward\ points\ earned}{Accumulated\ time\ in\ the\ session\ +\ travel\ time}$. It describes the average points earned per second when the model makes a target selection. The marginal return rate for selecting a target is calculated as the ratio between the target's EV and the foraging time required to locate it: $\frac{Expected\ value\ of\ Ti}{Foraging\ time\ to\ locate\ Ti}$. Note that the model uses the expected value of targets in the calculation of the marginal return rate and is therefore insensitive to variations in risk.

The time required to collect a target (i.e., response time) is determined by two components: a baseline foraging time and an attention-switching time. The baseline foraging time is the amount of time foragers need to locate a target, which should be affected by two key variables: the number of available instances of a particular target (Ti) and the total number of items on display. We assume that the baseline foraging time follows a log-normal distribution where the mean is a linear function of these two key variables. We estimated this functional relationship using a separate set of data collected from a baseline foraging experiment (i.e., Experiment 3, details of this experiment are in the Supplementary Materials).

In the baseline foraging experiment, participants foraged for a single sure target and automatically moved to a new patch without incurring any travel time cost after exhausting all instances of the target in the current patch. There were four between-subject conditions determined by the number of instances of the target at the onset of patches (2, 4, 9 and 17 as used in Experiments 1 and 2). The initial number of items on display was kept constant at 64 across all conditions. In short, the key manipulations in the baseline foraging task mimic the settings used in Experiments 1 and 2.

When foragers search among multiple possible targets, there is a switch cost when they shift their attention from searching for an old item to searching for a new item (Krinchik, 1974). Existing evidence shows that foragers tend to be slower when they switch to foraging for a new item (Wolfe et al., 2019). We also observe this pattern in our experiments. For each participant in the baseline hybrid foraging condition (Condition 1d), we estimated the time cost for switching attention by subtracting their average inter-click times between selections on the same target from their average inter-click times between selections on different targets. A paired samples t-test confirmed that the inter-click time between selections on two identical targets (M = 922 milliseconds) was significantly lower than between selections on two different targets (M = 1053 milliseconds), $t(41) = -8.65,\ p < 0.001,$ Cohen's d $= 1.33$. For simplicity, we keep the switch-cost time constant at the mean difference of 131 milliseconds in the simulations.

In sum, if the optimal model selects a target differing from the previous selection, the response time for making a selection is the sum of the baseline foraging time and the switch-cost time. If a selection is the same as the previous selection, the response time is equivalent to the baseline foraging time.

Simulation Results

We generated 50 sets of simulated data (analogous to recruiting 50 participants) from the optimal model for each condition in Experiments 1 and 2.

Equal-EV Conditions. As expected, when all possible targets had the same expected value (Experiment 1), the simulated optimal foraging behavior was modulated merely by prevalence across targets (Figure 9). The model first over-picked the most prevalent target and then started to over-pick the next most prevalent target (top row in Figure 9). The rare targets were consistently under-picked throughout patch foraging. Subsequently, when moving to a new patch, the left-behind proportion of the most prevalent target was the lowest, while that of the rarest target was the highest (bottom row in Figure 9). When targets were equally prevalent at the onset of patches (Condition 1a), the simulated foraging behavior mimicked a pattern of random selection.

Overall performance measures for the optimal model were similar to our empirical observations. That is, the simulated number of clicks in patches and the number of patches viewed throughout the hybrid foraging session (Table 5) are very close to those of human foragers (Table 2). However, the simulated patterns of patch foraging behavior qualitatively differ from our empirical observations, suggesting that participants did not always select the most profitable target during patch foraging.

Instead of foraging for the most prevalent target like our optimal model, human foragers tend to search for the most certain target. This is not a problem when the sure target is highly prevalent (e.g., Condition 1c) because a certainty-seeking foraging strategy is equivalent to the optimal prevalence-seeking strategy in this situation. As expected, the empirical patterns, observed in the common-sure condition (Condition 1c, see Figure 2), qualitatively approximate the patterns simulated from the optimal model. Nevertheless, when the sure target is rare in patches (e.g., Condition 1b), the risk-sensitive foraging strategy adopted by human foragers can lead to large deviations from the optimal model. As observed in the common-risk condition (Condition 1b, Figure 2), preferences for certainty caused participants to over-pick the low prevalent target, and under-pick the high prevalent target. These empirical patterns are opposite of those produced by the optimal model. Subsequently, the total number of points earned by the model is higher than human foragers, especially in the common-risk condition (Condition 1a: $M_{model-human} = 338,\ t(86) = 2.91,\ p = 0.005,$ Cohen's d $= 0.626$; Condition 1b: $M_{model-human} = 839,\ t(82) = 6.69,\ p < 0.001,$ Cohen's d $= 1.49$; Condition 1c: $M_{model-human} = 475,\ t(90) = 4.06,\ p < 0.001,$ Cohen's d $= 0.849$).

Unequal-EV Conditions. When targets had different expected values (Experiment 2), the simulated optimal foraging behavior was sensitive to these differences (Figure 10). The model first over-picked the highest EV target, and then started to over-pick the target with the next highest EV when the highest EV target was depleted (top row in Figure 10). The low EV targets were barely selected throughout patch foraging — the model tended to move to the next patch rather than spending the time to forage low EV stimuli. Subsequently, when moving to a new patch, the left-behind proportion of the highest EV target was the lowest, while the left-behind proportion of the lowest EV target was the highest (bottom row in Figure 10). These results suggest that in Experiment 2, the optimal foraging strategy is to collect most of the instances of the high EV targets (T3 and T4) in a patch and then immediately move to a new patch.

The simulated foraging behavior from the optimal model differs markedly from our empirical observations. In terms of overall performance measures, the number of clicks in patches simulated from the optimal model (Table 5) was less than that of human foragers (Table 2), while the number of patches viewed throughout the hybrid foraging session was higher. The model accumulated a higher total number of points by the end of the session, especially in Condition 2b (Condition 2a: $M_{model-human} = 1722,\ t(92) = 9.48,\ p < 0.001,$ Cohen's d $= 1.96$; Condition 2b: $M_{model-human} = 2931,\ t(93) = 9.79,\ p < 0.001,$ Cohen's d $= 2.01$; Condition 2c:

$M_{model-human} = 850,\ t(92) = 7.03,\ p < 0.001,$ Cohen's d $= 1.45$). The simulated patterns of patch-foraging behavior and patch-leaving behavior also qualitatively differ from our empirical observations.

When the risky targets were highly prevalent (Condition 2b), participants did not follow the optimal foraging strategy until the end of patch foraging. When the risky targets were not highly prevalent (Conditions 2a and 2c), participants consistently over-picked the low EV targets while under-picking the high EV targets (Figure 4), which is opposite to the predictions of the optimal model. These discrepancies between our empirical observations and the optimal simulated patterns highlight the potential influence of risk-sensitive preferences on hybrid foraging. Due to participants' certainty-seeking and risk-averse foraging behavior, they not only inefficiently spent time searching for low EV targets but also left patches too early when it was still profitable to continue collecting high-EV targets (see Condition b in Figure 7).

Modeling Conclusions

The simulation results from the optimal model demonstrate that the optimal strategy for the equal-EV conditions should be prevalence-seeking while for the unequal-EV conditions it should be sensitive to expected value. The comparisons between the simulated patterns and our empirical observations reveal that the risk-sensitive foraging strategy adopted by human foragers in most cases was not optimal. That is, they failed to always select the most profitable target during patch foraging and left patches without maximizing overall return.

General Discussion

The hybrid risky foraging paradigm mimics a wide range of real-world scenarios such as food hunting, grocery shopping, and medical screening. The current study extends the existing literature on both decision making and visual search by examining the influence of outcome uncertainty, expected value, and prevalence of targets in a hybrid foraging paradigm. Our primary findings suggest that human foragers tend to adopt a risk-sensitive strategy, meaning that they seek certainty and are averse to risk in hybrid foraging; at least, in the task implemented here.

Moreover, such a risk-sensitive strategy is robust, remaining dominant after changes in either the prevalence or expected value of targets. Note that individuals are not insensitive to prevalence and expected value. Participants were willing to search for and select risky targets when these targets were both prevalent and had high expected value, suggesting that they were sensitive to these two factors. Nevertheless, their foraging strategy was still dominated by risk sensitivity. Our modeling results additionally indicate that participants' risk-averse foraging behavior prevented them from maximizing their overall returns from foraging. As compared to an optimal model, participants over-picked low EV targets and under-picked high EV targets, and in some cases left a patch too early.

One question raised by the current findings is why are risk-sensitive preferences so persistent in hybrid foraging tasks? Participants consistently preferred certainty over risk, in spite of an increase in the prevalence or expected value of the risky targets. One possibility is that the use of constantly moving targets in our tasks may increase the difficulty of target searching, which could bias foragers toward a conservative foraging strategy. However, results from a replication using static targets showed that participants maintained a preference for sure payoff targets over risky ones (see Supplementary Materials). This suggests that the cognitive processes responsible for the emergence of risk-sensitive foraging behavior are not a simple side effect of our dynamic stimuli.

Building from existing findings in experience-based risky choice, we propose a couple hypotheses that may attribute to the risk-sensitive foraging behavior in our study. One possible cause of risk-averse foraging behavior may be related to the under-weighting of lower winning probabilities. Foragers in our tasks have the opportunity to repeatedly sample outcomes from different targets (i.e., options), and they receive instantaneous feedback on their selections. This is similar to decisions from experience, where decision-makers learn about options through sampling (e.g., Barron and Erev, 2003). Existing studies show that people tend to underestimate low probabilities in this case (Hertwig and Erev, 2009; Hertwig et al., 2004). For example, when choosing between a sure token for $100 (sure gain) and a gamble yielding $1000 with a 10%

chance or nothing with a 90% chance (risky gain), people who base their choices on their direct experience of these two options, prefer the sure gain over the risky gain because they perceive the likelihood of winning $1000 to be much lower than 10%. In hybrid-foraging tasks, this under-weighting of low probabilities from experience might make the riskiest target (with a winning probability of 20%) appear less attractive to foragers. Although, it seems unlikely that participants would underestimate the winning likelihood of the riskiest target in Experiment 2 to the extent that its perceived EV (Tversky and Kahneman, 1992) would fall below the true EV of the sure target.

Evidence in experience-based risky choice also suggests that decision-makers tend to update their knowledge of options based on their recent experience (Hertwig and Pleskac, 2010; Hertwig et al., 2004). Since foragers constantly receive feedback on their selections in hybrid foraging tasks, they may also update their knowledge about targets in a similar way. Previous studies in hybrid foraging show that the attention-switch cost (i.e., the additional time incurred when searching for a different target type) can lead to a response-priming effect (Tagu and Kristjánsson, 2022; Wolfe et al., 2016, 2018). That is, foragers are more likely to select the same type of item as the previously selected one than to switch to a new item. Our findings from the equal-prevalence conditions (see Figure 6 in the Supplementary Materials) align with these results and provide indirect evidence for a recency bias in our task. More specifically, a risky gain with a low winning probability would be less likely to happen in recent events, and thus have less impact on decisions as compared to a sure gain (Hertwig et al., 2004). This recency-biased knowledge updating could lead to a certainty-seeking strategy in our tasks.

Recency bias can result in a win-stay/lose-shift strategy in decision-making (Lejarraga and Hertwig, 2017; Nowak and Sigmund, 1993; Worthy and Maddox, 2014). Nevertheless, in the current risky hybrid foraging task, the observed behavior did not reflect the use of this heuristic (see Figure 7 in the Supplementary Materials). In the equal prevalence conditions of both experiments, forgers selected the target type matching their previous selection more frequently than predicted by chance, regardless of whether the previous selection yielded a return or not.

This is likely because switching between target types in foraging incurs additional attentional costs. Previous work has shown that a monetary cost for switching responses in an experience-based sequential choice task can increase choice inertia (i.e., staying with the same option), even if the average payout (i.e., EV) of that option is lower than others (Ashby and Teodorescu, 2019). The attention-switch cost might modulate the stay-switch behavior in risky hybrid foraging in a similar way. On the other hand, we suspect that selecting the same target for a run might encourage foragers to rely on a small sample size (e.g., the length of run) to update their knowledge of outcome distributions, which is consistent with the theory of under-weighting low probabilities in experience-based decisions. In short, it appears that risky hybrid foraging involves complex interactions between cognitive components of both decision-making and visual search. Future studies may advance our understanding of these interactions by extending foraging models for stay-switch behavior (e.g., Clarke et al., 2022; Le et al., 2023) to incorporate an outcome sampling algorithm inspired from decision-making theories (e.g., Plonsky et al., 2015; Teodorescu and Erev, 2014).

We note that the hybrid foraging tasks we used are not exactly the same as the typical experience-based risky choice paradigm. In typical decisions from experience, decision-makers usually make decisions solely based on the knowledge they learn from experience (Weber et al., 2004). In our experiments, foragers were provided with a complete description of targets (i.e., options) prior to starting forging. It is likely participants formed some knowledge about targets from this initial information, but they may still update their knowledge based on their experience in the task. Jessup et al. (2008) showed that when making repetitive choices between a certain reward and a risky gamble with fully specified descriptions of options on each trial, receiving trial-by-trial feedback can modulate decision-makers' weighting of objective probabilities and led to choice behavior resembling that observed in experience-based risky choices. This previous finding reveals that instantaneous feedback is a critical component for decision-making and could lead individuals to underweight low probabilities. Our results from the risky hybrid foraging task is in agreement with this previous finding.

The observed risk-averse foraging strategy may also be attributed to how foragers subjectively code gains and losses in foraging tasks. The distinction between gains and losses is typically based on a decision-maker's reference point (Trueblood et al., 2021; Tversky and Kahneman, 1992). The value of a reference point can be affected by many factors. For instance, Trueblood et al. (2021) showed that when decision makers chose between different types of saving accounts, their optimistic beliefs about their future wealth could result in the use of a positive-valued reference point. When the expected return from a savings account is lower than their belief-based reference point, decision makers may perceive the return from this account as a loss. In our hybrid foraging tasks, the set of targets always included a sure target. This may lead foragers to anticipate a positive return from a selection, because they can always earn some points by clicking on the sure target. As a result, foragers may adopt a positive-valued reference point to interpret values they receive while foraging. A zero-valued return in this circumstance would always be interpreted as a loss. Since risky targets frequently yield zero returns, foragers may perceive those targets as less valuable, even though they may have an identical or even higher expected value compared to other targets.

It is also possible that participants treat each target selection as a single shot gamble. The risk averse behavior of foragers in our task might reflect the tendency to avoid risks when playing a single gamble. It has been shown in Wulff et al.'s work (2015) that when making risky choices in a single-play environment, decision makers tended to follow choice strategies aiming at maximizing the short-term chance of winning rather than maximizing the long-term expected return. In foraging tasks, participants can repeatedly select the same targets. Thus, by the law of large numbers, there is much less risk of receiving zero points across multiple selections of the same risky target. Yet, people's behavior does not reflect this fact, suggesting they ignore the law of large numbers and behave as if each target selection is a single gamble.

Constraints on Generality

The current study examined the role of risk-sensitivity in hybrid foraging in a sample primarily composed of western adults. Since existing literature documents varying abilities in both hybrid foraging (e.g., Lloyd et al., 2023; Wiegand et al., 2019) and risky choices (e.g., Levin et al., 2007) across the lifespan, our findings of a risk-averse strategy in hybrid foraging may not generalize to all age groups. Future studies could examine how risk sensitivity in hybrid foraging differs across the lifespan using the current risky hybrid foraging paradigm.

We note some additional limitations of our study. In our experiments, we utilized simple visual representations (i.e., alphabetic letters) as options to minimize potential visual confounds. Future studies might want to employ stimuli involving more complicated visual components (e.g., shape, color) to study risky hybrid foraging behavior in more naturalistic, potentially ambiguous scenarios. Additionally, due to the dynamic nature of hybrid foraging search (i.e., targets are constantly moving and depleted with selection), future studies could use touch-based tablets/trackpads to make it easier to respond quickly (e.g., Á. Kristjánsson et al., 2014; Thornton et al., 2021; Zhang et al., 2017).

Hybrid foraging is an essential task in various cognitive domains (e.g., search in memory Hills et al., 2012; Lundin et al., 2023; also see Mehlhorn et al., 2015 for review). Despite many common cognitive components shared in various domains, it is unclear to what extent the current findings would hold across different cognitive tasks. Future studies may extend our understanding of the key principles of hybrid foraging by investigating different cognitive tasks.

We also note that the current study only examined the effect of risk on foraging behavior in the context of potential gains. However, in real-world searching scenarios, people may also encounter potential losses. For instance, when inspecting a house for purchase, people have to consciously search for possible damage in different rooms. We do not know whether our conclusions generalize to the context of potential losses. We suspect that framing effects (Tversky and Kahneman, 1981) may result in a different risk-sensitive foraging strategy in the context of losses, but future studies are needed to fully investigate this possibility. Moreover, the current study did not penalize selection of distractors. In reality, the error of collecting a poisonous mushroom can lead to fatal consequences. Other types of risk can arise as a consequence of selecting non-targets (e.g., predation risk, Thornton et al., 2021). It would be worth investigating how different types of risks interactively shape foraging strategies in hybrid foraging in future studies. Finally, the current study does not impose any limits on foraging time in patches, which is an important factor in shaping both foraging behavior (T. Kristjánsson et al., 2018) and risky choices (Edland and Svenson, 1993). Future studies may examine if the current findings can be generalized to time-limited situations.

Conclusion

To summarize, the current study investigated the interplay of outcome uncertainty, expected value of reward, and prevalence of target types on foraging behavior in hybrid foraging and found robust evidence for risk-sensitive foraging behavior. Our findings highlight the crucial role of outcome uncertainty in non-exhaustive hybrid foraging, and reveal complex interactions between decision making and visual search processes. Inspired by findings from both human decision-making and visual search, we propose potential cognitive processes that may lead to the observed risk-sensitive foraging behavior. Future investigations are needed to test those hypotheses and explore other potential mechanisms responsible for the emergence of risk-sensitive behavior in hybrid foraging.

Author Contributions

Yanjun Liu: conceptualization, data curation, formal analysis, investigation, methodology, software, visualization, writing- original draft, writing-review & editing. Jeremy Wolfe: conceptualization, funding acquisition, methodology, resources, supervision, validation, writing-review & editing. Jennifer Trueblood: conceptualization, funding acquisition, methodology, project administration, resources, supervision, writing-review & editing.

Acknowledgments

This work was supported by NSF SES-1846764 / 2305559 to JST, and NSF 2146617, NEI EY017001, and NCI CA207490 to JMW. We thank Dr. Thomas Hills and the anonymous reviewer for their constructive comments on this paper.

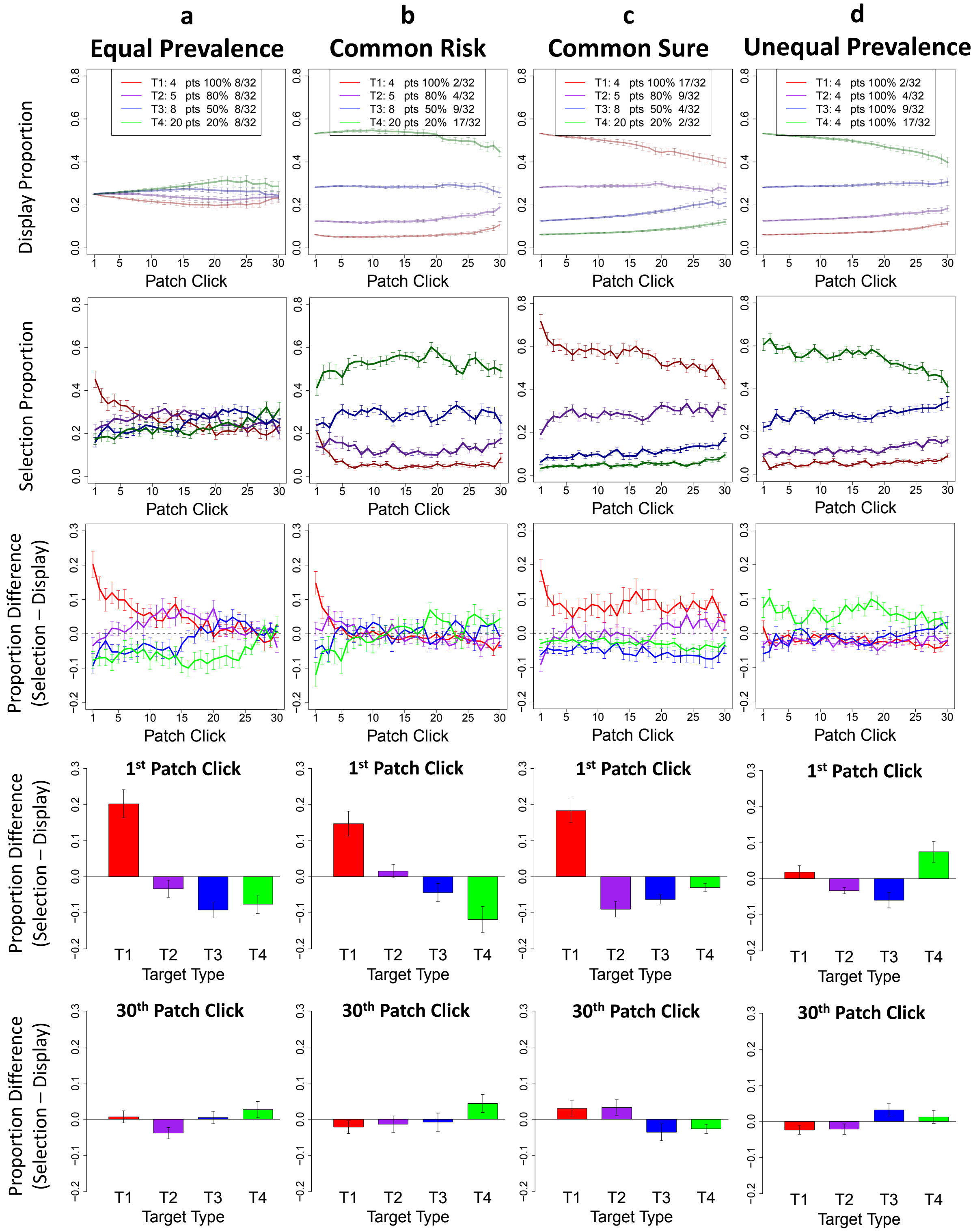
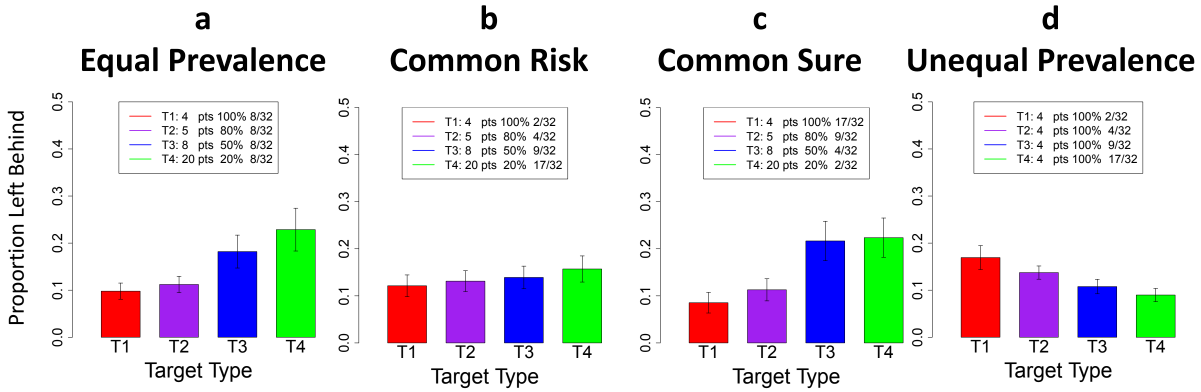


Figure 2

Changes in target display and target selection proportions within patches in different conditions of Experiment 1. Top Row: display proportions of each type of target at the 1^{st} *to the* 30^{th} *patch click. Second Row: selection proportions of each type of target at the* 1^{st} *to the* 30^{th} *patch click. Third Row: differences between selection and display proportions estimated at each patch click. Forth Row: proportion differences at the* 1^{st} *patch click. Bottom Row: proportion differences at the* 30^{th} *patch click. Error bars denote the standard error of the mean.*



a
Equal Prevalence

b
Common Risk

c
Common Sure

d
Unequal Prevalence

Figure 3

Average proportions of each target left behind when participants moved to a new patch in Experiment 1. The error bars denote the standard error of the proportions.

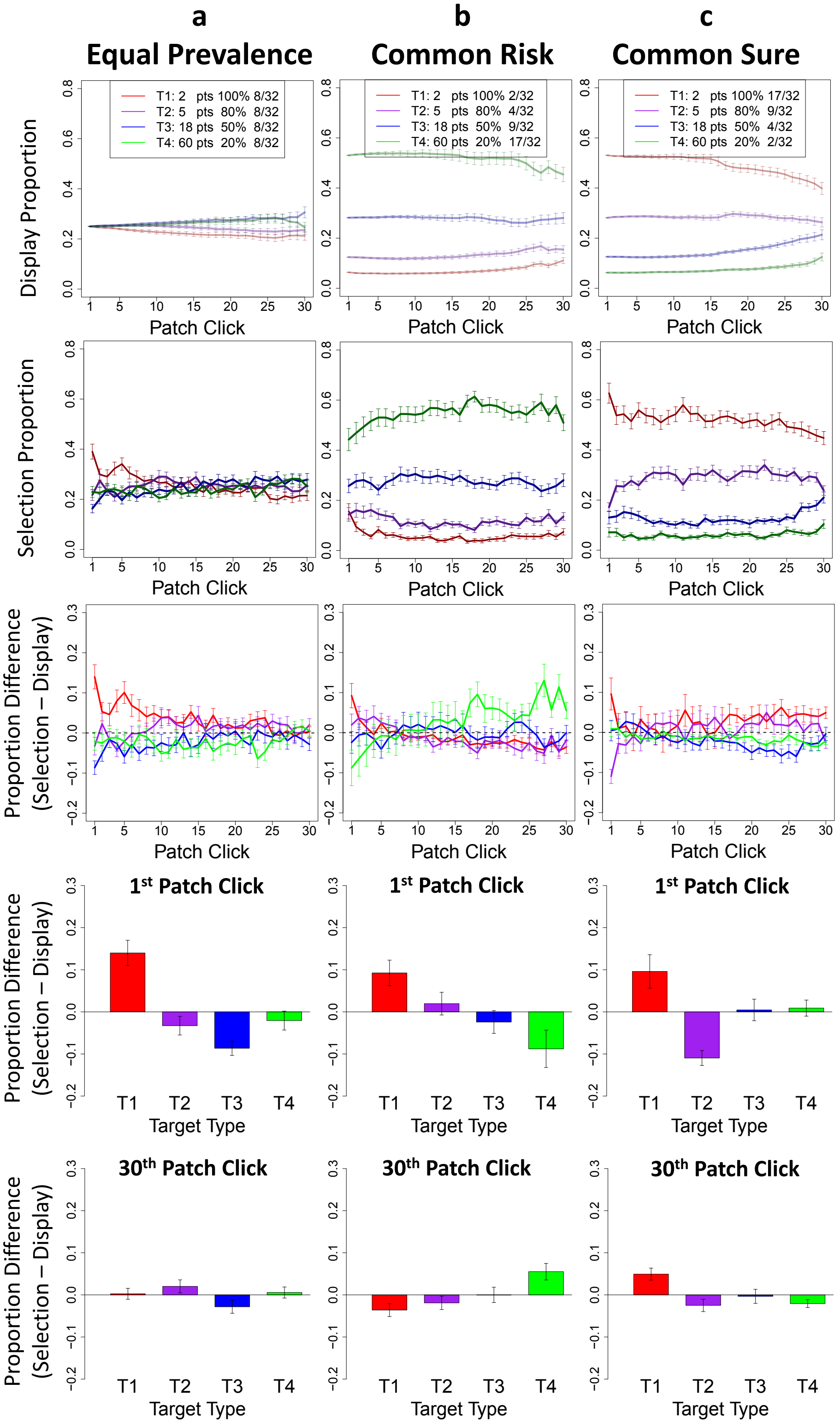


Figure 4

Changes in target display and target selection proportions within patches in different conditions of Experiment 2. Top Row: display proportions of each type of target at the 1*st to the* 30*th patch click. Second Row: selection proportions of each type of target at the* 1*st to the* 30*th patch click. Third Row: differences between selection and display proportions estimated at each patch click. Forth Row: proportion differences at the* 1*st patch click. Bottom Row: proportion differences at the* 30*th patch click. Error bars denote the standard error of the mean.*

Table 4

Results of ANOVA omnibus tests for effects in the robust linear regression models with robust standard errors: $\mathit{Proportion\ Difference} = 1 + \mathit{Target\ Type} * \mathit{Patch\ Click} * \mathit{EV}$ *comparing Experiments 1 (equal EV Condition) and 2 (unequal EV). Estimated coefficients are summarized in Table 2 in the Supplementary Materials.*

Condition	Term	Df	F	P-value
2a	Intercept	1	102.387	< 0.001
Equal Prevalence	Target Type	3	88.188	< 0.001
	Patch Click	1	64.128	< 0.001
	EV Condition	1	10.654	0.001
	Target Type × Patch Click	3	49.118	< 0.001
	Target Type × EV Condition	3	13.444	< 0.001
	Patch Click × Ev Condition	1	8.390	0.004
	Target Type × Patch Click × EV Condition	3	8.103	< 0.001
2b	Intercept	1	31.774	< 0.001
Common Risk	Target Type	3	13.001	< 0.001
	Patch Click	1	54.273	< 0.001
	EV Condition	1	6.555	0.010
	Target Type × Patch Click	3	23.801	< 0.001
	Target Type × EV Condition	3	1.574	0.193
	Patch Click × EV Condition	1	0.361	0.548
	Target Type × Patch Click × EV Condition	3	0.459	0.711
2c	Intercept	1	110.681	< 0.001
Common Sure	Target Type	3	73.862	< 0.001
	Patch Click	1	10.250	0.001
	EV Condition	1	20.527	< 0.001
	Target Type × Patch Click	3	14.396	< 0.001
	Target Type × EV Condition	3	13.902	< 0.001
	Patch Click × EV Condition	1	7.433	0.006
	Target Type × Patch Click × EV Condition	3	4.195	0.006

Table 5

Overall foraging performance generated by the optimal model throughout the hybrid foraging session.

		Number of Patch Clicks		Number of Viewed Patches		Inter-click Time (second)		Total Points	
Experiment	Condition	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Experiment 1	a: Equal Prevalence	30.869	0.082	26.320	0.471	0.967	0.002	3126.160	54.188
Equal EV	b: Common Risk	29.607	0.241	29.700	0.463	0.879	0.002	3426.080	37.132
	c: Common Sure	29.587	0.264	29.840	0.370	0.879	0.002	3440.800	33.064
	d: Unequal Prevalence	29.605	0.262	29.700	0.463	0.879	0.003	3425.360	42.298
Experiment 2	a: Equal Prevalence	14.312	0.204	40.360	0.485	1.238	0.005	5826.480	39.909
Unequal EV	b: Common Risk	22.081	0.183	36.940	0.240	0.899	0.003	8815.120	60.481
	c: Common Sure	10.376	0.811	52.060	1.731	1.213	0.041	3578.760	36.399

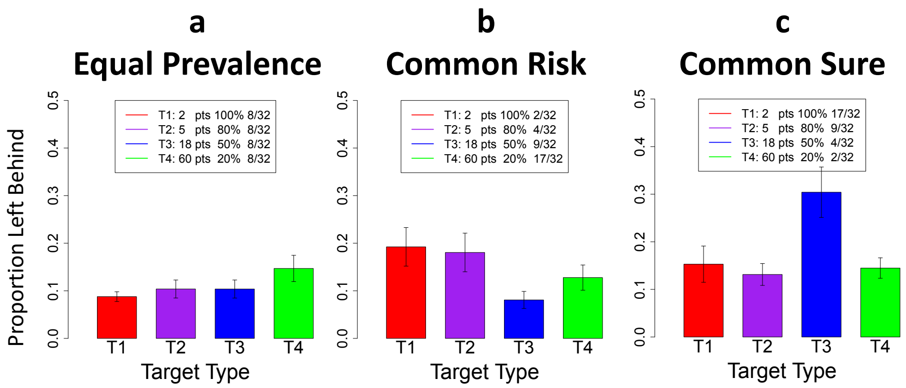


Figure 5

Average proportions of each target left behind when participants moved to a new patch in Experiment 2. The error bars denote the standard error of the proportions

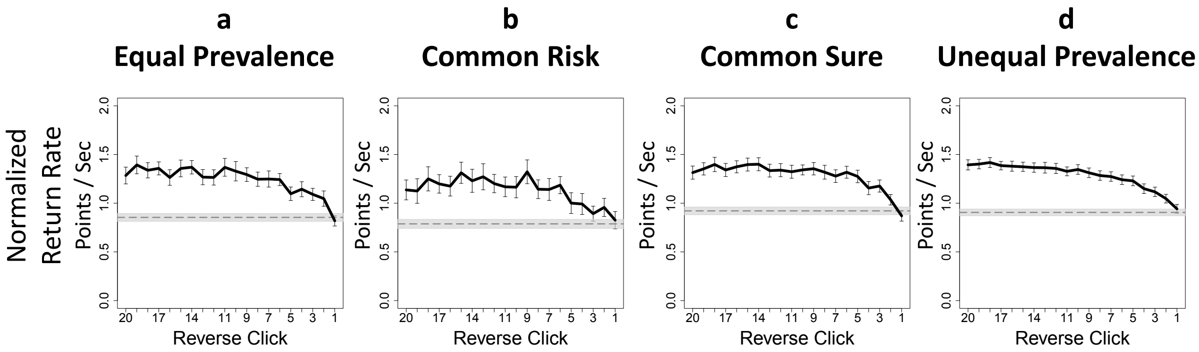


Figure 6

Return rates estimated from Experiment 1. The solid black lines show the instantaneous rate of return as a function of reverse clicks. Reverse click 1 is the final click before participants decided to move to the next patch. Reverse click 2 is the penultimate selection and so on, backwards in time. The error bars denote standard errors of instantaneous rates estimated at each reverse click. The dashed lines denote the corresponding average rates of return with the gray shaded ban denoting the ± standard errors.

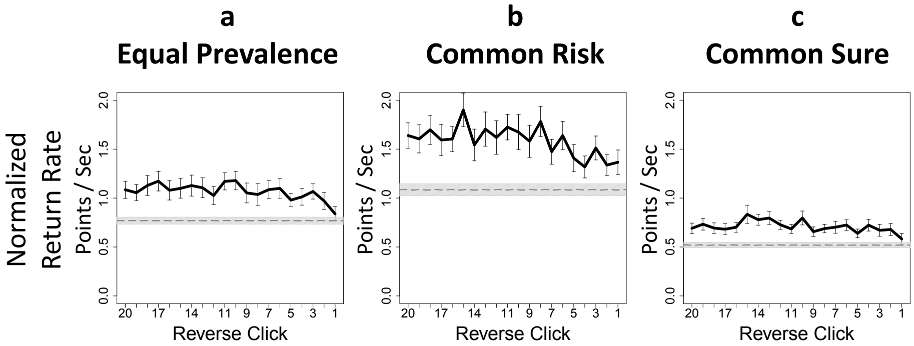


Figure 7

Return rates estimated from Experiment 2. The solid black lines show the instantaneous rate of return as a function of reverse clicks. Reverse click 1 is the final click before participants decided to move to the next patch. Reverse click 2 is the penultimate selection and so on, backwards in time. The error bars denote standard errors of instantaneous rates estimated at each reverse click. The dashed lines denote the corresponding average rates of return with the gray shaded ban denoting the ± standard errors.

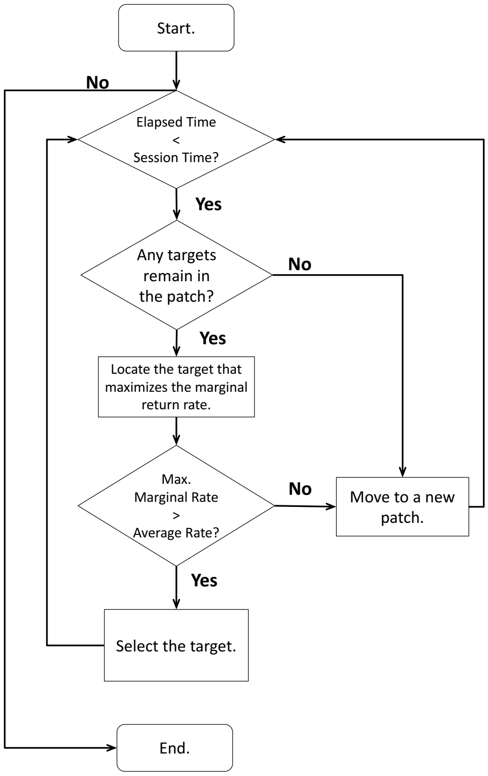


Figure 8

A flowchart of the optimal foraging model developed for the hybrid foraging task. Each diamond denotes a decision to be made. Each rectangle denotes a process to be executed. Each squircle denotes a start or end point of the system.

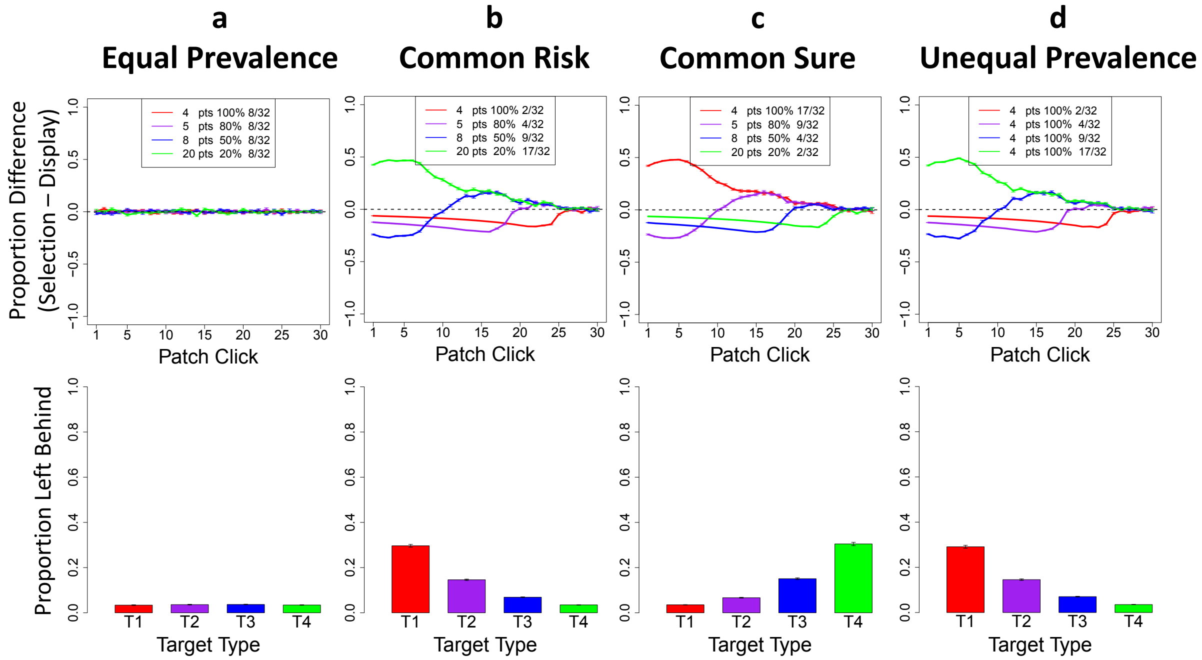


Figure 9

Foraging behavior simulated from the optimal hybrid foraging model for equal-EV conditions (Experiment 1). Top row: differences between selection and display proportions at each patch click for each target. Bottom row: the proportions of each target left behind when the model moved to a new patch. The error bars denote standard errors.

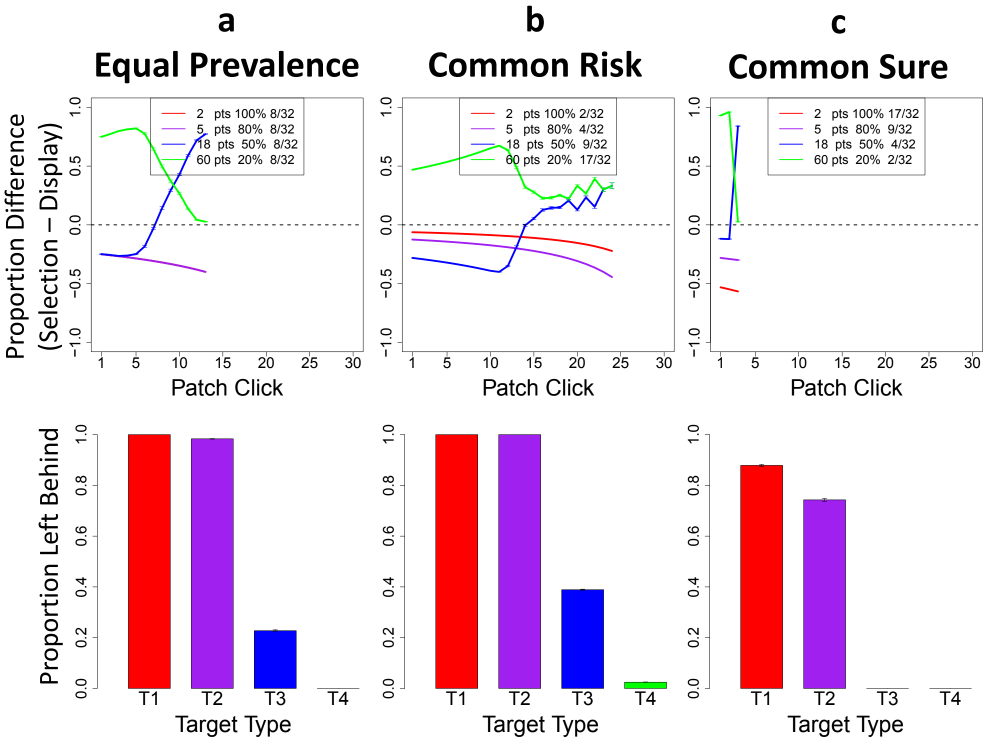


Figure 10

Foraging behavior simulated from the optimal hybrid foraging model for unequal-EV conditions (Experiment 2). Top row: differences between selection and display proportions at each patch click for each target. Bottom row: the proportions of each target left behind when the model moved to a new patch. The error bars denote standard errors.

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Supplementary Material: Risky Hybrid Foraging - the Impact of Risk, Reward Value, and Prevalence on Foraging Behavior in Hybrid Visual Search

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Supplementary Material: Risky Hybrid Foraging - the Impact of Risk, Reward Value, and Prevalence on Foraging Behavior in Hybrid Visual Search

The supplementary materials include additional analyses and studies conducted for the main paper. The sections are arranged in the order of their presence in the main paper.

Demographic Questionnaire

After completing the main foraging task, participants were asked to fill out a demographic questionnaire to report their age (in free-box response for numerical input only), gender (in choices: female, male, other; or in free-box response), and the highest level of education (in choices: less than high school, high school graduate, some college, 2 year degree, 4 year degree, professional degree, Doctorate).

Within Patch Foraging Behavior: Estimated Coefficients from Robust Regression Analyses

Due to heteroscedasticity and skewness in differences between selection and display proportions (see Figure 1), we used robust regression models with robust standard errors to statistically test the effects of key experimental predictors on these observed proportion differences. Robust regression models were fitted using the rlm function in the 'MASS' R package (Venables and Ripley, 2002). Coefficient tests were conducted with robust standard errors computed based on heteroscedasticity-consistent covariance matrix (HC3; Long and Ervin, 2000) using the package 'sandwich' in R (Zeileis et al., 2020). We estimated confidence intervals for the coefficients using bootstrap methods (Davison and Hinkley, 1997).

Equal-EV Conditions

Table 1 summarizes the estimated coefficients from robust regression models performed on data collected in Experiment 1. The robust regression modeled the difference between selection and display proportions as a linear function of Target Type, Patch Click and their interaction terms, after accounting for heteroscedasticity in the observed data.

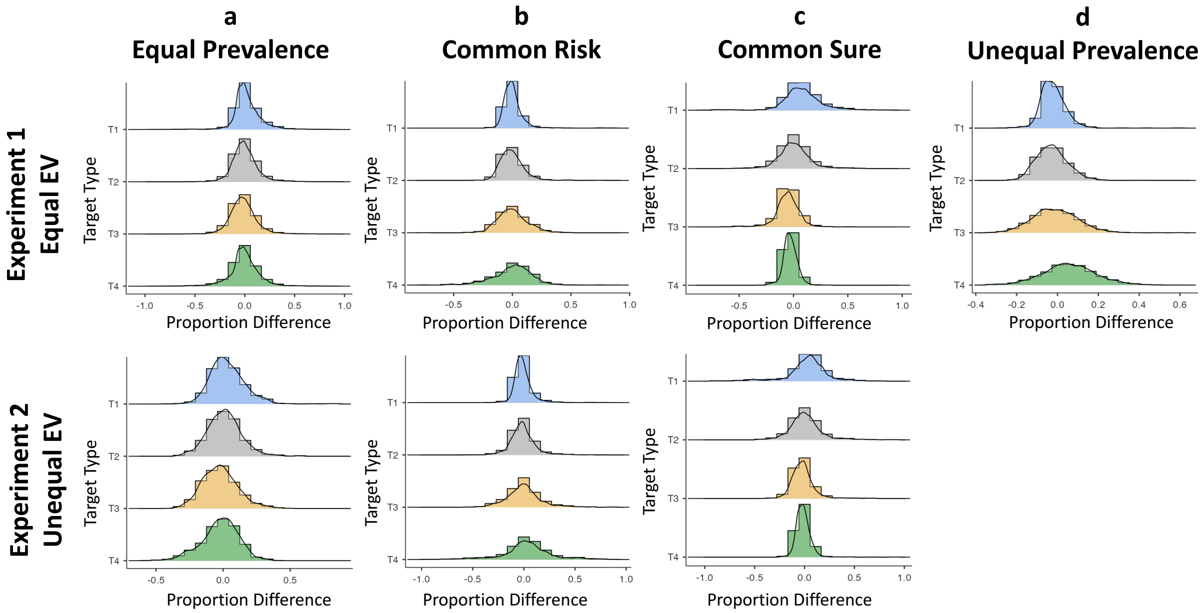


Figure 1

Densities of observed proportion differences of each target type in Experiment 1 (top panel) and Experiment 2 (bottom panel).

Unequal-EV Conditions

Table 2 summarizes the estimated coefficients from robust regressions performed on data collected from Experiment 2 and their respective prevalence-CV conditions in Experiment 1. The robust regression modeled the difference between selection and display proportions as a linear function of Target Type, Patch Click, EV Condition (i.e., equal EV vs. unequal EV), and their interaction terms, after accounting for heteroscedasticity in the observed data.

Comparisons of the Marginal and Average Click Rates

The rate of clicks (in units of clicks/second) describes how fast participants collect items (including clicks on both target and non-target letters). The instantaneous rate of clicks was estimated by dividing an acquisition by the amount of time spent acquiring an item. For instance, if a participant took 2 seconds to select a target and the selection yielded 4 points, then the instantaneous click rate is $\frac{1}{2}$ clicks/sec. The average click rate was calculated by dividing the total number of clicks by the total duration of the foraging session, including both the time spent on foraging within patches and the time spent on traveling between patches.

Equal-EV Conditions

As shown in Figure 2, the instantaneous click rates decreased as patch foraging progressed (top row of Figure 2). This is not surprising because targets became increasingly harder to locate with the depletion of instances. In the equal-prevalence condition (Condition 1a) and the common-sure condition (Condition 1c), the instantaneous click rates dropped to the average click rate when participants left a patch (Condition 1a: $t(37) = 1.61,\ p = 0.115,$Cohen's d $= 0.262$; Condition 1c: ($t(41) = 1.43,\ p = 0.161,$ Cohen's d $= 0.220$), following the predictions of MVT. In the common-risk condition (Condition 1b) and the unequal-prevalence condition (Condition 1d), the instantaneous click rates at the last click were slightly above the average click rates (Condition 1b: $t(33) = 3.4,\ p = 0.002,$ Cohen's d $= 0.583$; Condition 1d: $t(41) = 2.65,\ p = 0.011,$ Cohen's d $= 0.262$).

Unequal-EV Conditions

Similar to what we observed in Experiment 1, the instantaneous click rates decreased as patch foraging progressed (the bottom row in Figure 2), suggesting that participants took longer to find targets as their instances depleted. In the equal-prevalence condition (Condition 2a) and the common-sure condition (Condition 2b), participants' instantaneous click rates also dropped to their average click rates when they left a patch (Condition 2a: ($t(43) = 0.529,\ p = 0.6,$Cohen's d $= 0.080$; Condition 2c $t(43) = 0.919,\ p = 0.363,$Cohen's d $= 0.139$), which follows the predictions of MVT. However, when risky targets were highly prevalent (Condition 2b), participants left patches early, as the instantaneous click rate at the final click was above the average click rate, $t(44) = 3.23,\ p = 0.002,$ Cohen's d $= 0.482$.

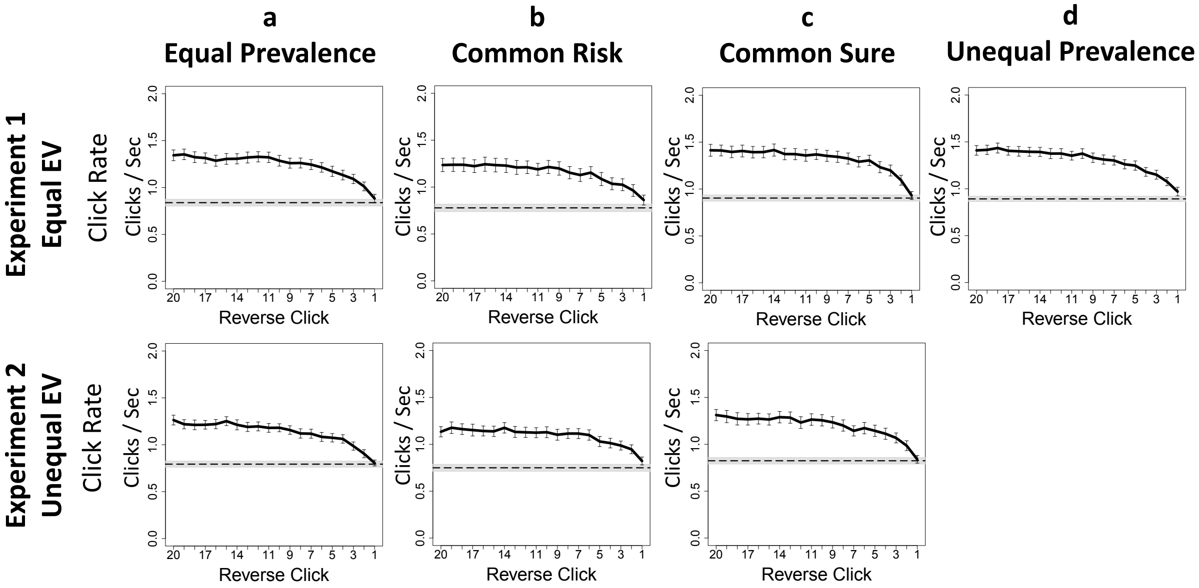


Figure 2

Click rates estimated in Experiment 1 (top panel) and Experiment 2 (bottom panel). The solid lines show the instantaneous rate of clicks as a function of reverse click. Reverse click 1 is the final click before participants decided to move to the next patch. Reverse click 2 is the penultimate selection and so on, backwards in time. The error bars denote standard errors of instantaneous rates estimated at each reverse click. The dashed lines show the corresponding average rate of clicks with the gray shaded bans denoting the ± standard errors.

Experiment 3: Baseline Foraging Behavior

We estimated the functional relationship between baseline foraging time and prevalence of targets in Experiment 3 (the pre-registration and the data are available at https://osf.io/bf9st/). In Experiment 3, participants were asked to forage for a single target type for five minutes and automatically moved to a new patch after exhausting all instances of the target in the current patch. A selection of the target would always yield 4 reward points. Moving to a new patch did not incur any travel time cost. The number of instances were manipulated into four between-subject conditions.

Method

Participants

A total of 200 participants (117 women, 82 men, 1 did not report; age: M = 42.49, SD = 13.48) recruited from MTurk using CloudResearch completed the study. Participants were paid a $0.50 base rate and were incentivized with a bonus scheme determined by the average points they earned per second: $0.10 for 1-2 points per second, $0.25 for 2-4 points per second, $0.50 for above 4 points per second and $0 for below 1 point per second. The average bonus participants received was $0.211.

14% of participants (N = 28) were excluded from the data analyses due to poor performance (i.e., their rate of earning points per second was less than 1 or they committed more than 20% false positive errors). The exclusion criteria were pre-registered. After the exclusions, we had 35 participants in Condition a, 45 in Condition b, and 44 in Condition c and 48 in d. The sample size was determined prior to starting the experiment, and the data was analyzed only after all data had been collected.

Materials

We programmed the baseline foraging task following the similar structure of the hybrid foraging task, except that (1) only one letter was assigned to represent a target; (2) the program automatically proceeded to a new patch after all instances of the target were collected from the current patch; (3) moving to a new patch did not incur transition time cost.

The initial number of target instances at the onset of patches (i.e., 2, 4, 9, 17, respectively for condition a, b, c and d) determined four between-subject conditions. The total number of items in display at the onset of patches, including both target and distractors, were fixed at 64 on average. These values parallel manipulations in Experiments 1 and 2.

Procedures

The procedures of Experiment 3 followed the schemes of Experiments 1 and 2 in general. Consented participants were randomly assigned to one of four prevalence conditions. At the start of the experiment, participants were informed that their task was to collect as many points as possible by selecting moving target letters for 5 minutes. After they read the payment schedules, they were informed about the identity of the target letter, its reward points, and its prevalence (i.e., “approximately xx percentage of the items in the patch will be targets”). When participants were ready, they proceeded to a short practice session to collect 60 points before they started the main foraging session.

The total number of targets in a patch was pseudo-randomized at the start of a patch, following the same procedures used in Experiments 1 and 2. Within a foraging patch, the target letter was displayed at the top of the screen and the points earning rate was displayed at the top left of the screen (see Figure 3). The feedback on selections were identical to that in Experiments 1 and 2. After participants collected all instances of the target letter in a patch, they automatically moved to a new patch. Between patches, there was a 250-millisecond lag. After completing the foraging session, participants were informed about the amount of bonus they earned and were asked to fill out a demographic questionnaire.

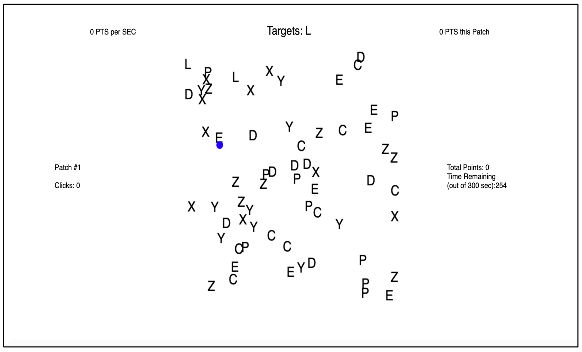


Figure 3

An example screenshot during the baseline foraging task from Experiment 3. Participants were asked to forage for a single target type for five minutes and automatically moved to a new patch after exhausting all instances of the target in the current patch. A selection of the target would always yield 4 reward points. Moving to a new patch did not incur any travel time cost.

Results

In all conditions, fewer than 3% of clicks were made on none-target items. Table 3 summarizes overall performance measures across conditions. The number of clicks participants made within patches were consistent with the experimental manipulation. When targets had fewer instances, participants were slower in collecting targets $(F(3, 88.6) = 29.1,\ p < 0.001,\ \omega^2 = 0.333)$, while viewed more number of patches $(F(3, 80.4) = 96.3,\ p < 0.001,\ \omega^2 = 0.628)$ throughout the baseline foraging session. In total, participants earned more points when targets were highly prevalent, $F(3, 92.3) = 39.047,\ p < 0.001,\ \omega^2 = 0.403$.

Figure 4 plots inter-click times between target selections against patch clicks in reversed order. Reverse click 1 denotes the last click in a patch. In all conditions, we observed that the inter-click times increased as patch foraging progressed, suggesting that participants took longer time to make a selection with the depletion of targets over time.

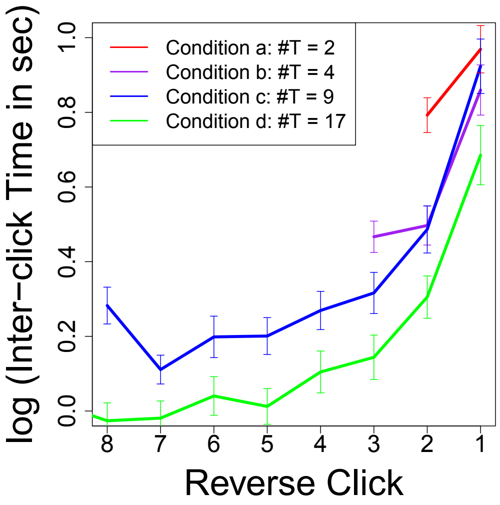


Figure 4
Logarithm of Inter-click times plotted as a function of reverse click for each condition in Experiment 3. Reverse click 1 is the final click before participants decided to move to the next patch. Reverse click 2 is the penultimate selection and so on, backwards in time. The error bar denotes the standard errors of the mean.

In addition, we observed that the inter-click time at a reverse click differed across conditions, despite that the number of target instances should be identical at each reverse click. This suggests that participants' foraging speed was affected by the number of targets in relation to the total number of items in display, rather than merely by the number of targets in display. For instance, when there was one target left for participants to collect (i.e., at reverse click 1), participants would have to search the last target among 63 items in Condition a (each patch had 2 target instances, and 1 instance had been collected at the penultimate patch click), while among 48 items in Condition d (17 target instances per patch and 16 were collected before the last click).

The results of a mixed linear regression model (Table 4) confirmed above observations. We modeled the logarithm of inter-click times (in units of seconds) as a linear function of the number of target instances in presence and the total number of items in display, after accounting for the random effect of individual differences in base times. The results show that the inter-click times decreased significantly with numbers of target instances ($F(1,1209) = 269.7,\ p < 0.001$), and increased significantly with total numbers of present items ($F(1,1213) = 157,\ p < 0.001$). Moreover, the interaction between these two variables had a significant effect on inter-click times, $F(1,108) = 58.1,\ p < 0.001$).

Conclusions

Our findings from the baseline foraging experiment (Experiment 3) show that both the number of target instances and the total number of items present on the screen affected participants foraging speed. We used the data collected in this experiment to describe the mean baseline foraging times for our optimal model simulations.

The Effect of Target Movement on Hybrid Foraging Behavior

We assessed the effect of searching difficulty on foraging behavior with a replication study of the equal-prevalence, unequal-EV condition (Condition a in Experiment 2). In this replication study (denoted as Condition 2a'), items (i.e., letters) were fixed at their initial locations throughout a patch foraging.

Method

Participants

Fifty participants (25 women, 25 men; age: M = 41.66, SD = 11.50) were recruited from MTurk using CloudResearch and completed a 15-minute hybrid foraging session. The payment schedule was identical to Experiment 2. We excluded participants who had low performance using the same exclusion criteria in Experiment 2. After the exclusions, we had 35 participants for data analyses.

Materials

The materials used in Condition 2a’ are identical to those used in Condition 2a.

Procedure

The procedures of Condition 2a’ are identical to those in Condition 2a, except that the locations of letters were fixed at their initial locations throughout a patch foraging. The initial locations of letters were randomized at the onset of a new patch.

Results

As illustrated in Figure 5, the within-patch foraging behavior observed in the static condition (Condition 2a’) was very similar to those observed in the dynamic version (Condition 2a). Participants over-picked the sure target while under-picking the risky targets at the start of patch foraging, and then selected targets randomly in the later stage of patch foraging. The results of a robust regression model confirmed that the movement of targets did not significantly alter the effects of riskiness and reward value on foraging behavior (see omnibus test results in Table 5; see coefficient test results in Table 6).

Conclusions

The results from the replication study suggest that participants still preferred safe targets over the risky targets, despite the movements of items in display.

Stay-Switch Behavior in Target Selection

Response Priming Effect

To examine how the subsequent selection was affected by a previous selection, we assessed the transition probabilities between targets. As depicted in Figure 6, when all targets were equally prevalent (Conditions 1a and 2a), participants tended to select the same target as their previous selection. When targets were unequally prevalent, participants tended to select the most prevalent targets, regardless the type of target they selected before. These findings were consistent with previous findings (Wolfe et al., 2019) of the response-priming effect in hybrid foraging behavior.

Stay-Switch Behavior Conditioned on Previous Gain/No-Gain

Figure 7 depicts the transition probabilities between sequentially collected targets in equal prevalence conditions of Experiments 1 (Equal-EV) and 2 (Unequal-EV), conditioned on either receiving a reward (i.e., Gain at t-1) or a zero return (i.e., No-Gain at t-1) from a previous click. In both gain and no-gain cases, we observed that foragers were more likely to stay with the same type of target, suggesting that a recent gain/no-gain might not play a dominant role in participants' stay-switch behavior during foraging. The overall proportion of switching did not significantly differ between the previous-gain and previous-no-gain cases in the equal prevalence conditions of both Experiments 1 and 2 (Equal-EV Exp1: $z = -1.65, p = 0.098$; Unequal-EV Exp2: $z = 0.486, p = 0.627$).

Table 1

Estimated coefficients from the robust regression models:
Proportion Difference $= 1 +$ *Target Type* $*$ *Patch Click for each condition in Experiment 1.*

Condition	Term	β	SE	z	p	95% CI
1a Equal Prevalence	Intercept	0.103	0.010	10.144	< 0.001	[0.088, 0.119]
	T2	-0.093	0.013	-6.959	< 0.001	[-0.113, -0.072]
	T3	-0.176	0.013	-13.590	< 0.001	[-0.199, -0.153]
	T4	-0.195	0.014	-14.341	< 0.001	[-0.216, -0.174]
	Patch Click	-0.004	0.0005	-8.024	< 0.001	[-0.005, -0.003]
	T2 : Patch Click	0.004	0.001	6.634	< 0.001	[0.003, 0.006]
	T3 : Patch Click	0.008	0.001	11.593	< 0.001	[0.006, 0.009]
	T4 : Patch Click	0.006	0.001	9.334	< 0.001	[0.005, 0.007]
1b Common Risk	Intercept	0.027	0.005	5.542	< 0.001	[0.014, 0.040]
	T2	-0.020	0.008	-2.422	0.015	[-0.038, -0.0003]
	T3	-0.046	0.010	-4.829	0.000	[-0.065, -0.026]
	T4	-0.062	0.013	-4.657	< 0.001	[-0.080, -0.042]
	Patch Click	-0.002	0.0003	-7.316	< 0.001	[-0.003, -0.001]
	T2 : Patch Click	0.001	0.0004	1.837	0.066	[-0.0002, 0.002]
	T3 : Patch Click	0.003	0.001	5.557	< 0.001	[0.002, 0.004]
	T4 : Patch Click	0.005	0.001	7.167	< 0.001	[0.004, 0.006]
1c Common Sure	Intercept	0.097	0.009	10.485	< 0.001	[0.085, 0.108]
	T2	-0.133	0.012	-10.978	< 0.001	[-0.149, -0.116]
	T3	-0.152	0.010	-14.799	< 0.001	[-0.169, -0.135]
	T4	-0.120	0.010	-12.266	< 0.001	[-0.135, -0.102]
	Patch Click	-0.002	0.0005	-3.198	0.001	[-0.002, -0.001]
	T2 : Patch Click	0.004	0.001	5.847	< 0.001	[0.003, 0.005]
	T3 : Patch Click	0.002	0.001	3.104	0.002	[0.001, 0.003]
	T4 : Patch Click	0.001	0.001	2.033	0.042	[0.0001, 0.002]
1d Unequal Prevalence	Intercept	-0.013	0.003	-4.313	< 0.001	[-0.023 , -0.003]
	T2	-0.020	0.005	-4.131	< 0.001	[-0.035 , -0.006]
	T3	-0.024	0.008	-3.154	0.002	[-0.038 , -0.009]
	T4	0.077	0.009	8.593	< 0.001	[0.063, 0.091]
	Patch Click	-0.001	0.0002	-3.286	0.001	[-0.001 , -0.0001]
	T2 : Patch Click	0.001	0.0003	2.890	0.004	[0.0001, 0.002]
	T3 : Patch Click	0.002	0.0004	5.013	< 0.001	[0.001, 0.003]
	T4 : Patch Click	0.0001	0.0005	0.268	0.789	[-0.001, 0.001]

Table 2

Estimated coefficients from the robust regression model:
Proportion Difference $= 1 +$ *Target Type* $*$ *Patch Click* $*$ *EV Condtion comparing Experiments 1 (equal EV) and 2 (unequal EV).*

Condition	Term	β	SE	z	p	95% CI
2a Equal Prevalence	Intercept (T1, Equal-EV)	0.104	0.010	10.119	< 0.001	[0.089 , 0.119]
	T2	-0.093	0.013	-6.955	< 0.001	[-0.113, -0.073]
	T3	-0.176	0.013	-13.567	< 0.001	[-0.198, -0.154]
	T4	-0.195	0.014	-14.299	< 0.001	[-0.216, -0.174]
	Patch Click	-0.004	0.0005	-8.008	< 0.001	[-0.005, -0.003]
	Unequal EV	-0.043	0.013	-3.264	0.001	[-0.063, -0.022]
	T2 : Patch Click	0.004	0.001	6.632	< 0.001	[0.003 , 0.006]
	T3 : Patch Click	0.008	0.001	11.575	< 0.001	[0.006, 0.009]
	T4 : Patch Click	0.006	0.001	9.311	< 0.001	[0.005, 0.007]
	T2 : Unequal EV	0.022	0.017	1.283	0.200	[-0.007, 0.051]
	T3 : Unequal EV	0.061	0.017	3.625	< 0.001	[0.031, 0.091]
	T4 : Unequal EV	0.104	0.018	5.757	< 0.001	[0.074, 0.132]
	Patch Click : Unequal EV	0.002	0.001	2.897	0.004	[0.001, 0.003]
	T2 : Patch Click : Unequal EV	-0.001	0.001	-1.384	0.166	[-0.003, 0.001]
	T3 : Patch Click : Unequal EV	-0.004	0.001	-4.286	< 0.001	[-0.005, -0.002]
	T4: Patch Click : Unequal EV	-0.003	0.001	-3.657	< 0.001	[-0.005, -0.002]
2b Common Risk	Intercept (T1, Equal-EV)	0.027	0.005	5.637	< 0.001	[0.012, 0.041]
	T2	-0.020	0.008	-2.454	0.014	[-0.042, 0.002]
	T3	-0.047	0.010	-4.870	< 0.001	[-0.068, -0.025]
	T4	-0.063	0.013	-4.707	< 0.001	[-0.086, -0.039]
	Patch Click	-0.002	0.0003	-7.367	< 0.001	[0.003, -0.001]
	Unequal EV	-0.016	0.006	-2.560	0.010	[-0.035, 0.004]
	T2 : Patch Click	0.001	0.0004	1.859	0.063	[-0.0004, 0.002]
	T3 : Patch Click	0.003	0.001	5.584	< 0.001	[0.002, 0.004]
	T4 : Patch Click	0.005	0.001	7.230	< 0.001	[0.003, 0.006]
	T2 : Unequal EV	-0.001	0.011	-0.082	0.935	[-0.028, 0.033]
	T3 : Unequal EV	0.017	0.014	1.235	0.217	[-0.011, 0.046]
	T4 : Unequal EV	0.034	0.019	1.815	0.069	[0.002, 0.064]
	Patch Click : Unequal EV	0.0002	0.0004	0.601	0.548	[-0.001, 0.001]
	T2 : Patch Click : Unequal EV	0.0003	0.001	0.482	0.630	[-0.002, 0.002]
	T3 : Patch Click : Unequal EV	-0.001	0.001	-0.863	0.388	[-0.002, 0.001]
	T4: Patch Click : Unequal EV	-0.0002	0.001	-0.249	0.803	[-0.002, 0.002]
2c Common Sure	Intercept (T1, Equal-EV)	0.097	0.009	10.521	< 0.001	[0.086, 0.109]
	T2	-0.133	0.012	-10.987	< 0.001	[-0.149, -0.118]
	T3	-0.152	0.010	-14.794	< 0.001	[-0.168, -0.135]
	T4	-0.119	0.010	-12.277	< 0.001	[-0.137, -0.103]
	Patch Click	-0.002	0.000	-3.202	0.001	[-0.002, -0.001]
	Unequal EV	-0.062	0.014	-4.531	< 0.001	[-0.079, -0.045]
	T2 : Patch Click	0.004	0.001	5.861	< 0.001	[0.003, 0.005]
	T3 : Patch Click	0.002	0.001	3.070	0.002	[0.001, 0.003]
	T4 : Patch Click	0.001	0.001	2.009	0.045	[0.0001, 0.002]
	T2 : Unequal EV	0.071	0.018	4.009	< 0.001	[0.047, 0.094]
	T3 : Unequal EV	0.098	0.015	6.429	< 0.001	[0.075, 0.122]
	T4 : Unequal EV	0.075	0.014	5.239	< 0.001	[0.052, 0.098]
	Patch Click : Unequal EV	0.002	0.001	2.726	0.006	[0.001, 0.003]
	T2 : Patch Click : Unequal EV	-0.003	0.001	-2.804	0.005	[-0.004, -0.001]
	T3 : Patch Click : Unequal EV	-0.003	0.001	-3.399	0.001	[-0.004, -0.002]
	T4: Patch Click : Unequal EV	-0.002	0.001	-2.528	0.011	[-0.003, -0.001]

Table 3

Overall foraging performance in Experiment 3 throughout the baseline foraging session.

	Number of Patch Clicks		Number of Viewed Patches		Inter-click Time (second)		Total Points	
Condition	Mean	SD	Mean	SD	Mean	SD	Mean	SD
a: #T = 2	2.033	0.107	63.400	20.677	2.460	0.705	484.343	163.031
b: #T = 4	4.070	0.113	41.600	12.718	1.935	0.648	643.822	200.675
c: #T = 9	9.067	0.254	24.068	8.492	1.551	0.488	828.000	299.875
d: #T = 17	17.053	0.588	16.688	5.493	1.219	0.527	1083.333	366.121

Table 4

Estimated coefficients from the linear mixed regression model: $log(Interclick\ Time) = (intercept|sub) + Number\ of\ Target * Total\ Number\ Items$*. The random effect of individual differences is captured by the term: (intercept | sub)*

Term	β	SE	t	df	p	95% CI
Intercept	0.185	0.024	7.640	160	< 0.001	[0.138, 0.233]
Number of Target Instance	-0.049	0.003	-16.420	1209	< 0.001	[-0.054, -0.043]
Total Number of Items	0.036	0.003	12.530	1213	< 0.001	[0.030, 0.042]
Number of Target Instance	0.011	0.001	7.630	108	< 0.001	[0.008, 0.014]

Table 5

Results of ANOVA omnibus tests for effects in the robust linear regression models with robust standard errors: Proportion Difference $= 1 +$ *Target Type* $*$ *Patch Click* $*$ *Movement Condition comparing Condition 2a (moving items) and Condition 2a' (static items).*

Term	Df	F	P-value
Target Type	3	39.663	< 0.001
Patch Click	1	25.797	< 0.001
Movement Condition	1	4.814	0.028
Target Type × Patch Click	3	17.115	< 0.001
Target Type × Movement Condition	3	2.305	0.075
Patch Click × Movement Condition	1	0.393	0.531
Target Type × Patch Click × Movement Condition	3	1.781	0.148

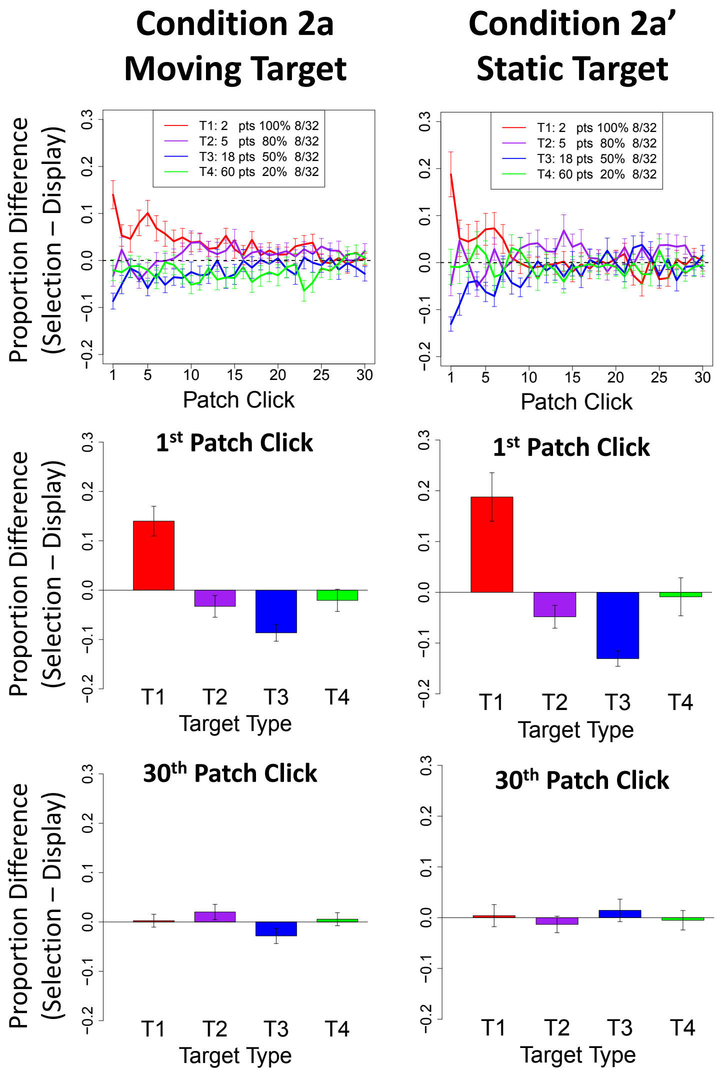


Figure 5

Within-patch foraging behavior estimated from the equal prevalence, unequal-EV conditions using moving letters (Condition 2a, left panel) and static letters (Condition 2a’, right panel). Top Row: differences between selection and display proportions estimated at each patch click. Middle Row: proportion differences at the 1*st* *patch click. Bottom Row: proportion differences at the* 30*th* *patch click. Error bars denote the standard error of the mean.*

Table 6

Estimated coefficients from the robust regression model with robust standard errors: $Proportion\ Difference = 1 + Target\ Type * Patch\ Click * Movement\ Condition$. *Condition 2a had moving letters, whereas Condition 2a' had static letters.*

Term	β	SE	z	p	95% CI
Intercept (T1, Dynamic)	0.061	0.008	7.422	< 0.001	[0.046 , 0.077]
T2	-0.071	0.011	-6.346	< 0.001	[-0.091, -0.050]
T3	-0.115	0.011	-10.594	< 0.001	[-0.135, -0.095]
T4	-0.092	0.012	-7.803	< 0.001	[-0.113, -0.073]
Patch Click	-0.002	0.000	-5.079	< 0.001	[-0.003, -0.001]
Condition 2a’	-0.030	0.014	-2.194	0.028	[-0.053, -0.009]
T2 : Patch Click	0.003	0.001	5.501	< 0.001	[0.002, 0.004]
T3 : Patch Click	0.004	0.001	6.650	< 0.001	[0.003, 0.005]
T4 : Patch Click	0.003	0.001	4.999	< 0.001	[0.002, 0.004]
T2 : Condition 2a’	0.032	0.018	1.767	0.077	[0.004, 0.065]
T3 : Condition 2a’	0.011	0.018	0.593	0.553	[-0.020, 0.041]
T4 : Condition 2a’	0.045	0.020	2.285	0.022	[0.015, 0.077]
Patch Click : Condition 2a’	0.0004	0.001	0.627	0.531	[-0.001, 0.002]
T2 : Patch Click : Condition 2a’	-0.0005	0.001	-0.507	0.612	[-0.002, 0.001]
T3 : Patch Click : Condition 2a’	0.001	0.001	1.129	0.259	[-0.001, 0.003]
T4: Patch Click : Condition 2a’	-0.001	0.001	-1.031	0.302	[-0.003, 0.001]

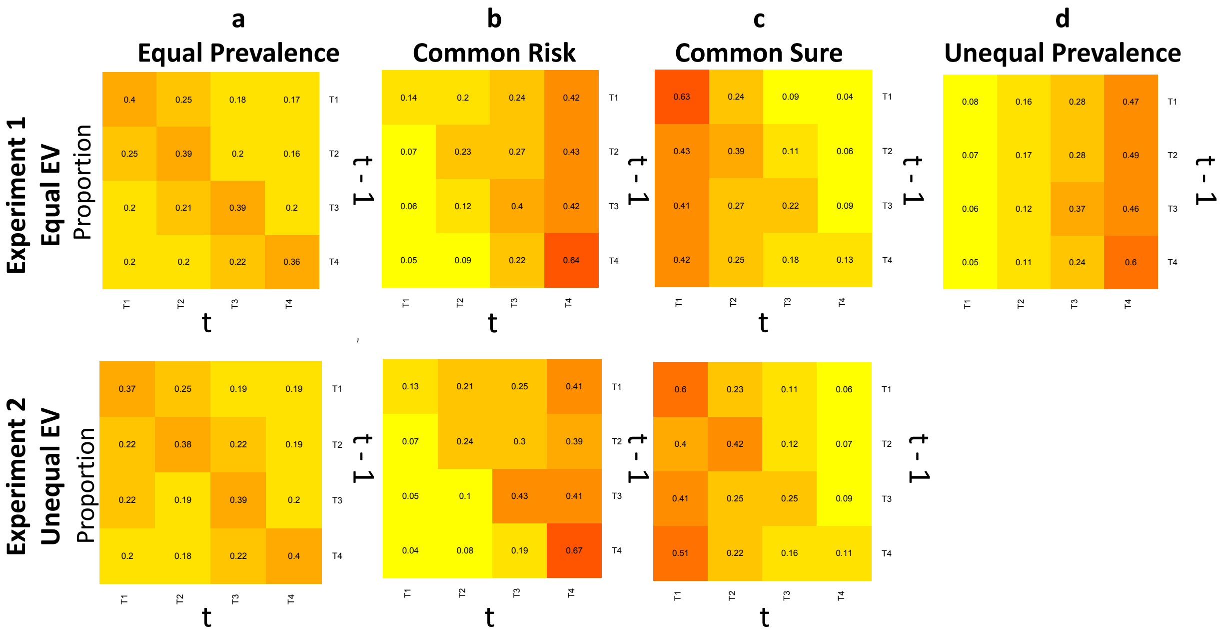
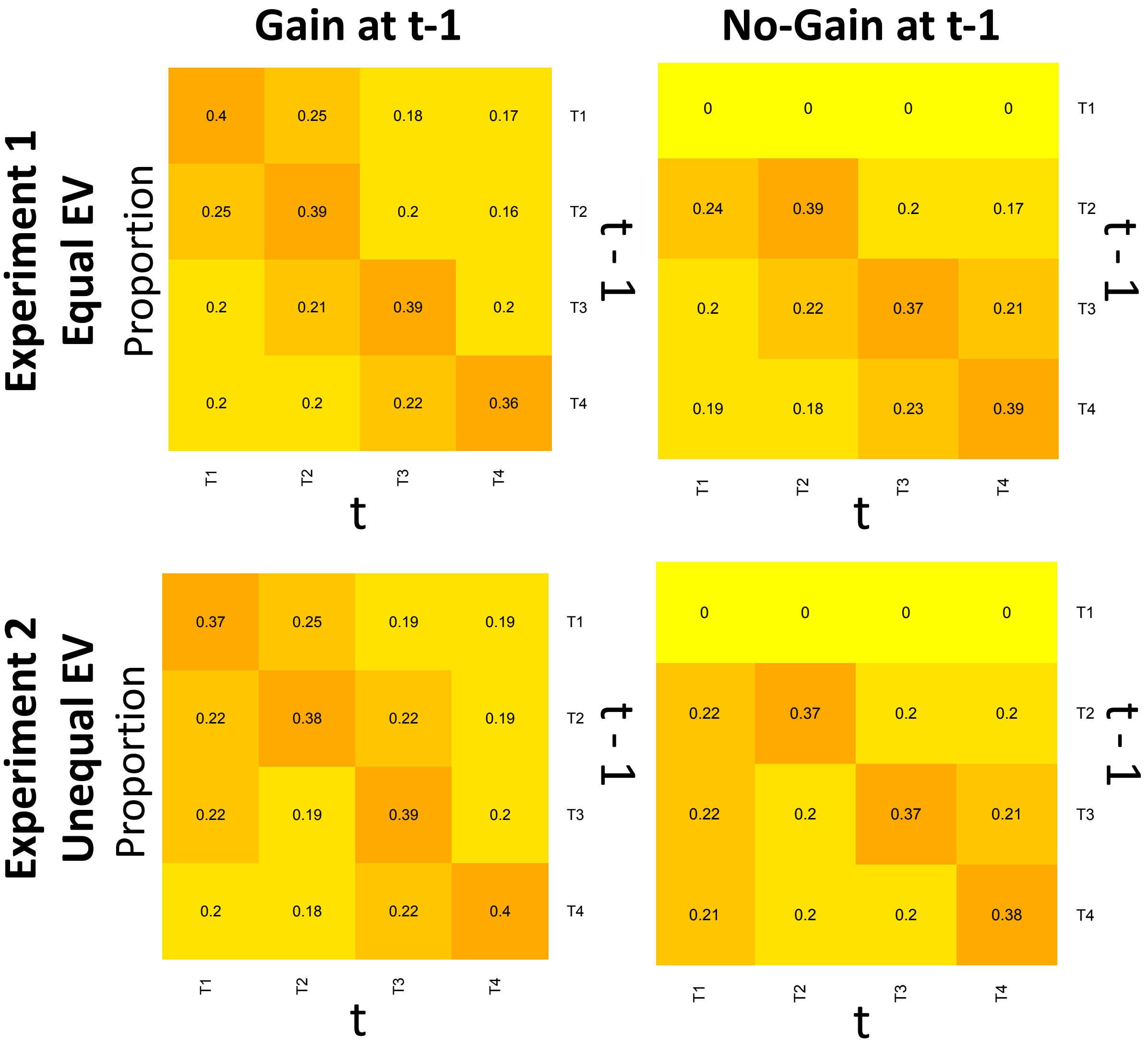


Figure 6

Transition probabilities between sequentially collected targets in Experiment 1 (Equal-EV, top row) and Experiment 2 (Unequal-EV, bottom row). Each row of the matrix denotes the type of target being selected before. Each column of the matrix demotes the type of target being selected at the current selection. The sum of each row is 1.



	T1	T2	T3	T4
T1	0.4	0.25	0.18	0.17
T2	0.25	0.39	0.2	0.16
T3	0.2	0.21	0.39	0.2
T4	0.2	0.2	0.22	0.36

	T1	T2	T3	T4
T1	0	0	0	0
T2	0.24	0.39	0.2	0.17
T3	0.2	0.22	0.37	0.21
T4	0.19	0.18	0.23	0.39

	T1	T2	T3	T4
T1	0.37	0.25	0.19	0.19
T2	0.22	0.38	0.22	0.19
T3	0.22	0.19	0.39	0.2
T4	0.2	0.18	0.22	0.4

	T1	T2	T3	T4
T1	0	0	0	0
T2	0.22	0.37	0.2	0.2
T3	0.22	0.2	0.37	0.21
T4	0.21	0.2	0.2	0.38

Figure 7

Transition probabilities between sequentially collected targets in equal prevalence conditions of Experiments 1 (Equal-EV, top row) and 2 (Unequal-EV, bottom row), conditioned on either receiving a reward (i.e., Gain at t-1, left column) or a zero return (i.e., No-Gain at t-1, right column) from a previous click. Each row of the matrix denotes the type of target being selected before. Each column of the matrix demotes the type of target selected at the current selection. The sum of each row is 1.

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