Computational mechanisms underlying how humans adapt their choices to the average effort of the environment

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Abstract

Would the tallest hill in Amsterdam seem as effortful to climb in the Alps? Effort is relative, and deciding to exert ourselves can depend on how effortful other options in the environment are on average. But how people decide whether to exert effort as the average effort distribution of the environment changes remains unclear. Across three experiments, participants completed a novel task choosing whether to accept an offered level of physical effort for rewards or wait for potentially easier alternatives. Participants completed this task in both 'easy' and 'hard' environments with different average effort distributions. We found that people dynamically adjusted their effort preferences based on the environment, becoming less willing to exert mid-levels of effort in easier environments. A computational model tracking average effort rates could explain these choice behaviour patterns. These results provide a computational framework for understanding how effort-based choice is influenced by the environment.

Keywords: effort; opportunity costs; sequential decision-making; foraging; motivation

Introduction

Effort-based decisions require evaluating whether exerting effort is 'worth it' for potential rewards. Whilst previous research has established that humans are generally effort averse in binary choice paradigms (Chong et al., 2017), real world decisions often occur sequentially - we must decide whether to accept an effortful opportunity now or wait for potentially easier options later (Mobbs, Trimmer, Blumstein, & Dayan, 2018). Foraging theories predict such choices should be influenced by the 'opportunity costs of time' (Niv, Daw, Joel, & Dayan, 2007; Garrett & Daw, 2020), by comparing the current option against the overall distribution of effortful opportunities in the environment, i.e. the average effort rate (Charnov, 1973). Despite theoretical predictions, empirical evidence demonstrating how humans adapt effort-based choice to the average effort rate of the environment, and the computational mechanisms underlying this, remains limited. We address this by investigating whether and how the average effort rate in the environment modulates effort-based decisions in humans.

Methods

We developed a novel task where participants (study 1: n=38; study 2: n=40; study 3: n=38) made sequential decisions in time-limited blocks about whether to accept and exert offered levels of physical effort (grip force at 20%, 40%, or 60% of maximum strength) for random rewards, or choose to wait, which progresses straight to the next offer. Thus waiting may be beneficial to save time and effort that could be spent on less effortful offers later on. Participants completed blocks in both 'easy' environments (higher probability of low-effort offers) and 'hard' environments (higher probability of high-effort offers), with identical offer types across environments but different probability distributions. Studies differed in whether participants received explicit instruction about environmental statistics (study 1) or had to learn them implicitly (studies 2-3). We analysed choice behaviour using generalized linear mixed-effects models and developed computational models to characterize how participants tracked and adapted their choices to environmental effort rates.

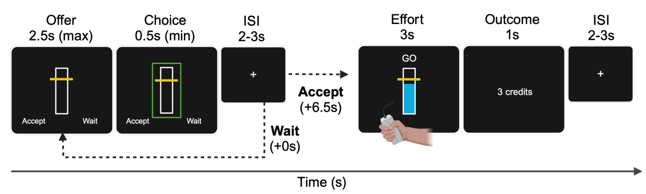

Figure 1: **Task structure**. Participants decided whether to accept offers to exert effort for reward, or wait for better offers, within time-limited blocks. Accept choices required exerting the required effort (20%, 40%, or 60% of participants' maximum grip strength on a hand-held dynamometer, individually calibrated), by squeezing to keep the blue bar above the yellow line for at least 1s out of a 3s window. These effort levels were chosen to avoid fatigue. If successful, the participant received a random number of credits unrelated to the effort level. Credits received were converted to bonus payment. Wait choices progress straight to the next offer.

Results

Effort-based choice sensitive to average effort

Across all three studies, participants' behaviour aligned with predictions of foraging theory (Charnov, 1973; Garrett & Daw, 2020): participants were significantly less willing to accept mid-effort opportunities in easy compared to hard environments (study 1: odds ratio OR = 1.97, z = 2.81, p = .005; study 2: OR = 1.62, z = 3.96, $p < .001$; study 3: OR = 4.92, z = 6.17, $p < .001$. **Figure 2a**). This finding remained significant even after controlling for previous choice, trial number in the block, and reward history. Whilst we found a small effect of the environment for low or high effort offers in individual studies, this was not replicated across studies.

Participants also demonstrated sensitivity to local fluctuations in effort demands, showing increased acceptance rates following exposure to high-effort offers (all $p < .001$); **Figure 2b**). Thus participants appear to adapt their choices to both global and local fluctuations in the average effort rate.

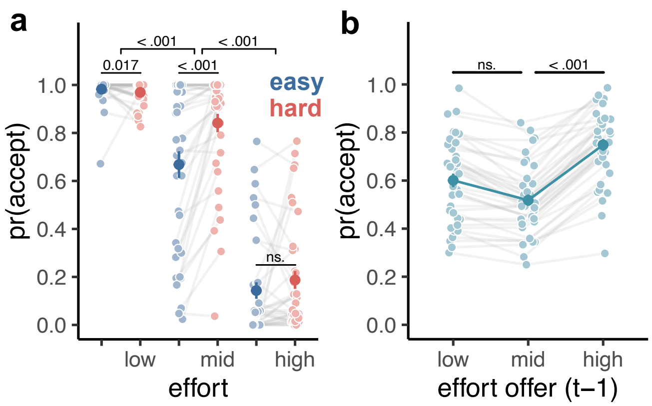

Figure 2: **Study 3: Humans are sensitive to the average effort rate of the environment.** **a**: Proportion of accept choices, $pr(accept)$, for each effort offer and environment. Results replicated in all studies. Error bars: standard error of the mean (SEM). **b**: $pr(accept)$ as a function of the previous effort offer. Error bars: SEM.

Average effort rate model captures choices

To understand the latent processes by which participants adapted their choices to the environment, we fit computational models that tracks fluctuations in the average effort rate over time (Constantino & Daw, 2015).

Tracking the average effort rate. The average effort rate per unit time, ρ, was updated on each trial, i, through an effort prediction error δ, controlled by learning rate α:

$$\rho_{i+1} = \rho_i + [1 - (1-\alpha)^{\tau_i}] \cdot \delta_i \tag{1}$$

$$\delta_i = \frac{E_i}{\tau_i} - \rho_i \tag{2}$$

Importantly, the updates account for the time cost, τ, associated with the choice on that trial: τ will be larger if the participant chooses to accept compared to wait.

Offer value modulated by average effort. The estimated average effort influences the subjective value of the current offer, V, based on standard effort discounting models (Chong et al., 2017). Value is the expected reward minus effort cost, plus an additive influence of average effort,

$$V_i = R_i - \kappa E_i^2 + \kappa \rho_i \tag{3}$$

Thus offer value will increase with increases in average effort. The discount parameter κ represents sensitivity to effort (high κ means increased sensitivity). The model's choices to accept were made stochastically using a softmax choice function with inverse temperature β.

Model comparison and simulations. We used maximum likelihood estimation to fit and estimate the model parameters. We found that including τ provided a better fit to the data (BIC; study 2 = 8,331, study 3 = 4,919) than standard learning models that did not include this term (study 2 = 8,341, study 3 = 4,957). This suggests that participants were sensitive to the different time costs of accepting versus foregoing an opportunity. However, this was not the case for study 1 (with τ = 4,509, without τ = 4,502).

Model simulations of the τ-learning model with each participant's fitted parameters successfully reproduced the key environment effect observed for all studies (study 3 simulations shown in **Figure 3a**). Individual differences in effort sensitivity (κ) correlated with the magnitude of environmental adaptation (**Figure 3b**), suggesting that those more sensitive to effort costs were also more responsive to the environmental average effort. Preliminary fMRI results suggest that fronto-basal ganglia circuits may be involved in tracking both offer values and environmental statistics related to effort demands.

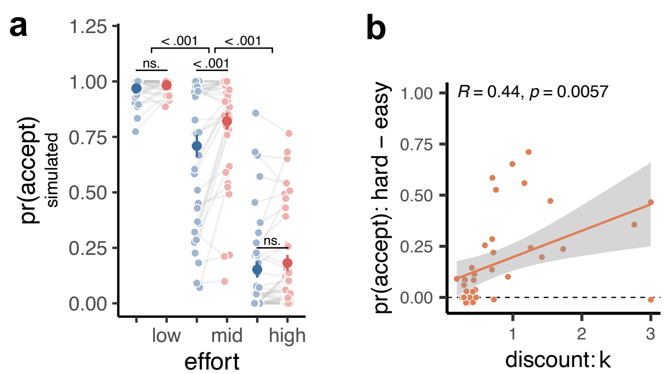

Figure 3: **Study 3: τ-learning model can replicate participant choices.** **a**: Simulated $pr(accept)$, for each effort offer and environment. **b**: Correlation of discount parameter, κ, with the magnitude of the environment effect. Positive y-axis values indicate increased acceptance rate in hard compared to easy environments for the mid-effort level. R: Pearson's correlation coefficient.

Discussion

Our findings provide novel evidence that humans learn and adapt their choices to environmental effort demands, supporting a computational framework where effort-based opportunity costs dynamically influence choice behaviour. This work advances our understanding of how the brain evaluates effort in ecological settings where choices are sequential and depend on other possibilities in the environment.

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