S1 Text: Maintaining Homeostasis by Decision-Making

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1 Random walk to generate gambles for virtual foraging task

1.1 General idea

We propose that decision making aimed at maintaining homeostasis (i.e., aimed at avoiding to die from hunger) can be investigated by using gambles that are derived within the mathematical framework of random walks.

- To maintain homeostasis, a biological agent has to keep its internal energy resources or energy points x above zero at any (discrete) time point i (with $x,\ i \in \mathbb{N}_0$).
- In each trial (i.e., at each new foraging decision), the agent starts (the random walk) with internal resources x_0 at time point $i = 0$. Within each trial, the agent passes through n time steps (i.e., "days").
- At each time step $n = 1$, the agent's internal resources incur a sure cost$-c$ (with $c \in \mathbb{N}_0$), which mirrors the consumption of energy (e.g., in terms of calories).
- To replenish the internal resources, the agent choses a risky foraging option and probailistically receives its outcomes at each time step n. That is, within a given time step $n = 1$ the agent can gain an amount g (with $g \in \mathbb{N}_0$) with probability p. This would, for example, correspond to collecting berries or to hunting deer, where berries could provide a lower gain (less calories) but have a higher probability than deer. The probabilities of finding berries or hunting down deer could, for example, vary according to different seasons or environments.
- Alternatively, if the agent does not gain anything, the internal resources only incur the sure cost$-c$ with probability q (where $q = 1 - p$).
- The gain is assumed to be equal or larger than the cost, otherwise the agent would not strive for it, therefore $g \geq c$.

This situation represents a random walk starting at x_0 with

- a step size of $g - c$ and a probability p of going right and
- a step size of$-c$ and a probability q of going left.

The random walk has a lower absorbing barrier at $x_b = 0$, which mirrors dying from hunger. Within this framework, gambles can be constructed as a function of p (and thus q), n, x_0, c, and g.

1.2 Assumptions

A number of simplifications are made:

1. The agent makes one single decision at the beginning of each trial (e.g., the agent decides whether to collect berries or to hunt deer and sticks to that decision throughout the number of days). That is, the gambles consist of compound lotteries, which comprise n sequential lotteries.
2. The agent does not deplete the food sources and does not get more proficient at obtaining food. That is, the probabilities p and q are constant within each trial.
3. Similarly, cost c and gain g are constant within each round.
4. Costs do not differ between foraging options. For example, collecting berries and hunting deer are assumed to have the same costs (in terms of calories spent).
5. Here, only a lower absorbing barrier is considered. An upper absorbing barrier (e.g., death due to overeating) is not included.
6. Dying from hunger represents the only threat to homeostasis (e.g., there are no predators).
7. Only a single variable (the amount of internal energy resources) has to be kept within a homeostatic range (e.g., there is no need to obtain specific nutrients and no conflicts or opportunity costs with respect to other activities such as sleep or reproduction).

1.3 Outcome distributions of the random walk

In the following, the probability distributions of random walks will be described. The description of random walks will increase in complexity until all features outlined above can be incorporated.

1.3.1 Simple random walk starting at zero

A random walk is called *simple* if steps to the right have the step size $+1$ and steps to the left have the step size -1 (i.e., if $c = 1$ and $g = 2$; since $g - c$ is the step size to the right and since$-c$ is the step size to the left). Let's assume the agent starts the random walk at zero. Let X_n denote the random variable which indicates the position of the agent after n time steps. Then,

$$p = P(X_1 = 1)$$
$$q = 1 - p = P(X_1 = -1)$$

Let W_n denote the number of steps to the right within the first n steps. Then W_n has a binomial distribution.

$$P(W_n = a) = \binom{n}{a} p^a\, q^{n-a}, \quad a \in \mathbb{N}_0.$$

If there are a steps to the right $(+1)$ and therefore $n - a$ steps to the left (-1) then

$$X_n = a(+1) + (n - a)(-1) = 2a - n.$$

If n is even then X_n is also even and if n is odd then X_n is also odd. Therefore, if n and x are not either both even or both odd then $P(X_n = x) = 0$. Put differently, the range of X_n is

$$X_n = \{-n, -n + 2, -n + 4, \ldots, n - 4, n - 2, n\}.$$

After each number of steps n there are $n + 1$ possible positions. That is, the range of X_n contains $n+1$ elements. If the agent has visited a certain position at a certain time step n, the agent can visit it again at $n + 2$, $n + 4$, $\ldots$ time steps. Another way of saying this is that if x and n are both even or odd $P(X_n = x) \geqq 0$, otherwise $P(X_n = x) = 0$. $W_n = a$ if and only if $X_n = 2a - n$. Writing $x = 2a - n$, so that $a = \frac{n+x}{2}$ and $n - a = \frac{n-x}{2}$, the probability distribution of X_n is

$$P(X_n = x) = \binom{n}{\frac{n+x}{2}} p^{\frac{n+x}{2}}\, q^{\frac{n-x}{2}}.$$

1.3.2 Simple random walk starting at position x_0

Now, let's assume that the agent does not start the random walk at zero but at x_0. Let $X_n(x_0)$ denote the random variable which indicates the position of the agent after n time steps in a simple random walk starting from x_0. Then,

$$p = P(X_1 = x_1 = x_0 + 1)$$
$$q = 1 - p = P(X_1 = x_1 = x_0 - 1)$$

and

$$X_n(x_0) = a(+1) + (n-a)(-1) + x_0 = 2a - n + x_0.$$

The range of $X_n(x_0)$ is

$$X_n(x_0) = \{-n + x_0, -n + x_0 + 2, -n + x_0 + 4, ..., \\ n + x_0 - 4,\, n + x_0 - 2,\, n + x_0\}.$$

Writing $x = 2a - n + x_0$, so that $a = \frac{n+x-x_0}{2}$ and $n - a = \frac{n-x+x_0}{2}$, the probability distribution of $X_n(x_0)$ is

$$P(X_n(x_0) = x) = \binom{n}{\frac{n+x-x_0}{2}} p^{\frac{n+x-x_0}{2}} q^{\frac{n-x+x_0}{2}}.$$

1.3.3 Random walk with unequal step sizes

Now, let's assume that step sizes to the right and step sizes to the left can take values $\neq \pm 1$. Steps to the right have the size $g - c$ and steps to the left have the size $-c$. Then,

$$p = P(X_1(x_0) = x_1 = x_0 + g - c)$$
$$q = 1 - p = P(X_1(x_0) = x_1 = x_0 - c)$$

and

$$X_n(x_0) = a(g-c) + (n-a)(-c) + x_0 = ag - nc + x_0.$$

The range of $X_n(x_0)$ is

$$X_n(x_0) = \{-nc + x_0, -nc + x_0 + g, -n + x_0 + 2g, ..., \\ (g-c)n + x_0 - 2g,\, (g-c)n + x_0 - g,\, (g-c)n + x_0\}.$$

If the agent has visited a certain position at a certain time step n, the agent can visit it again at $n + g$, $n + 2g$, ... time steps. Writing $x = ag - nc + x_0$, so that $a = \frac{nc+x-x_0}{g}$ and $n - a = \frac{n(g-c)-x+x_0}{g}$, the probability distribution of $X_n(x_0)$ is

$$P(X_n(x_0) = x) = \binom{n}{\frac{nc+x-x_0}{g}} p^{\frac{nc+x-x_0}{g}} q^{\frac{n(g-c)-x+x_0}{g}}.$$

1.3.4 Absorbing barrier at zero

So far the random walk has been unrestricted. That is, it had no (absorbing) barrier (and thus dying was not possible). In a random walk with an absorbing barrier at zero $x_b = 0$ the range of $X_n(x_0)$ only includes elements ≥ 0. Conceptually, if one imagines the random walk as a tree, in which new branches are added at each time step n, one has to first calculate the probability distribution within the full tree (i.e., without considering the barrier). Then, to calculate the probability distribution of a random walk with an absorbing barrier at zero, all downstream branches starting from visits at zero (or values below zero) have to be "pruned" (i.e., subtracted) from the full tree, which is given by the corresponding random walk without absorbing barrier.

To calculate the probabilities of starvation, i.e. the probabilities of reaching zero (or values below zero) within n time steps, one has to perform the following three steps.

1. Determine all time steps h_i when "hits" of the barrier can occur (i.e., time steps n in which the agent in an unrestricted walk can be at $x_b = 0$; with $h \leq n$; $i < n$).
2. For all those hits of the barrier h_i, calculate the probabilities of the agent being at $x_b = 0$ for the first time.
3. Add up the probabilities of the agent being at $x_b = 0$ for the first time at all time steps h_i when hits of the barrier occur.

(Note that for step sizes to the left unequal to $\neq -1$, analogous calculations have to be made for all cases in which the agent can be at a position $x < 0$ without passing through zero. E.g. if $c = 2$, the random walk can go directly from $+1$ to -1. For simplicity these cases are not explicitly described below but the rationale is the same.)

Hits of the barrier Determine the hits of the barrier h_i within n time steps for all i (i.e., the first time that the range of $X_n(x_0)$ includes zero). The agent can visit the barrier x_b at h_1, h_1+g, h_1+2g, h_1+3g, ... time steps until $h_i \leq n$.

Probabilities of hitting the barrier for the first time The probability for the agent in a random walk (starting from x_0) to be at $x_b = 0$ for the first time after n steps is defined as

$$f_n(x_0) = P(X_n(x_0) = x_b)$$

and

$$X_r(x_0) \neq x_b, \quad 0 < r < n.$$

To calculate $f_n(x_0)$, one needs to calculate the probability for the agent in a random walk (starting from x_0) to be at $x_b = 0$ *not necessarily for the first time* after n steps, which is defined as

$$u_n(x_0) = P(X_n(x_0) = x_b)$$

There is no explicit formula for $f_n(x_0)$ for random walks with unequal step sizes and an absorbing barrier. But $f_n(x_0)$ can be found as a function of $u_n(x_0)$. At the first hit of the barrier h_1

$$f_{h_1}(x_0) = u_{h_1}(x_0)$$

To find the probability of hitting the barrier for the first time at h_2, let's consider the example of a simple random walk starting at one (i.e., $x_0 = 1$). The agent can hit $x_b = 0$ after 1, 3, 5,... time steps (i.e., h_1, $h_1 + g$, $h_1 + 2g$, ... time steps; and thus $h_1 = 1$, $h_2 = 1 + g$, $h_3 = 1 + 2g$, ...). There are two mutually exclusive ways in which the agent can be at $x_b = 0$ at the second hit of the barrier $h_2 = 3$.

- First, the agent visits zero for the first time at h_2 (i.e., at $h_2 = 3$ with probability $f_{h_2}(x_0)$).
- Second, the agent repeatedly visits zero. That is, the agent visits zero for the first time at h_1 (i.e., at $h_1 = 1$ with probability $f_{h_1}(x_0) = u_{h_1}(x_0)$) *and returns to zero* after $g = 2$ further time steps. That is, the probability of going from the first hit of the barrier h_1 to the second hit of the barrier h_2 within $g = 2$ time steps is $u_g(x_b)$. Therefore, the probability of having repeatedly visited zero at h_2 is

$$f_{h_1}(x_0)\, u(x_b).$$

Since the first and the second way of reaching zero are mutually exclusive, they can be added up. Therefore, at the second hit of the barrier h_2

$$u_{h_2}(x_0) = f_{h_2}(x_0) + f_{h_1}(x_0)u_g(x_b)$$

and

$$f_{h_2}(x_0) = u_{h_2}(x_0) - f_{h_1}(x_0)u_g(x_b).$$

More generally, there are i mutually exclusive ways in which the agent can hit the barrier $x_b = 0$ at h_i (with probability $u_{h_i}(x_0)$).

- First, the agent visits the barrier x_b for the first time at time step h_i (with probability $f_{h_i}(x_0)$).
- Second, the agent repeatedly visits the barrier. That is, the agent visits the barrier for the first time at one of the previous time steps $h_{i-1}, h_{i-2}, h_{i-3}$, ... , h_1(with probabilities $f_{h_{i-1}}(x_0)$, $f_{h_{i-2}}(x_0)$, $f_{h_{i-3}}(x_0)$, ... , $f_{h_1}(x_0) = u_{h_1}(x_0)$) *and returns to the barrier* after g, $2g$, $3g$, ... , $(i-1)g$ further time steps.

  That is, the probabilities of going from the hits of the barrier $h_{i-1}, h_{i-2}, h_{i-3}$, ... , h_1 to the hit of the barrier h_i are $u_g(x_b), u_{2g}(x_b), u_{3g}(x_b)$, ... , $u_{(i-1)g}(x_b)$.

  Therefore, the probability of having repeatedly visited the barrier $x_b = 0$ at h_i is

$$f_{x_0,h_{i-1}}u_{0,g} + f_{x_0,h_{i-2}}u_{0,2g} + f_{x_0,h_{i-3}}u_{0,3g} + \ldots + f_{x_0,h_1}.$$

Therefore,

$$f_{h_i}(x_0) = u_{h_i}(x_0) - f_{h_{i-1}}(x_0)u_g(x_b) - f_{h_{i-2}}(x_0)u_{2g}(x_b) - \ldots - f_{h_i}(x_0).$$

Note that the values of the indices within a product have to add up to h_i. Note also that the range of X_n contains $n + 2 - i$ elements for $i \geqq 1$ (where i are the number of hits of the barrier).

Adding up probabilities of hitting the barrier for the first time To find the probability of having reached the absorbing barrier at $x_b = 0$ within n time steps (i.e., the probability of starvation p_{starve}), add up the probabilities of being at $x_b = 0$ for the first time at all possible hits h_i of the barrier.

$$P(X_n(x_0) = 0) = f_{h_i}(x_0) + f_{h_{i-1}}(x_0) + \ldots + f_{h_1}(x_0)$$

2 Calculating statistical moments

2.1 Expected value

To calculate the first statistical moment, i.e., the expected value of a random walk with an absorbing barrier x_b (at zero) at time step n, one has to first calculate the probabilities of all elements $P(X_n(x_0) = x)$ within the range of $X_n(x_0)$ and then take the sum of all those probabilities multiplied by their respective values $P(X_n(x_0) = x)\, x$.

The rationale is similar as above for finding the probabilities of hitting the absorbing barrier. To find the probabilities of being at a certain position x in a random walk with an absorbing barrier (at zero), one has to first calculate the probability distribution within the corresponding full tree (i.e., without considering the barrier). Then, all downstream branches starting from visits at zero (or values below zero) have to be "pruned" (i.e., subtracted) from the full tree. The time steps when the random walk can hit zero h_i and the probabilities when the random walk reaches zero $f_{h_i}(x_0)$ have already been determined above.

- First, calculate the probability of being in x in the corresponding full tree without absorbing barrier P_{full}. (This probability corresponds to $u_{h_i}(x_0)$ above.)

$$P_{full}(X_n(x_0) = x)$$

- Second, calculate the downstream branches. That is, the probabilities of going from the barrier x_b to x (at all time steps h_i when the barrier was hit). (These probabilities correspond to $u_g(x_b)$, $u_{2g}(x_b)$, $u_{3g}(x_b), \ldots$, $u_{(i-1)g}(x_b)$ above.)

$$P(X_{n-h_i}(x_b) = x), P(X_{n-h_{i-1}}(x_b) = x), P(X_{n-h_{i-2}}(x_b) = x), \ \ldots \ , P(X_{n-h_1}(x_b) = x)$$

The probability of being in position x in a tree with an absorbing barrier at $x_b = 0$ is

$$\begin{aligned} P_b(X_n(x_0) = x) = & P_{full}(X_n(x_0) = x) - f_{h_i}(x_0) P(X_{n-h_i}(x_b) = x) + \\ & - f_{h_{i-1}}(x_0) P(X_{n-h_{i-1}}(x_b) = x) - \ldots - f_{h_1}(x_0) P(X_{n-h_1}(x_b) = x). \end{aligned}$$

The expected value (EV) is the weighted sum over all J elements $x_1, x_2, \ldots, x_J$ within the range of $X_n(x_0)$. The number of elements J is $n + 2 - i$ for $i \geqq 1$ (where i are the number of hits of the barrier; for $i = 0$, i.e., no hits of the barrier, J equals $n + 1$).

$$EV = \sum_{j=1}^{J} P(X_n(x_0) = x_j)\, x_j$$

2.2 Variance and skewness

The second and third statistical moments, i.e., variance (Var) and skewness (Skw) are calculated as follows

$$Var = \sum_{j=1}^{J} P(X_n(x_0) = x_j)\, (x_j - EV)^2$$

$$Skw = \frac{\sum_{j=1}^{J} P(X_n(x_0) = x_j)\, (x_j - EV)^3}{Var^{\frac{3}{2}}}$$

S2 Text: Maintaining Homeostasis by Decision-Making

Supporting results

1. Model including only a free parameter for p_{starve}

To address whether p_{starve} or EV contributed more to participants' decisions, we also devised a model in which the decision probability was determined solely by a sigmoid transformation of the difference in p_{starve} (but not of the difference in EV; Model 1). Taking both frames into account, this model performed slightly better than the model which only included EV as shown by fixed- and random-effects analyses (see S6 Table). This suggests that overall p_{starve} contributed more to participants' choices than EV. When fitting this model separately to the foraging and the casino frames, the model that only included p_{starve} explained choices better in the foraging frame but the model that only included EV explained choices better in the casino frame. These results suggest that p_{starve} seemed to have a greater influence in the biological context of the foraging frame and EV seemed to play a comparatively greater role in the purely economic context of the casino frame. This pattern complements the finding that in the model that included frame-specific weighting parameters for the parameter estimates for p_{starve} (Model 10) participants minimized p_{starve} more in the foraging than in the casino frame.

2. Model testing for the effect of the number of foraging days

The gambles in the foraging frame comprised a different number of days, which corresponded to a different number of possible outcomes in the foraging and equivalently in the casino frame.

Possibly, the different number of possible outcomes could translate into different weightings of p_{starve}. For example, the increasing levels of complexity due to the increasing number of possible outcomes might make participants more conservative, resulting in a more pronounced minimization of p_{starve}. To test this possibility, we devised a model, in which we included three different weighting parameters (ξ_{d1}, ξ_{d2}, and ξ_{d3}) for p_{starve} in the gambles with 1, 2, or 3 foraging days. We compared this model to the model that was based on EV and p_{starve} globally (Model 7). Fixed- and random-effects analyses showed that the simpler model outperformed the more complex model that included day-specific weighting parameters (see S7 Table). Thus, the conjecture that different numbers of possible outcomes led to different weightings of p_{starve} could not be supported.

3. Detailed comparison of parameter estimates between the two frames

In the main text, we showed that across participants $\xi_{foraging}$ was smaller than ξ_{casino}. We confirmed that this difference was not driven by an outlier participant for whom ξ_{casino} was more than 3 SD higher than the mean. The difference remained significant after excluding this participant ($p<.05$). A similar pattern emerged when fitting the winning model (Model 7) separately to the foraging and casino frames (and separately to the first and second blocks): All weighting parameters of p_{starve} were significantly smaller than zero across participants (sign test on parameters: foraging both blocks ξ: $p<.001$; casino both blocks ξ: $p<.005$; foraging-block 1 ξ: $p<.001$; foraging-block 2 ξ: $p<.001$; casino-block 1 ξ: $p<.005$; casino-block 2 ξ: $p<.005$). In models of foraging frame weighting parameters were smaller than in models of the casino frame. This effect reached trend level when including data from both blocks ($p=.053$) or block 1 ($p=.053$). For block 2 the effect was significant ($p<.05$).

We note that the options in casino frame were all presented as single-step gambles whereas the options in the foraging frame were presented as sequential gambles. Thus, both the difference between single-step and sequential gambles, and the different framing, could potentially underlie the smaller parameter estimates for p_{starve} in the foraging frame. To disambiguate these possibilities, we directly compared gambles in foraging frame with a single foraging day (i.e., single-step foraging gambles) with the corresponding single-step casino gambles (120 gambles per frame) in Model 10. We still found a trend for $\xi_{foraging}$ being smaller than ξ_{casino} (sign test comparing $\xi_{foraging}$ and ξ_{casino}: $p=.053$). We also fitted the winning model (Model 7) separately to the foraging and the casino frames gambles and only included single-step gambles. $\xi_{foraging}$ was significantly smaller ξ_{casino} ($p<.05$). These results suggest that the difference between sequential and single-step presentation was not the only factor driving participants' stronger minimization of p_{starve} in the foraging versus the casino frame. Instead, framing per se seems to impact the degree of p_{starve}-minimization.

4. Comparison of parameter estimates for different energy levels and number of days

Participants did not receive feedback on the outcomes in the task. This also entails that they did not see the intermediate outcomes in the foraging task (i.e., the outcomes after each foraging day). Additionally, the number of foraging days was related to the number of initial energy points in the gambles used in the present study. Since we wanted p_{starve} to be non-zero in all gambles, the number of energy points was always 1 in options with 1 foraging day. The lack of feedback and the relation of the number of foraging days to initial energy levels could have resulted in a superposition of opposing effects: Participants could focus on p_{starve} differently depending on the number of days and/or the initial foraging level. To test this, we compared the parameter estimates for p_{starve} when including different types of trials within the winning model (Model 7).

We fitted models separately to options with (a) an energy level of 1 and 1 foraging day (120 trials per frame), (b) an energy level of 1 and 2 foraging days (120 trials per frame), and (c) an energy level of 2 and 2 or 3 foraging days (240 trials per frame). Within the foraging frame, we did not find evidence for differences in the magnitude of the parameter estimates when performing pairwise comparison across participants using sign tests (all p's>0.2, even without correction for multiple comparisons). The same was true in the casino frame (all p's>0.2). When additionally splitting the options with an energy level of 2 into those with 2 and those with 3 foraging days, the same pattern emerged. Neither in in the foraging frame nor in the casino frame any pairwise comparison reached significance (all p's>0.05, even without correction for multiple comparisons).

These supplemental analyses suggest that within the gambles used in the current study the magnitude of p_{starve} was not different for different combinations of energy levels and foraging days.

5. Testing for the use of outcome distributions including values below zero in the foraging frame

To mirror starvation, the outcome distributions of the options used in the task did not include values below zero and participants were explicitly instructed about this. Nevertheless, in the foraging frame it is possible that participants did not correctly "prune" the values below zero in their estimation of the outcome distributions and may have included them in the approximation of the statistical moments (e.g., in the "tree" depicted in Fig 1C, participants could erroneously include an outcome of -1). In the casino frame, the outcome distributions were explicitly signaled using pie charts and therefore participants had no reason at all to falsely include values below zero. Erroneously including values below zero could theoretically mimic an (enhanced) behavioral weight of p_{starve}. The results of the following two different types of analyses make this unlikely.

First, in the options used in the current study negative outcomes could be falsely estimated for options with an energy level of 1 and 2 foraging days and for options with energy level of 2 and 3 days but not otherwise. In the other options the lowest outcome was zero (i.e., energy level of 1 and 1 day; energy level of 2 and 2 days). In the previous section, we reported that the magnitude of p_{starve} did not differ between the four different combinations of energy levels and foraging days employed, which indicates that the weighting of p_{starve} did not depend on the inclusion of values below zero.

Second, we calculated the outcome distributions that included values below zero for all options and derived the statistical moments for these distributions. We then compared the models of model families 1 and 3 since these two families were based on statistical moments. Random- and fixed-effects analyses showed that family 3 provided the best fit—even under the assumption that participants erroneously included values below zero in their estimation of the outcome distributions in the foraging frame (S8 Table).

Taken together, two types of supplemental analyses showed that participants' reliance of p_{starve} cannot be explained by the possibility that participants erroneously included values below zero in the outcome distributions.

6. Detailed comparison between the two blocks of the foraging frame

We note that the model comparisons were not as decisive when only considering data from foraging-block 2 (see Tables 2-4) compared to when considering all data or data from foraging-block 1. Foraging-block 2 was the last block that participants performed and therefore participants may have been less attentive, which could translate into higher parameter estimates for decision noise. We indeed found a trend for higher parameters estimates of decision noise in foraging-block 2 versus foraging-block 1 ($t(21)=-1.83$: $p=.082$). Importantly, we found no significant difference in parameters of p_{starve} between foraging-blocks 1 and 2 ($p=.16$), which makes it unlikely that participants weighted p_{starve} less in foraging-block 1 than in foraging-block 2 (i.e., it is unlikely that participants become less reliant on the probabilities of the zero outcomes).

7. Model comparisons based on AIC

The model comparisons reported in the main text were based on BIC. In addition, we performed all model comparisons on the basis of AIC, which penalizes model complexity less severely than BIC in our data. Overall, the results of the model comparisons were consistent for BIC and AIC (see S1, S2, S4, and S5 Tables). We note two differences. First, the overall fixed-effects analysis using AIC tended to favor family 2 instead of family 3 (S1 Table) but the random-effects analysis still favored family 3 albeit not strongly (S2 Table). This effect was driven by the casino frame and in particular the first block of the casino frame. Nevertheless, in line with the BIC analyses, the overall winning model (Model 10), which included two frame-specific weighting parameters for p_{starve}, outperformed both models of family 2 (Models 5 and 6) by a large margin when performing fixed-effects analyses based on AIC (Model 5: -2261; Model 6: -2308; Model 10: -3094). This was the case even though Model 10 contains less parameters than Model 5 and the same number of parameters as Model 6 (Model 5: 3 parameters; Model 6: 4; Model 10: 3). Second, in the comparison within model family 3, AIC favored the more complex model that included weighting parameters for Var and Skw in addition to a weighting parameter for p_{starve} (Model 9) while BIC favored the simpler model that only included a weighting parameter for p_{starve} (Model 7; see Tables 4 and S4 Table). We stress that the BIC is commonly regarded as the more principled measure and that these differences merely concern details of the specific overall winning model but do not invalidate our main result that models based on homeostatic considerations explained participants' choices over and above standard economic models.

8. Questionnaire analyses

For exploratory analyses, we also obtained participants' meta-cognitive assessments of real-life risks in different domains. Specifically, we explored whether the parameter estimates derived from Model 10 for $\xi_{foraging}$ or ξ_{casino} correlated with the relevant subscores on the DOSPERT scale. However, this was not the case (all p's>.05, even without correction for multiple comparisons) and thus at present we do not make claims about how behavior in our task translates into meta-cognitive assessments of real-life risks.

Supporting methods

Additional task description—foraging frame

The depiction of the foraging frame comprised three components: An energy bar, a number of days, and two foraging options with probabilistic costs and gains. Participants had to decide between the two foraging options, which were depicted as pie charts with two sectors. One sector showed the probability of successful foraging with the associated variable amount of energy points to gain and the other sector showed the probability of unsuccessful foraging, which was always associated with a gain of zero energy points. Participants were told that for each day the chosen foraging option was played out (i.e., the respective points to gain were added to the energy bar according to the probabilities depicted in the pie chart). In addition, one energy point was deducted from the energy bar on each day to mirror energy consumption. If, at any point, the energy bar reached zero points, the participant had died from starvation within that trial and would thus receive no money. Otherwise, the final number of points would be exchanged for money. Participants did not see the outcomes of their choices. In each trial, participants first saw the energy bar and the number of days for 1 s and then had a maximum of 8 s to decide between the left and right option, which were counterbalanced for position. Their choice was indicated with an asterisk for 0.5 s and after a fixation cross of 0.75 s the next trial started.

Additional task description—casino frame

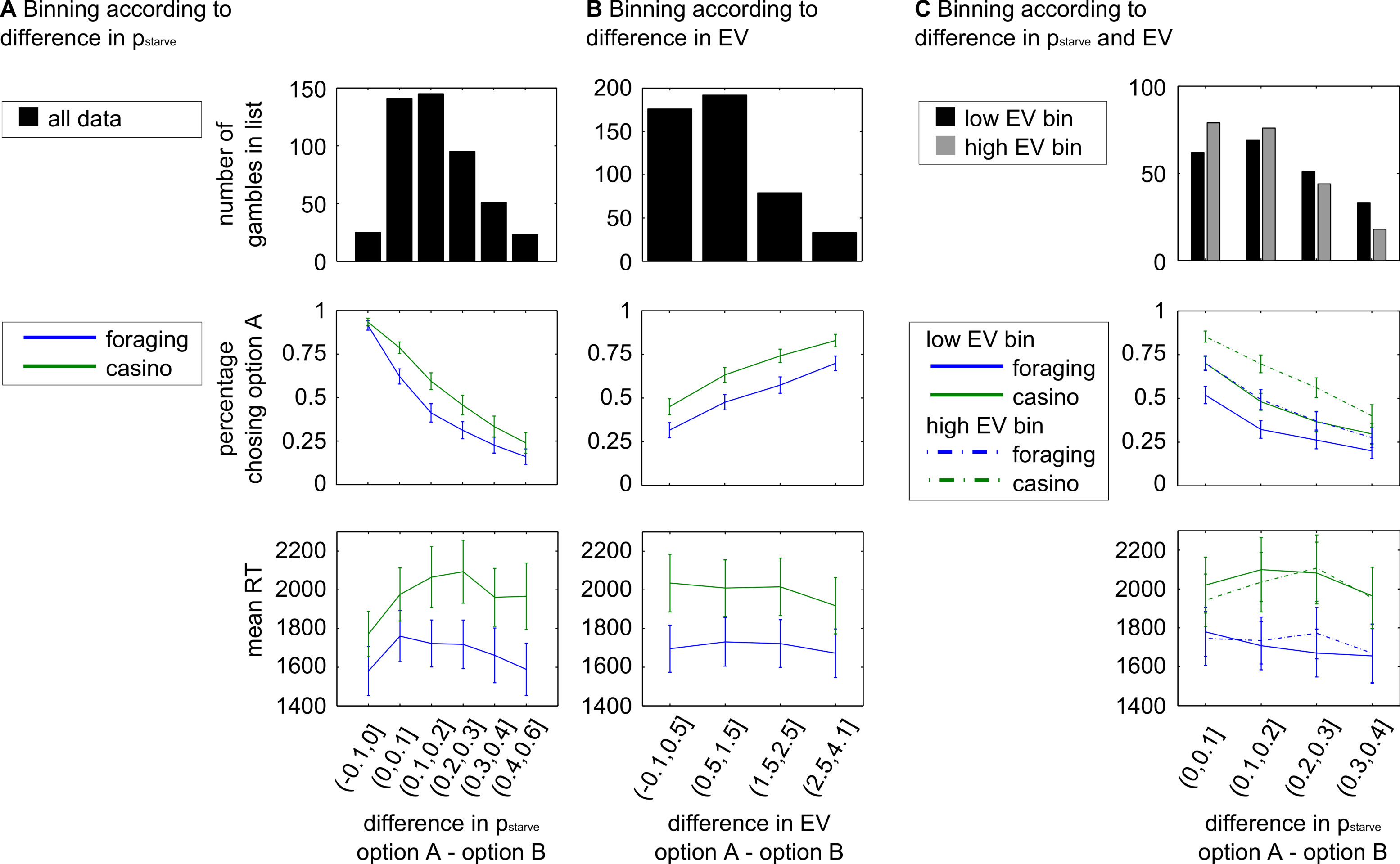
In the casino frame, participants had to decide between two wheel-spinning-like gambles that were depicted as pie charts with two to four sectors depicting the probabilities of different amounts to gain. Probabilities and amounts corresponded to the possible outcomes in the foraging frame. The number of outcomes in the foraging frame depended on the number of days. Gambles with one day had two outcomes and each additional day resulted in one additional outcome. The sectors were ordered according to ascending amounts to gain in anti-clockwise fashion. The lowest amount to gain was always zero, and its probability corresponded to p_{starve} in the foraging frame. Otherwise the casino frame was similar to the foraging frame: Points were to be exchanged for money. No outcomes were revealed. Left and right options were counterbalanced for position. Participants had up to 6 s to decide. Their choice was indicated with an asterisk for 0.5 s and after a fixation cross of 0.75 s the next trial started.

Questionnaire

To enable us to explore potential relationships between behavior in our task and participants' meta-cognitive assessments of real-life risk, they completed a 30 item version of the domain-specific risk-taking (DOSPERT) scale [1] at the end of the experimental session. The DOSPERT scale assesses (a) participants' tendencies to engage in risky behaviors, (b) their perceptions of risk, and (c) their expected benefits from risky behavior in six different domains, namely investing, gambling, health, recreational, ethical, and social. Since the domains investing, gambling, health and recreational were most closely related to our task, we correlated these subscores with parameter estimates derived from the overall winning behavioral model Model 10 (i.e., parameter estimates for $\xi_{foraging}$ or ξ_{casino}).

Supporting references

1. Johnson JG, Wilke A, Weber EU. Beyond a trait view of risk taking: A domain-specific scale measuring risk perceptions, expected benefits, and perceived-risk attitudes in German-speaking populations. Polish Psychol Bull. 2004;35(3):153–63.



A Binning according to difference in p starve
B Binning according to difference in EV
C Binning according to difference in p starve and EV
all data
number of gambles in list
150
100
50
0
200
100
50
low EV bin
high EV bin
percentage chosing option A
1
0.75
0.5
0.25
foraging
casino
low EV bin
foraging
casino
high EV bin
foraging
casino
mean RT
2200
2000
1800
1600
1400
(-0.1,0]
(0,0.1]
(0.1,0.2]
(0.2,0.3]
(0.3,0.4]
(0.4,0.6]
(-0.1,0.5]
(0.5,1.5]
(1.5,2.5]
(2.5,4.1]
difference in p starve option A - option B
difference in EV option A - option B

S1 Table. Model family comparison: relative log-group Bayes factors based on AIC

	Relative log-group Bayes factors based on AIC (smaller is better)								
	Family 1 Moments without p_{starve}				Family 2 Rank-dependent utility		Family 3 Moments and p_{starve}		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	EV	EV Var	EV Skw	EV Var Skw	Prelec-I	Prelec-II	EV p_{starve}	EV Var p_{starve}	EV Var Skw p_{starve}
All	0	-1387	-2037	-2139	-2261	**-2308**	-2244	-2274	-2287
Foraging	0	-930	-1435	-1529	-1557	-1528	-1557	-1624	**-1707**
Casino	0	-755	-991	-1059	-1132	**-1161**	-1107	-1136	-1108
Foraging-block 1	0	-511	-721	-772	-810	-794	-820	-827	**-855**
Foraging-block 2	0	-450	-700	-806	-802	-804	-789	-814	**-888**
Casino-block 1	0	-402	-490	-532	-565	**-580**	-556	-563	-554
Casino-block 2	0	-380	-557	-583	-601	-578	-603	**-613**	-602

For a fixed-effects analysis, log-group Bayes factors based on AIC were calculated relative to the simplest model (Model 1). Smaller log-group Bayes factors indicate more evidence for the respective model versus the baseline model. The log-group Bayes factors of the winning models according to fixed-effects analyses are written in bold font. The models included free parameters for the respective variables listed. See Table 2 for results based on BIC. AIC, Akaike information criterion; EV, expected value; Var, variance; Skw, skewness; p_{starve} starvation probability; BIC, Bayesian information criterion

S2 Table. Model family comparison: exceedance probabilities based on AIC

	Exceedance probabilities based on AIC (higher is better)		
	Family 1 Moments without p_{starve}	Family 2 Rank-dependent utility	Family 3 Moments and p_{starve}
All	0.0010	0.3599	**0.6391**
Foraging	0.0002	0.0079	**0.9919**
Casino	0.0008	**0.9036**	0.0956
Foraging-block 1	0.0017	0.0047	**0.9936**
Foraging-block 2	0.0110	0.0314	**0.9576**
Casino-block 1	0.0007	**0.7672**	0.2321
Casino-block 2	0.0552	0.1230	**0.8218**

The highest exceedance probabilities according to random-effects analyses are written in bold font.

See Table 3 for results based on BIC. AIC, Akaike information criterion; p_{starve} starvation probability; BIC, Bayesian information criterion

S3 Table. Model comparison for all data points: individual model fits according to BIC

	BIC (smaller is better)								
	Family 1				Family 2		Family 3		
	Moments without p_{starve}				Rank-dependent utility		Moments and p_{starve}		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	EV	EV Var	EV Skw	EV Var Skw	Prelec-I	Prelec-II	EV p_{starve}	EV Var p_{starve}	EV Var Skw p_{starve}
P1	615	614	**611**	614	617	618	611	614	617
P2	560	562	562	565	561	564	**560**	564	565
P3	620	593	565	568	572	576	**561**	562	566
P4	637	572	551	549	523	525	517	519	**505**
P5	468	461	454	457	454	457	**451**	454	457
P6	631	574	525	528	531	530	**523**	525	527
P7	667	600	612	597	598	601	599	**595**	598
P8	659	547	491	489	494	497	**489**	492	492
P9	657	417	318	300	284	**283**	286	288	291
P10	**664**	665	664	668	667	670	664	668	671
P11	589	575	577	577	580	581	**575**	576	580
P12	667	597	607	592	592	595	593	**589**	592
P13	630	410	382	353	328	331	330	327	**323**
P14	659	540	481	479	467	470	**465**	468	472
P15	425	427	421	421	423	**415**	425	427	420
P16	667	620	**564**	568	573	567	569	571	570
P17	635	578	476	**476**	505	491	490	482	477

P18	650	556	500	501	**466**	469	483	486	523
P19	650	609	599	598	568	**566**	576	580	571
P20	649	595	537	540	**532**	534	532	532	535
P21	662	610	577	579	564	**562**	566	568	572
P22	**460**	462	461	465	465	468	461	465	468

Smaller BIC values indicate more evidence for the respective model. The BIC values of the winning models according to fixed-effects analyses are written in bold font. The models included free parameters for the respective variables listed. BIC, Bayesian information criterion; EV, expected value; Var, variance; Skw, skewness; p_{starve} starvation probability

S4 Table. Comparison within the winning model family: exceedance probabilities based on AIC

	Exceedance probabilities based on AIC (higher is better)		
	Family 3		
	Moments and p_{starve}		
	Model 7 EV p_{starve}	Model 8 EV Var p_{starve}	Model 9 EV Var Skw p_{starve}
All	0.0147	0.0616	**0.9237**
Foraging	0.0001	0.0022	**0.9977**
Casino	0.2521	0.6588	**0.0891**
Foraging-block 1	0.0826	0.0044	**0.9130**
Foraging-block 2	0.0007	0.0001	**0.9992**
Casino-block 1	**0.9515**	0.0170	0.0315
Casino-block 2	**0.8416**	0.1422	0.0162

The highest exceedance probabilities according to random-effects analyses are written in bold font. See Table 4 for results based on BIC. AIC, Akaike information criterion; EV, expected value; Var, variance; Skw, skewness; p_{starve} starvation probability; BIC, Bayesian information criterion

S5 Table. Comparison of an additional model including frame-specific parameters: relative log-group Bayes factors and exceedance probabilities based on AIC

	Family 3 Moments and p_{starve}			Additional model
	Model 7 EV p_{starve}	Model 8 EV Var p_{starve}	Model 9 EV Var Skw p_{starve}	Model 10 EV forage-p_{starve} casino-p_{starve}
Relative log-group Bayes factors – all data (smaller is better)	0	-30	-43	**-850**
Exceedance probabilities – all data (higher is better)	0.0000	0.0001	0.0076	**0.9923**

Log-group Bayes factors based on AIC were calculated relative to the simplest model (Model 7). Smaller log-group Bayes factors indicate more evidence for the respective model versus the baseline model. The log-group Bayes factor of the winning model according to fixed-effects analysis and the highest exceedance probability according to random-effects analysis are written in bold font. See Table 5 for results based on BIC. AIC, Akaike information criterion; EV, expected value; Var, variance; Skw, skewness; p_{starve} starvation probability; BIC, Bayesian information criterion

S6 Table. Comparison of a model based solely on EV with a model based solely on p_{starve}

	Model 1 EV		Model 11 p_{starve}	
	Log-group Bayes factors (smaller is better)	Exceedance probabilities (higher is better)	Log-group Bayes factors (smaller is better)	Exceedance probabilities (higher is better)
All	0	0.1996	**-490**	**0.8004**
Foraging	0	0.0177	**-812**	**0.9823**
Casino	**0**	**0.8237**	161	0.1763
Foraging-block 1	0	0.0596	**-407**	**0.9404**
Foraging-block 2	0	0.0630	**-448**	**0.9370**
Casino-block 1	**0**	**0.6034**	44	0.3966
Casino-block 2	**0**	**0.9249**	106	0.0751

Log-group Bayes factors based on BIC were calculated relative to the simpler model (Model 1). Smaller log-group Bayes factors indicate more evidence for the respective model versus the baseline model. The log-group Bayes factor of the winning model according to fixed-effects analysis and the higher exceedance probability according to random-effects analysis are written in bold font. BIC, Bayesian information criterion; EV, expected value; p_{starve} starvation probability

S7 Table. Comparison of a model with day-specific weighting parameters for p_{starve}

			Additional model with day-specific weighting parameters	
	Model 7 EV p_{starve}		Model 12 EV one-day-p_{starve} two-days-p_{starve} three-days-p_{starve}	
	Log-group Bayes factors (smaller is better)	Exceedance probabilities (higher is better)	Log-group Bayes factors (smaller is better)	Exceedance probabilities (higher is better)
All	**0**	**0.9902**	248	0.0098
Foraging	**0**	**0.9474**	18	0.0526
Casino	**0**	**0.9987**	159	0.0013
Foraging-block 1	**0**	**0.9966**	74	0.0034
Foraging-block 2	0	**0.8719**	**-11**	0.1281
Casino-block 1	**0**	**1.0000**	87	0.0000
Casino-block 2	**0**	**1.0000**	72	0.0000

Log-group Bayes factors based on BIC were calculated relative to the simpler model (Model 7). Smaller log-group Bayes factors indicate more evidence for the respective model versus the baseline model. The log-group Bayes factor of the winning model according to fixed-effects analysis and the higher exceedance probability according to random-effects analysis are written in bold font. BIC, Bayesian information criterion; EV, expected value; p_{starve} starvation probability

S8 Table. Comparison of models based on the assumption that participants falsely included values below zero in the outcome distributions in the foraging frame.

	Family 1 Moments without p_{starve}				Family 3 Moments and p_{starve}		
	Model 1	Model 2	Model 3	Model 4	Model 7	Model 8	Model 9
	EV	EV Var	EV Skw	EV Var Skw	EV p_{starve}	EV Var p_{starve}	EV Var Skw p_{starve}
Model family comparison: relative log-group Bayes factors (smaller is better)							
Outcome distributions *without* values < 0	0	-884	-1390	-1437	-1511	-1532	**-1569**
Outcome distributions *including* values < 0	0	-945	-1366	-1465	-1514	-1562	**-1610**
Model family comparison: exceedance probabilities (higher is better)							
Outcome distributions *without* values < 0	0.0071				**0.9929**		
Outcome distributions *including* values < 0	0.0016				**0.9984**		
Comparison within the winning model family: exceedance probabilities (higher is better)							
Outcome distributions *without* values < 0	-				**0.8627**	0.0108	0.1265
Outcome distributions *including* values < 0	-				**0.7029**	0.0820	0.2151

Please note that only data from the foraging frame was included since participants had no reason at all to falsely include values below zero in the casino frame. Log-group Bayes factors based on BIC were calculated relative to the simplest model (Model 1). The difference in the log-group Bayes factor of

Model 1 based on outcome distributions *without* values < 0 versus that of Model 1 based on outcome distributions *including* values < 0 was +7. The data for the models based on outcome distributions *without* values < 0 are partly presented in Tables 2 and 4 and are included here for comparison. Smaller log-group Bayes factors indicate more evidence for the respective model versus the baseline model. The log-group Bayes factor of the winning model according to fixed-effects analysis and the highest exceedance probability according to random-effects analysis are written in bold font. BIC, Bayesian information criterion; EV, expected value; Var, variance; Skw, skewness; p_{starve} starvation probability