Humans decide to help others more often in poor environments

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Abstract

Prosocial behaviours are essential for solving global challenges. Typically these behaviours are measured using economic games or tasks where people decide between helping or not. However, in everyday life, current behaviours are interrupted with alternatives. Across three samples, people (total *n*=510) watched a movie whilst encountering opportunities to interrupt it to benefit another person or themselves. Crucially, participants decided in poor and rich environments where the average reward values of opportunities changed. We demonstrate a robust environmental influence on decisions that benefit others. People were more willing to interrupt their behaviour to help others in poor compared to rich environments. Computational modelling revealed that the opportunity costs of different environments were valued distinctly for others. Factors of utilitarianism, empathy and motivation, captured variability in opportunity costs for others. We show that when we decide to engage in prosocial behaviours depends on the environment which is critical as environments change.

Introduction

Humans constantly decide whether to interrupt what they are doing to try something else. However, current experimental paradigms often present people with two options to decide between, which do not reflect these kinds of decisions people face in everyday life (*1–3*). Indeed, in the real world we come across opportunities to interrupt what we are doing for other potential rewards. We are asked to stop to help kids with homework or make tea for our partners whilst watching TV or scrolling through social media. Theories from behavioural ecology describing non-human animal behaviour suggest that deciding when to act depends on the opportunity costs in one's environment—i.e., the value of what we are doing now compared to everything else we could be doing (*4–6*). How these environmental influences extend to human behaviour is beginning to be uncovered (*1*, *7*), yet whether these influences extend to decisions that affect other people is still unknown. This is despite such prosocial behaviours being key to solving global challenges (*8*) and for societal cohesion broadly (*9–11*). Indeed, the nature of altruism is a fundamental question of being human (*12*). Does when we decide to help others depend on the richness of our environment?

Human prosocial behaviour is often measured using economic games such as the dictator game, trust game, or the prisoner's dilemma (e.g., *13–16*). Other studies have compared two-alternative forced choices between exerting effort for rewards or resting (*17*, *18*). While these paradigms present people with many decisions, they may not capture the types of everyday behaviours and prosocial decisions that our brains evolved to solve (*2*, *19*, *20*). In real-world settings, one's current behaviour is interrupted by a choice to help others, or to do something else more beneficial for oneself. Decision-making researchers have begun to measure these more naturalistic behaviours using paradigms and approaches from behavioural ecology (*7*, *21–25*). How different environments affects decisions to act to help other people, however, remains unclear. This is despite many decisions we make having direct impacts on other people, and not only ourselves (*26*).

More broadly, research in social psychology has examined the environmental factors that determine when we help others. For example, the presence of others (*27–31*), the urgency of the situation (*32*, *33*), or the perceived costs of acting (*34–36*) can influence how likely we are to act to help (*10*). The impact of the broader environmental context, however, is less clear. The richness of one's social environment—i.e., relationships, social network, etc.—relates to levels of prosocial behaviour (*37–41*), but the specific impact of one's economic environment is highly debated (*42*). Some studies report that those who are financially poorer may be more prosocial (*43–45*), while others report the opposite (*11*, *46–48*). However, these studies are often correlational and do not experimentally manipulate the environment. Therefore, whether poorer environments lead to higher levels of prosociality, and the mechanisms that ultimately drive decisions about when to help others are still unknown.

In both humans and non-human animals, one's environment strongly influences decisions about when and how to act (*3*, *5*, *7*, *19*, *25*). Studies on foraging behaviour have shown that the quality, or richness, of an animal's environment determines how it chooses its prey. A seminal study in birds showed that in rich environments, where the average quality of prey is higher, animals will forgo low-quality prey and instead selectively wait for better options (*49*). When the environment is poor—i.e., where the average quality of prey is lower—animals will eat the low-quality prey at the same rate as higher quality prey they encounter. This environmental influence on deciding when to act for oneself has been observed in a wide range of animals, from worms to monkeys (*4*, *6*, *19*) and more recently in humans (*22*, *23*). To date, most human studies have focused on decisions within a foraging context, such as whether to explore a patch in which one resides, or leave to exploit an alternative patch (*50*). Here we were interested in whether the richness of one's environment influences decision-making about when to interrupt behaviour to help others in a similar or different manner to those decisions that only affect ourselves.

To accomplish this we combined well-established theories and computational principles about animal behaviour from behavioural ecology and decision neuroscience (*1*) to test the impact of poor and rich environments on decisions about when to help others. Across 3 separate studies (study 1 n = 237, study 2 n = 219, study 3 n = 54), we adapted a prey selection paradigm where people watched a movie and encountered opportunities to earn potential rewards by exerting a fixed amount of physical effort, calibrated to their own ability (**Figure 1a**). Crucially, on some trials, participants had the chance to interrupt their ongoing behaviour to win rewards for an anonymous other person. The opportunities signalled the magnitude and probability of receiving the reward, and their frequency differed in constructed poor and rich environments. If the participant decided to act and pursue the opportunity, the movie would disappear while they completed the effort task. If the participant declined the opportunity, they did not have to take any action; the movie continued playing and the opportunity disappeared after a few seconds. We instructed participants that their decisions would be completely anonymous, and that the other player would be unaware that the participant would be earning rewards on their behalf. This allowed the 'other' trials to be identical in all aspects to 'self' trials except for the reward recipient, and controlled for motives such as reciprocity and reputation affecting prosocial decisions.

Across all 3 studies, we show a robust environmental influence on decisions to act that is stronger when deciding to help others compared to oneself. We found that participants were more likely to interrupt their behaviour in poor environments than in rich ones as the quality of the reward increased, and that this environmental effect was larger when deciding for others. Computational modelling revealed that opportunity costs were distinctly encoded for self and others in different environments, and that people were equally sensitive to value when deciding for others in a poor environment as for themselves in a rich environment. Distinct factors of utilitarianism and empathy/motivation, but not psychiatric traits, were related to variability in opportunity costs for others. Together, we demonstrate that choosing to act to help others depends on the quality of one's environment, and that this environmental influence is stronger than when deciding to help oneself.

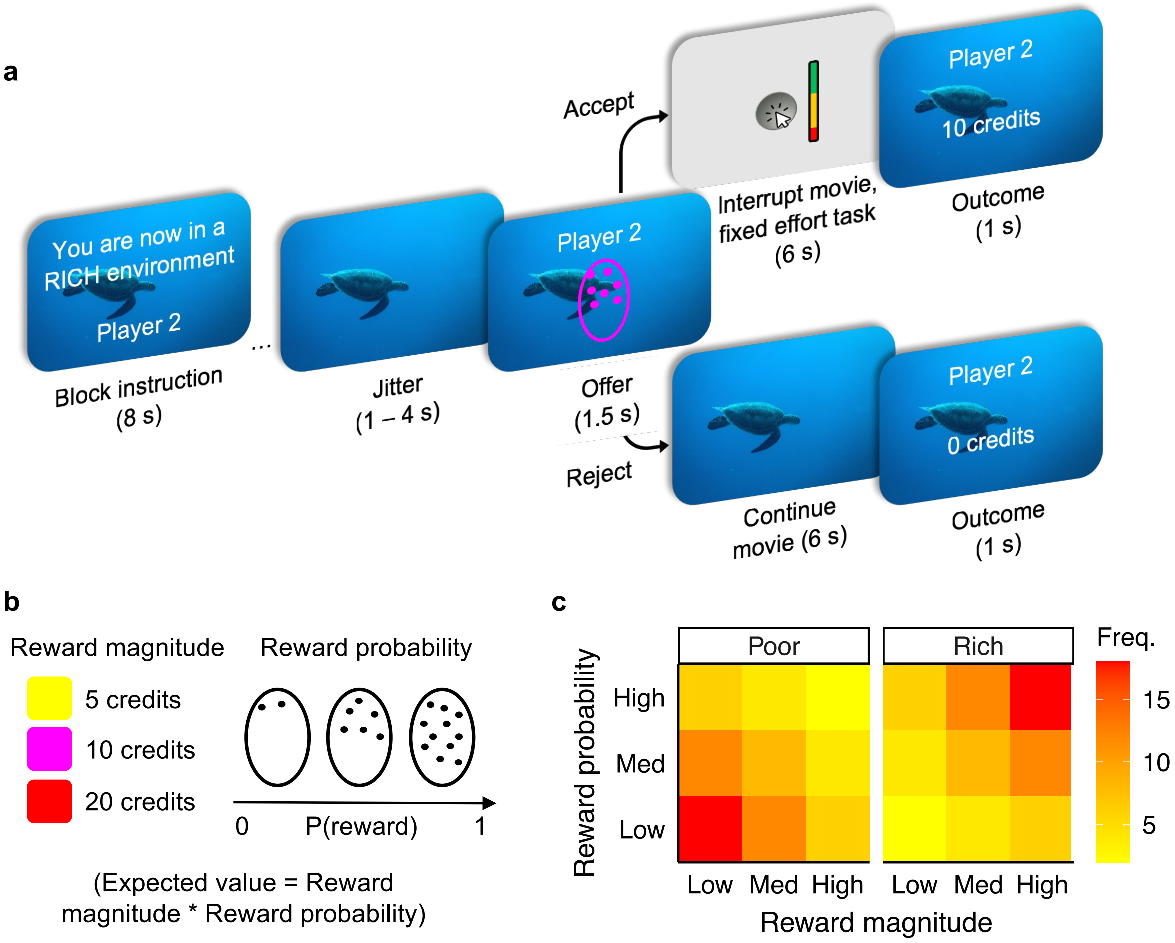

Figure 1. Prosocial Ecology Task. Participants watching an episode of a nature documentary encountered opportunities to earn rewards. **(a)** The task was divided into blocks of trials that differed based on the environment and reward recipient. At the start of each block, the task signalled to the participant whether they were in a poor or a rich environment and whether they were playing for themselves or an anonymous other. Within each block, participants saw opportunities (coloured ovals with dots inside) to earn potential rewards while watching the movie. The colour and number of dots of the offer **(b)** represented the potential reward's magnitude and probability, respectively. If participants chose to accept the opportunity, the movie was hidden and

a brief effort task appeared (note: study 3's effort task duration was 3 s). This task had participants repeatedly press an on-screen button (studies 1 and 2, displayed here) or squeeze a handheld grip device (study 3; see Methods) to 60% or 50% of their maximum effort threshold, respectively. The screen would then display the amount of reward earned, based on the colour of the opportunity. The screen would sometimes display "0 credits" based on the reward's probability (more likely if the number of dots was low), if the participant rejected the offer, or if the participant failed the effort task. If participants instead chose to decline the opportunity, no action was required and the offer disappeared while the movie continued to play. The same movie played across all the blocks. In half of the blocks, participants earned rewards for themselves and for an anonymous other person in the other half. The blocks also differed in environmental richness, with half of the blocks comprising a poor environment and the other half a rich environment. **(c)** Importantly, both environments saw the same range of reward magnitude and probabilities. However, on average, reward opportunities in the poor environment were lower in magnitude and probability compared to those in the rich environment. The frequency shown in the heatmap here refers to the number of trials in studies 1 and 2 (note: study 3 had twice as many trials) for the different levels of reward magnitude and probability.

Results

People act to help others more in poor compared to rich environments

Participants in study 1 (*n* = 237 participants, aged 18–35 years, *M* (*SD*) = 28.8 (4.4); self-reported gender: 124 women, 112 men, 1 non-binary) completed the novel Prosocial Ecology Task (**Figure 1**). We tested our central pre-registered hypothesis (AsPredicted #102887) that the richness of the environment would influence decisions to act for others differently from decisions that benefit oneself. To do so, we built a generalised linear mixed-effects model (see Methods) that included environment (poor vs. rich), recipient (self vs. other), and the expected value of the reward (magnitude*probability) as predictors of choices to act—i.e., to skip part of the movie and pursue other potential rewards. We found that, as expected value increased, participants were more likely to choose to act in the poor environment compared to the rich one, and that this difference was greater when the choice benefitted the other person relative to oneself (three-way interaction: odds ratio (OR) = 1.49, 95% confidence interval [1.05, 2.12], $z = 2.20$, $p = 0.027$, **Figure 2a**, see **Table S1** for full model results). In other words, people decided to act more often in poor environments compared to rich ones, and this environmental influence was stronger when making prosocial decisions than self-benefitting ones.

In line with our pre-registration, we ran several control analyses to account for potential effects of fatigue and previously seen opportunities. We first included trial number, as a proxy for fatigue, to the model before also adding the previous trial's choice and expected value. After controlling for all these variables, we still found that people were more likely to help others in poor environments (three-way interaction: OR = 1.42 [1.10, 1.83], $z = 2.69$, $p = 0.007$). We also observed that participants were less likely to choose to act over time (OR = 0.52 [0.48, 0.57], z = 15.07, $p < 0.001$), but were more likely to act if they had done so on the previous opportunity (OR = 1.21 [1.09, 1.35], z = 3.53, $p < 0.001$). There was no statistically significant effect of the expected value on the preceding opportunity (OR = 0.97 [0.93, 1.01], z = 1.65, p = 0.098, BF_{01} = 47.17; see **Table S2** for full results). In other words, the observed environmental interaction on participants' choices was present even after accounting for potential effects of fatigue or autocorrelation in choices (e.g., by repeating the same actions from previous trials).

We also tested our pre-registered analysis of reward magnitude and probability as separate predictors to examine if expected value effects were driven by reward magnitude or probability alone. We observed that participants were more likely choose to act at higher reward magnitudes (OR = 2.33 [2.09, 2.60], z = 15.03, $p < 0.001$) and at higher probabilities (OR = 7.05 [6.00, 8.32], z = 23.51, $p < 0.001$). People were more likely to choose to act for themselves than for others when the probability was high (reward probability*recipient: OR = 0.83 [0.71, 0.97], z = 2.29, p = 0.022, see **Table S3** for full model results).

Second, we ran a control analysis to test whether participants could still exert the required effort (60% of their maximum button presses) at the end of the experiment by measuring participants' effort thresholds again after completing the main task (see Methods). We found that people were still able to achieve the required effort, with higher effort post-task compared to the start ($t_{(233)}$ = 10.55, $p < 0.001$, d = 0.69 [0.60, 0.79]). We also checked that participants were able to successfully perform the effort task after choosing to act and found that participants were indeed highly successful (M = 99.4% success rate) for both self and other. At the end of the study we asked participants how much they enjoyed watching the movie and whether they had seen it previously. The majority of participants had not seen the movie before (208 *no* vs. 29 *yes*, $\chi^2_{(1)}$ = 135.19, $p < 0.001$) and overall enjoyment was high (M (SD) = 6.90 (2.09), 0 = *did not enjoy at all,* 9 = *very much enjoyed*; t-test against neutral rating: $t_{(236)}$ = 17.64, $p < 0.001$, d = 1.15 [0.93, 1.41]). This suggests that interrupting the movie indeed elicited an opportunity cost. In summary, study 1 showed participants were more likely to decide to act to help others in poor environments, and these effects were not driven by fatigue, the influence of the previous trial, or inability to perform the effort task.

Opportunities to help are accepted more for self than other

Previous studies have shown that despite humans being willing to help others, for example by splitting amounts of money (*15*) or putting in effort to earn rewards (*17*, *18*, *51*, *52*), they are somewhat selfish and much less willing to benefit others than they are to benefit themselves. In such studies, people will unevenly divide a pot of money between themselves and others and exert less effort to win rewards for others. We found that even though participants had the option to carry on watching a movie, they still interrupted their behaviour to help others a significant portion of the time (46.44%, *SD* = 23.49%; *t*-test comparing against 0%: $t_{(236)}$ = 30.43, $p < 0.001$, d = 1.98 [1.77, 2.24]). However, they maintained a self-bias consistent with other studies where they chose to act to help others less often compared to opportunities that benefitted themselves (self vs. other: OR = 0.14 [0.10, 0.19], z = 12.94, $p < 0.001$; **Figure 2b**). We also observed that the self vs. other difference increased at greater expected values (recipient*expected value: OR = 0.48 [0.39, 0.59], z = 6.94, $p < 0.001$).

People are more willing to act in poor environments

Research in behavioural ecology shows that the richness of the environment affects animals' decisions to forage for food (*4*, *49*, *50*). Models of prey selection predict that in rich environments, where the quantity and quality of food is high, animals will become more selective in their foraging behaviour. In poorer environments, animals become less selective and are more likely to forage for food that they might have otherwise refused in a rich environment. In line with these models, we found that, for equivalent opportunities, people were more likely to choose to act in the poor environment compared to the rich one (poor vs. rich: OR = 0.50 [0.40, 0.62], z = 6.36, $p < 0.001$; **Figure 2**; see **Table S1** for full results). For example, participants encountered medium magnitude/probability opportunities at the same rate in both environments (see central squares in **Figure 1c**). However, they were significantly more likely to accept an opportunity when it appeared in the poor environment compared to when the same opportunity appeared in the rich environment (see also *22*).

Greater environmental effect on money earned for others

Finally, we tested whether differences in decisions to act were reflected in the number of credits participants earned for themselves and the other person, which translated into bonus money at the end of the study. Importantly, the opportunities presented for self were identical to those presented for other, across both environments (see Methods). We found that participants earned more credits in the rich environment relative to the poor one (poor vs. rich: b = 146.93 [141.11, 152.75], z = 49.65, $p < 0.001$), and more credits for themselves than for others (self vs. other: b = –33.86 [–39.69, –28.01], z = 11.40, $p < 0.001$). Reflecting choice behaviour, we found a significant interaction between environment and recipient showing that participants earned more money for others in the poor environment relative to the rich one, compared to this difference for themselves (b = –35.25 [–42.62, –27.88], z = 9.39, $p < 0.001$; **Figure S1**). In essence, participants earned substantially more from opportunities for themselves than for others when in rich environments. In poor environments their own earnings were much closer to those for the other.

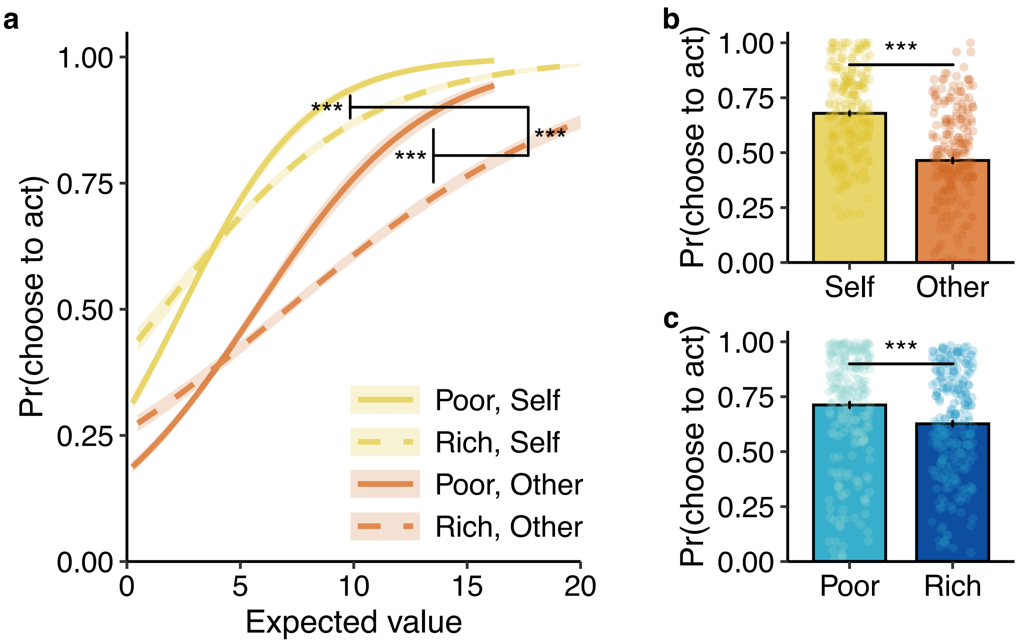

Figure 2. Humans decide to help others more often in poor environments. Results from study 1 (n = 237). **(a)** There was a significant interaction between recipient, environment, and reward expected value. As the expected value increased, participants were more likely to act to help others in poor environments compared to rich ones. This environmental effect was less influential when decisions benefitted oneself. The shaded bands around the lines represent 95% confidence intervals of the mean. **(b)** In line with previous studies, participants chose to exert effort to earn rewards more for themselves than for others. **(c)** Participants were more likely to choose to act in the poor environment compared to the rich one, for equivalent opportunities. Each dot represents a participant's average for the given condition. Error bars represent the standard error of the mean; *** $p < 0.001$.

Robust environmental influences on helping others

Next, we sought to replicate our effects in an independent online sample of participants (n = 219, mean age = 27.7 years (SD = 4.8), 108 women, 107 men, 4 non-binary). For study 2, we preregistered (AsPredicted #107076) the same task and hypotheses as in study 1. We again found a stronger effect of environment on choices to act for others relative to oneself (three-way interaction: OR = 2.55 [1.67, 4.01], z = 4.21, $p < 0.001$, **Figure 3a**, see **Table S4** for full results). This effect again remained significant after accounting for potential effects of fatigue and previously encountered opportunities (three-way interaction: OR = 2.54 [1.67, 3.96], z = 4.24, $p < 0.001$). As in study 1, participants were less likely to choose to act as the task progressed but were more likely to act if they had done so on the preceding opportunity (all

ps < 0.015). Here, participants were also less likely to act if the preceding expected value was higher ($p = 0.017$; see **Table S5** for full results). Again participants enjoyed watching the movie (M (SD) = 6.89 (2.05), t-test against neutral rating: $t_{(218)} = 17.27$, $p < 0.001$, $d = 1.17$ [0.94, 1.45]) and the majority and not seen it before (175 *no* vs. 44 *yes*, $\chi^2_{(1)} = 78.36$, $p < 0.001$). All other key findings from study 1 were replicated (see Supplementary Results).

Environmental effects extend to different types of effort and recipient

In study 3, we tested whether our findings extended to different forms of effort and recipients ($n = 54$, aged 18–32 years, M (SD) = 21.9 (3.2), 39 women, 15 men). We invited participants to the lab where they anonymously met the other person before performing the same task as above. To introduce the participant to the other person, we used a previously established role assignment procedure (*17*, *18*, *53*). This procedure allows participants to meet each other yet does not reveal any identifying information such as gender, age, or physical characteristics (see Methods) to minimise any influence of these factors on prosocial decisions. For this in-person version, participants used a grip-force device to exert physical effort, rather than rapidly pressing an on-screen button using the computer mouse. Before completing the task, we measured their maximum voluntary contraction (MVC) and used a fixed effort level of 50% MVC for the effort task, to threshold it to their own ability.

Replicating our findings from studies 1 and 2, we found a stronger effect of the environment on participants' decisions of when to act to help others (three-way interaction: OR = 1.92 [1.32, 2.80], $z = 3.40$, $p < 0.001$; **Figure 3d**, see **Table S6** for model results). This significant interaction remained when controlling for trial number as well as the choice and expected value on the preceding opportunity (three-way interaction: OR = 2.05 [1.41, 3.01], $z = 3.70$, $p < 0.001$). Participants were again less likely to act on an opportunity over time and more when the preceding expected value was higher (all ps < 0.001), but we found no significant effect of their previous choice on their current decision to act ($p = 0.49$; see **Table S7** for model results). Participants again enjoyed watching the movie (M (SD) = 7.59 (1.47), t-test against neutral rating: $t_{(53)} = 15.51$, $p < 0.001$, $d = 2.11$ [1.59, 3.05]) and the majority had not seen it before (45 *no* vs. 9 *yes*, $\chi^2_{(1)} = 24.00$, $p < 0.001$). All other key findings remained the same as in the two previous studies (see Supplementary Results).

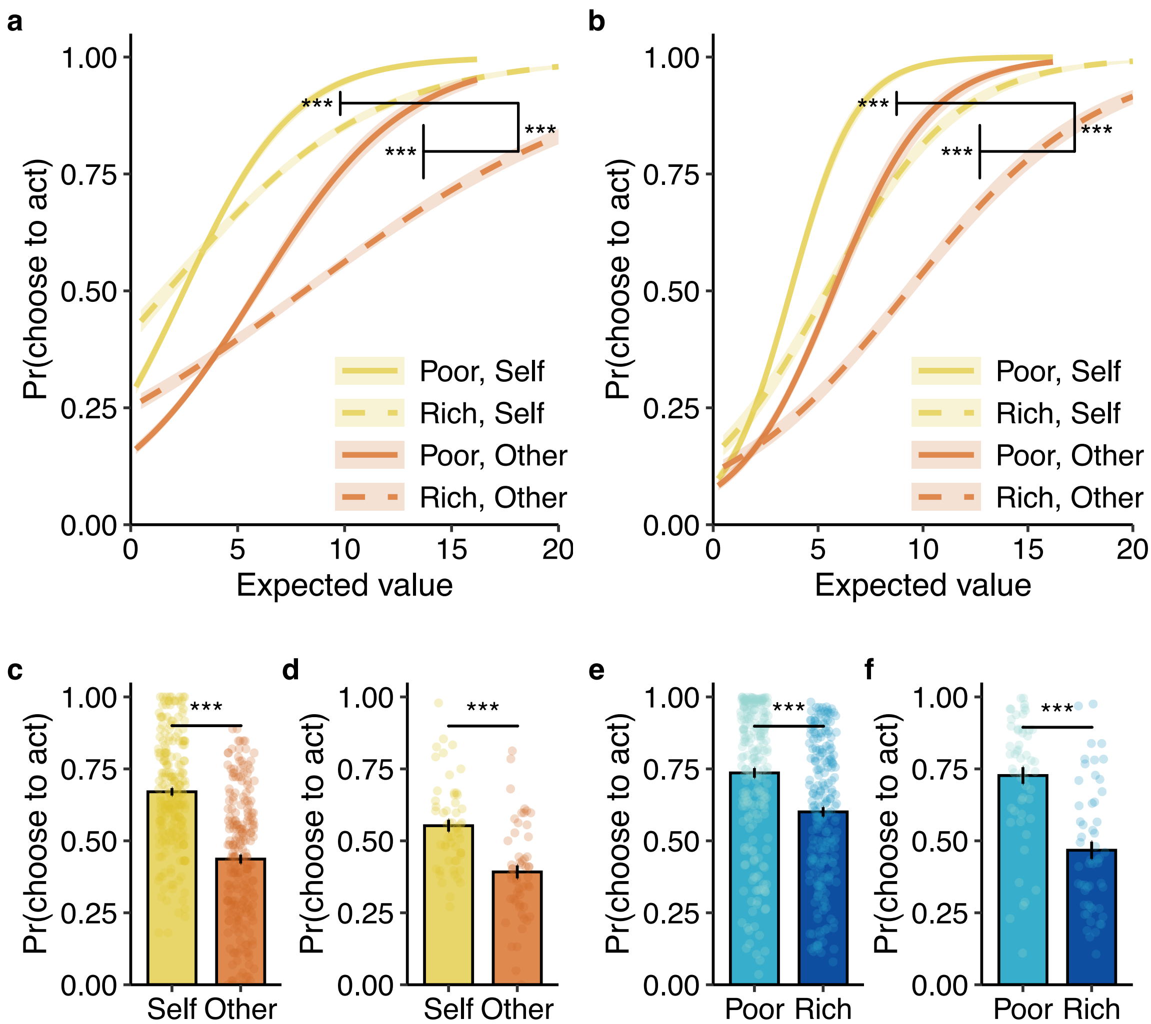

Figure 3. Environmental effects on deciding to help others are robust across studies. Results from study 2 (n = 219) and study 3 (n = 54). For all three studies there was a significant interaction between recipient, environment, and expected value. **(a, study 2; b, study 3)** At higher expected values, participants were more likely to act to help others in poor environments compared to rich ones. When the decision to act benefitted oneself, the environment had less of an impact. The shaded bands around the lines represent 95% confidence intervals of the mean. **(c, study 2; d, study 3)** On average, participants chose to act to earn rewards more for themselves than for others. **(e, study 2; f, study 3)** Participants were more likely to choose to act for a given opportunity when it appeared in a poor environment as compared to a rich one. Plotted here are the probabilities of accepting opportunities with the same mean expected value across both environments. Each dot represents a participant's average for that condition. Error bars represent the standard error of the mean; *** $p < 0.001$.

Participants over-exert for themselves and in poor environments

Study 3 additionally allowed us to examine how much physical force participants exerted in the different environments and for the different recipients. We calculated the normalised area under the curve of the force exerted on a hand-grip device and examined whether this was modulated by deciding for self vs. other, environment, and expected value (see Methods).

Participants exerted more force at higher expected values in the poor environment compared to the rich one (environment*expected value: $b = -0.016$, [–0.026, –0.005], $z = 2.94$, $p = 0.003$; **Figure 4**), but there was no overall interaction between recipient and environment ($b = 0.004$ [–0.022, 0.029], $z = 0.29$, $p = 0.78$, $BF_{01} = 82.29$). We found that participants exerted more force to benefit themselves than for others overall (self vs. other $b = -0.054$ [–0.074, –0.034], $z = 5.52$, $p < 0.001$). Together these findings suggest that participants over-exerted in poor environments when the expected value was higher and for opportunities for themselves.

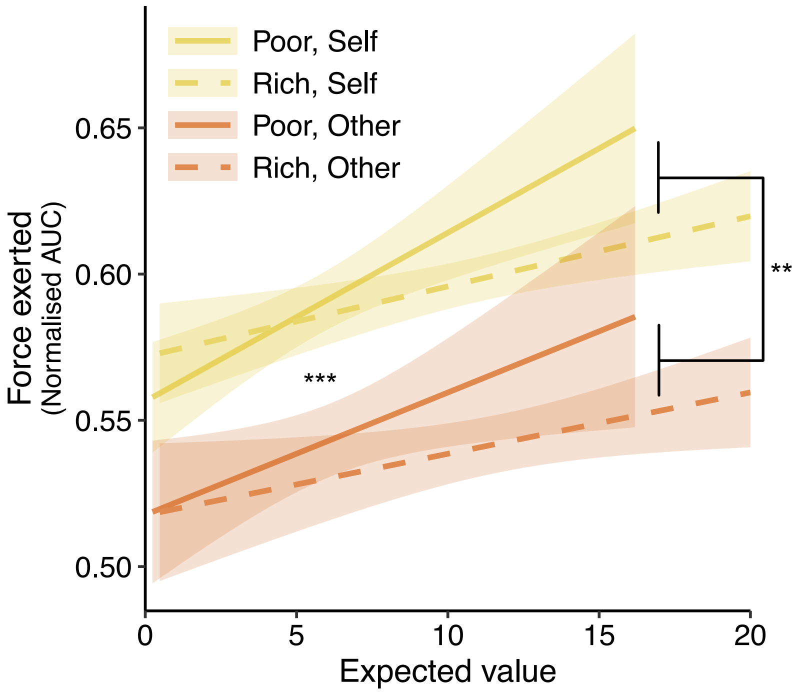

Figure 4. Participants over-exert to earn rewards for themselves and in poorer environments. Overall participants in study 3 exerted significantly more physical force when trying to win potential rewards for themselves than for others. There was a significant interaction between environment and expected value which showed that participants tended to exert more force in poor environments when the expected value was higher. AUC: area under the curve; shaded bands around the lines represent 95% confidence intervals of the mean; ** $p < 0.01$, *** $p < 0.001$.

Opportunity cost parameters are encoded distinctly for prosocial and self-benefitting decisions

Linear mixed effects models showed that participants were more influenced in poor environments than in rich ones to help others compared to themselves. However, these models cannot quantify latent influences on participants' behaviour in terms of weighting opportunity costs, sensitivity to value, or non-linear influences on decision-making. We therefore built a wide range of computational models based on decision neuroscience to quantify how opportunity costs of different environments influenced decisions to act for self and other, and fit them to the choice data from the 3 studies to maximise power (total $n = 510$). These models quantified whether the opportunity costs (o parameter) differed between environments, between recipients, or whether a single parameter applied across all conditions. Higher opportunity costs suggest that alternatives (continuing to watch the movie, avoiding the effort task, etc.) may be more worthwhile to pursue than the current opportunity. We also included a value sensitivity (inverse temperature) parameter (β) that captured the degree to which value sensitivity influenced choice consistency and to fit the models to behaviour. Each class of model tested whether this value sensitivity parameter differed between environments, between recipients, or a single parameter was sufficient. Finally, based on studies in economics we included models that varied the functional form by which opportunity costs discounted probabilistic rewards (*54–58*) (see Methods).

We found that participants' choices to act were best explained by a model with distinct opportunity cost ($o_{self/poor}$, $o_{self/rich}$, $o_{other/poor}$, $o_{other/rich}$) and value sensitivity ($\beta_{self/poor}$, $\beta_{self/rich}$, $\beta_{other/poor}$, $\beta_{other/rich}$) parameters for each environment and recipient, as well as a single risk aversion (α) parameter on the reward magnitude. This model had the highest exceedance probability and explained a large portion of the variance in choices ($R^2 = 0.83$). Data simulations showed that the model was robust and had excellent model identifiability (**Figure 5a**) and parameter recovery (**Figure 5b**, see Methods).

First, comparing the four opportunity cost parameters, we found a larger environmental effect on opportunity costs to help others compared to helping oneself (recipient*environment: b = 0.10 [0.06, 0.13], $z = 5.66$, $p < 0.001$; **Figure 5c**), reflecting the model-free results. Opportunity costs were higher in rich environments (poor vs. rich: b = 0.13 [0.11, 0.15], $z = 13.44$, $p < 0.001$) and when the outcome affected another person (self vs. other: b = 0.34 [0.31, 0.37], $z = 21.39$, $p < 0.001$). In other words, when deciding to act for both self and others, opportunity costs were smaller in the poor environment compared to the rich one. When the decision benefitted another person, this difference between environments grew wider, suggesting that one's current environment affects decisions to act help other others more than decisions for oneself.

Next, testing the value sensitivity parameters, we found that value sensitivity in the poor environment for others reached the same level as the rich environment for self. A Bayesian *t*-test provided strong Bayesian evidence of no difference between the two conditions ($t_{(507)}$ = 1.22, $p = 0.22$, $BF_{01} = 18.98$, **Figure 5d**). This suggests that people were equally sensitive to the opportunity costs when making other-benefitting decisions in poor environments as they were when making self-benefitting decisions in rich environments.

We additionally observed that participants were more value-sensitive to opportunities that benefitted themselves overall (self vs. other: b = –1.48 [–1.67, –1.29], z = 15.27, p < 0.001) and to those that appeared in poor environments (poor vs. rich: b = –1.33 [–1.50, –1.15], z = 14.71, p < 0.001). The interaction between recipient and environment was not statistically significant (b = 0.32 [–0.01, 0.65], z = 1.93, p = 0.054). Finally, we found that participants were generally risk averse at higher reward magnitudes (one-sample t-test on the α parameter: M (SE) = 0.39 (0.01); $t_{(507)}$ = 60.55, p < 0.001, d = 2.69 [2.43, 2.98]).

Therefore, computational modelling revealed how people were influenced by opportunity costs and value sensitivity when making prosocial decisions. The processing of opportunity costs confirmed our findings from model-free behaviour, while computations of value sensitivity suggested that how sensitive people are to making prosocial decisions in poor environments can be equivalent to self-benefitting decisions in rich environments.

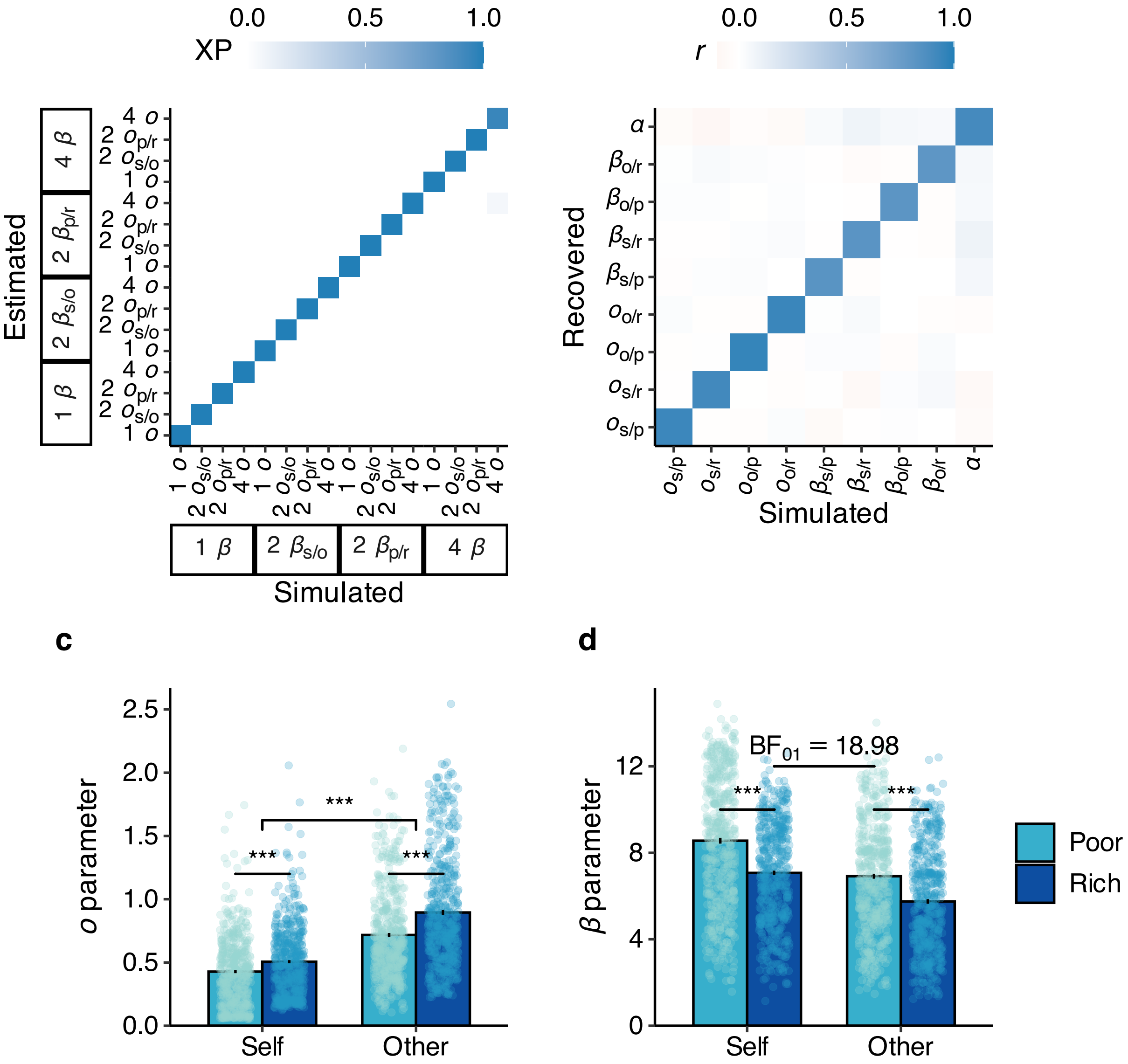

Figure 5. Computational modelling revealed that the opportunity costs of different environments were encoded distinctly for others and self. The winning model included separate opportunity cost and value sensitivity parameters for self and other in each environment, as well as a risk aversion parameter on the potential reward's magnitude. Presented here are the models that included a risk aversion parameter (α) on reward magnitude. **(a)** The models were robustly identifiable compared to other models in the model space. Presented here are the exceedance probabilities for simulated vs. estimated models that included a risk aversion parameter on reward magnitude (see **Figure S2** for fit statistics for all models). **(b)** Simulations of the winning model showed good recovery of all parameters in the model (*r*s > 0.80). **(c)** The winning model showed a significant interaction between recipient and environment showing opportunity costs were lower when deciding to help others in poor compared to rich environments. **(d)** There was strong Bayesian evidence of no difference in value sensitivity to opportunity costs of prosocial decisions in poor environments compared to self-benefitting decisions in rich environments (BF_{01} = 18.98). The error bars represent the standard error of the mean; the coloured dots represent the estimated parameters for each participant. The axis label subscripts s, o, r, and p in panels **a** and **b** represent the self, other, rich, and poor conditions, respectively. XP = exceedance probability; *** $p < 0.001$.

Opportunity costs for other-benefitting decisions are related to empathy and utilitarianism

We next examined the relationship between the estimated computational parameters and individual differences in social cognition and behaviour as well as depression, anxiety, and apathy. To do so, we conducted a factor analysis on the questionnaires that participants completed (see Methods). This allowed us to extract underlying dimensions of behaviour measured across the questionnaires (e.g., depression and anxiety scores were highly correlated, $r_{(504)} = 0.77$) while also aiding in conceptual interpretation and statistical inference by reducing the number of comparisons. The analysis revealed three distinct dimensions across the subscales of the questionnaires (**Figure 6a**). Factor 1 (‘Psychiatric traits’) included high loadings from measures of depression, anxiety, and behavioural and social apathy, Factor 2 (‘Empathy and emotional motivation’) included high loadings from measures of cognitive and affective empathy and emotional apathy, and Factor 3 (‘Utilitarianism’) included high loadings from measures of utilitarianism—i.e., beliefs related to maximizing well-being for all.

We correlated each factor with participants’ parameter estimates from the winning model (**Figure 6b;** *p*-values were FDR adjusted, see Methods). The factor ‘Utilitarianism’ showed significant negative correlations with opportunity costs in both rich ($r_{(504)} = –0.18$, $p < 0.001$) and poor ($r_{(504)} = –0.14$, $p = 0.007$) environments when deciding for others, but not when deciding for oneself (self-poor: $r_{(504)} = –0.06$, $p = 0.29$, $BF_{01} = 8.06$; self-rich: $r_{(504)} = –0.01$, $p = 0.86$, $BF_{01} = 17.62$), with strong Bayesian evidence favouring no difference. The factor ‘Empathy and emotional motivation’ showed a significant negative correlation with opportunity costs only in rich environments when deciding for others ($r_{(504)} = –0.11$, $p = 0.041$), but not when deciding for oneself (self-poor: $r_{(504)} = –0.03$, $p = 0.60$, $BF_{01} = 14.35$; self-rich: $r_{(504)} = –0.01$, $p = 0.86$, $BF_{01} = 17.55$), also with strong Bayesian evidence favouring no difference. This suggests that, for those higher in empathy and with stronger beliefs about maximizing others’ well-being, the opportunity costs when deciding to help others are smaller, leading them to be more likely to interrupt their ongoing behaviour to help. Importantly there was also Bayesian evidence that psychiatric traits did not explain variance in computing opportunity costs for others (all BF_{01}s > 3.40; see **Table S8**).

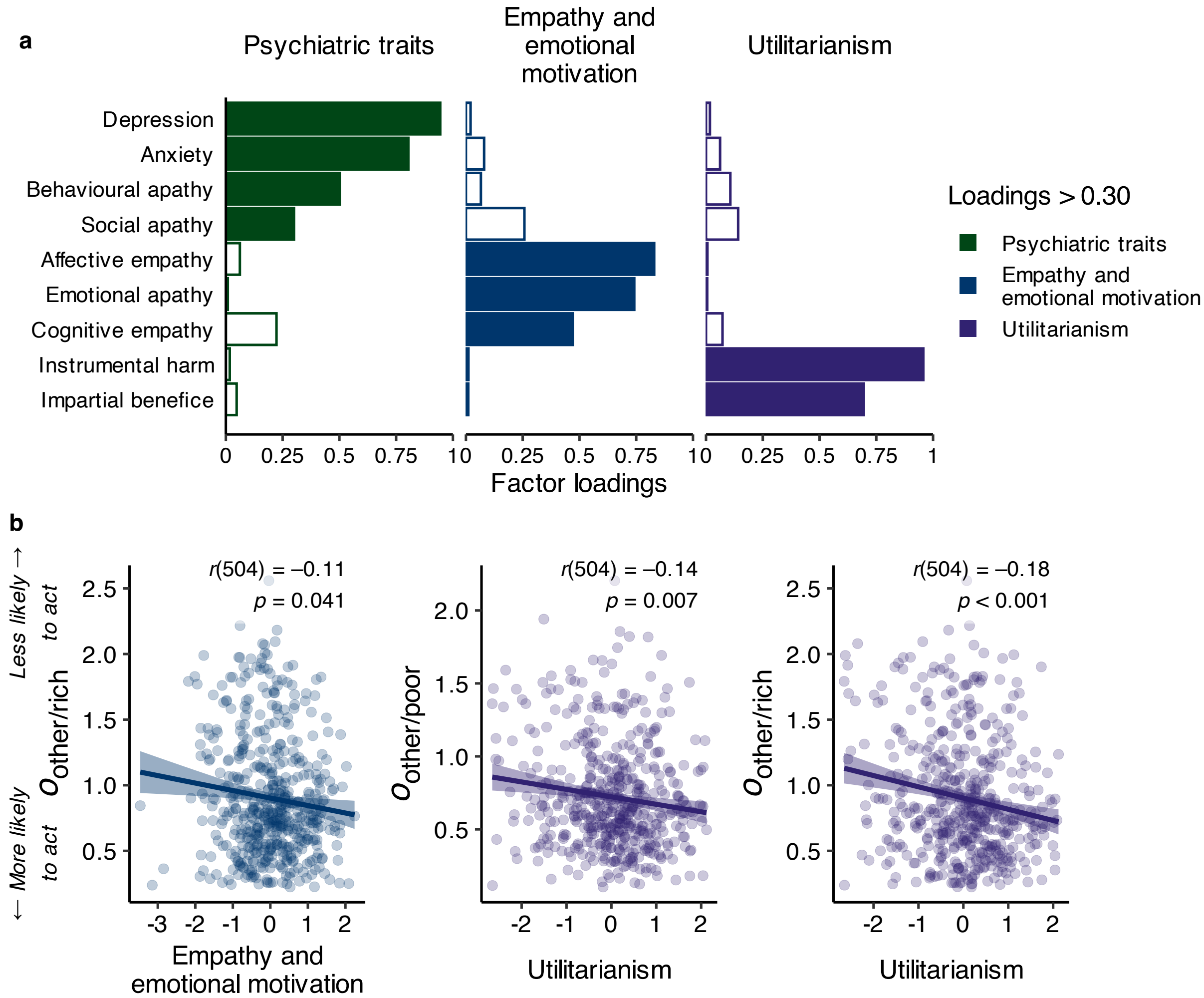

Figure 6. Variability in opportunity costs for others relates to empathy and utilitarianism. (a) Individual factor loadings for the subscales of the questionnaires administered. Our factor analysis revealed three dimensions of behaviour related to psychiatric traits, empathy and emotional motivation, and utilitarianism. Note: the loadings displayed here are absolute values. **(b)** The factors 'Empathy and emotional motivation' and 'Utilitarianism' related to opportunity costs when deciding for others. Those who are more empathetic and emotionally motivated, or with stronger utilitarian beliefs, may find helping others less costly and may be more willing to interrupt their behaviour to help others.

Discussion

Prosocial behaviours are key to building and maintaining social connections and well-being. However, previous studies have typically assessed these behaviours by presenting people with two options to decide between rather than choosing when to act prosocially. Other work in behavioural ecology and social psychology suggests that deciding when to act depends on one's environment, but whether the environment's richness impacts prosociality is unknown. Across 3 studies we show that deciding when to help others is indeed influenced by one's environment. Participants were more likely to act to earn rewards in poor compared to rich environments, and the strength of this environmental effect was enhanced when deciding for others. Computational modelling revealed that decisions were determined by comparing expected rewards with different opportunity costs for each environment and recipient. Distinct factors of utilitarianism, and empathy/motivation, but not psychiatric traits, were related to variability in computing opportunity costs when deciding for others. People were also similarly sensitive to the value of opportunities in rich environments for themselves as for opportunities in poor environments for others. Together these findings show a stronger environmental influence on decisions about when to help others compared to decisions for ourselves.

In the laboratory, prosocial behaviours are often assessed using economic games, where two or more options are presented simultaneously, and often a decision is required. This can give rise to behaviour that appears prosocial, but may instead be a consequence of the study's design—e.g., choosing an effortful option to avoid boredom or to appease the experimenter (*59–61*). In nature, however, choosing between options is rarely done simultaneously (*1*, *2*, *62*, *63*). Rather, choices are made sequentially, where the decision is either to accept or reject the current option (*64*). Our design allowed participants to freely choose when to act to help an anonymous stranger, rather than forcing an action on every trial. Importantly, using this ecological design, participants were still surprisingly prosocial and willing to interrupt their behaviour roughly half of the time to help others. This finding contributes to debates surrounding the nature of human altruism (*12*). People will stop doing something enjoyable to experience a cost to help another person, even though this will not result in any reward for themselves.

A fundamental debate in social psychology is whether poorer or richer people are more or less prosocial. Existing work has often used self-report or observational designs which has led to mixed findings regarding whether poor environments alter prosociality (*11*, *43–48*). Here, using an experimental design, we show that directly manipulating one's environment to be poor can shift decisions towards helping others. This finding may at first appear counterintuitive, as opportunities in the poor environment were overall worse compared to the rich environment. However, this pattern of behaviour can be seen in many non-human animals when foraging for food (*4*, *6*, *19*). In poor environments, opportunity costs are lower due to the alternatives also being poor, and so searching for high-quality options can be time-consuming. In rich environments, where higher-quality options are more abundant, selectively waiting to act on high-value opportunities can maximise rewards while minimising costs (e.g., time spent searching). This suggests the environmental effect observed on other-benefitting decisions may reflect fundamental mechanisms shared with other non-human animals (*1*, *3*, *7*, *25*). An interesting avenue for future research is to observe these mechanisms in more natural settings by manipulating one's immediate, real-world environment (*65*, *66*). How these environmental factors translate to one's broader socioeconomic environment remains to be investigated, but here we suggest a paradigm to use in future studies where the influence of the environment is critical to assess.

Other work in humans and non-human primates suggests that contextual features of one's environment that drive when to act are tracked via a habenula–insular circuit (*24*, *67*). Our computational modelling suggests that these features, specifically expected reward values, are discounted by distinct opportunity costs for different environments and recipients, before being used to decide when to act. Future work may examine how the brain represents these opportunity costs, and whether, like for physical effort, they are represented in distinct areas for self and others (*18*). Opportunity costs also related to individual levels of empathy/emotional motivation and utilitarianism, yet not to psychiatric traits. This suggest that people who are more empathetic and emotionally motivated, or with stronger utilitarian beliefs, find it less costly and are more willing to interrupt their behaviour to help others, which may challenge purely cognitive accounts of vicarious experience as a motivator for decisions to act. It also supports theoretical accounts of the links between empathy and altruism (*68*) showing that in paradigms where people engage in costly helping, such costly helping is more prevalent in individuals with higher self-reported empathy. Intriguingly, emotional motivation is also crucial here (*69*, *70*), with those reporting the highest emotional motivation weighting opportunity costs less strongly and therefore being more willing to act to help others.

Our computational modelling also allowed us to compare sensitivity to the rewards for self and other and between rich and poor environments. The value sensitivity (i.e., inverse temperature) parameter captures the stochasticity in choices. Higher values indicate that choices are more strongly influenced by an opportunity's value, and lower values indicate more randomness or exploration in choices. Intriguingly, we found that people on average were similarly value sensitive to offers for themselves in rich environments as for others in poor ones, suggesting that self and other became more computationally similar depending on the environmental context in which the decision is being made. Together with our choice behaviour findings, people appear to be only slightly selfish in poor environments but are much more selfish in rich environments. It would be interesting for future studies to probe whether corresponding neural representations follow this same pattern, particularly in brain areas such as the anterior cingulate gyrus and subgenual anterior cingulate cortex which have been shown to track prosocial decisions more strongly than self-benefitting ones (*71*).

In addition to these strengths there are also limitations. Across all three studies we also found that most participants enjoyed watching the movie and had never seen it before. This suggests that their decisions to interrupt the movie to act were biased by true opportunity costs, rather than simply a desire to avoid a boring movie. Nevertheless, future studies with even higher ecological validity could be developed to test how the stronger environmental influence we observed extends outside of the lab. Relatedly, it would be interesting to examine whether and in what species the environmental influence on helping conspecifics is present. Another limitation and future direction is that we focused on physical effort as the additional cost participants had to encounter to help themselves or others. We are often faced with decisions whether to interrupt and exert cognitive effort, such as helping out a colleague with their work whilst we have our own work to complete. Testing the boundaries of the environmental effect to different types of cost, such as cognitive or time costs is important and beyond the scope of the current study.

Overall, we robustly show that humans are more likely to choose to help others in poor than in rich environments. Variability in tracking opportunity costs of different environments for others relates to empathic and utilitarian traits but not to anxiety or depression. Moreover, the sensitivity to values that help others in poor environments is similar to helping oneself in a rich environment. These findings have implications for elucidating when and why humans decide to help others and could be critical for understanding prosocial decision-making as environments change.

Methods

Participants

All studies presented in this paper were approved by the research ethics committees at the University of Birmingham and the University of Oxford. All participants provided written informed consent. Online participants were compensated at the rate of £6 per hour with a potential bonus up to £2; in-person participants were compensated at the rate of £10 per hour with a potential bonus up to £5.

Study 1. We recruited 323 people through the online platform Prolific to take part in the study. Data were collected between June 2022 and August 2022. Our preregistered exclusion criteria (AsPredicted #102887) included failing at least 50% of attention checks, and overall acceptance rates below 10% in the prosocial ecology task. In total, 14 participants were excluded for failing the attention checks. We also excluded participants from analysis based on the following criteria that we did not preregister: failing an attention check question in the Questionnaire of Cognitive and Affective Therapy (QCAE; 6 participants), failing to correctly self-identify as Player 1 in debriefing questions at the end of the session (12 participants), and those with acceptance rates above 90% (54 participants). This last criterion was used in an earlier study with a similar design (*24*). If a participant met one or more of the above criteria they were excluded from the final sample and further analysis. The final sample consisted of 237 people (aged 18–35 years, *M* (*SD*) = 28.8 (4.4); self-reported gender: 124 women, 112 men, 1 non-binary).

Study 2. We recruited 301 people through the online platform Prolific to take part in the study. Data were collected between September 2022 and October 2022. We preregistered the same exclusion criteria as study 1 in addition to excluding participants with overall acceptance rates above 90% (AsPredicted #107076). In total, 16 participants failed at least 50% of the attention checks, 1 participant had an overall acceptance rate below 10%, and 46 participants had overall acceptance rates above 90%. We also excluded participants who failed the QCAE attention check (10 participants) and those who failed to self-identify as Player 1 in the debriefing questions (9 participants). The final sample consisted of 219 people (aged 18–35 years, *M* (*SD*) = 27.7 (4.8), self-reported gender: 108 women, 107 men, 4 non-binary).

Study 3. We recruited 55 people through the University of Birmingham and University of Oxford communities to participate in the study. Data were collected in two phases: between November 2019 and March 2020 and between December 2022 and January 2023. We used the same exclusion criteria as in study 1 and study 2. Study 3, however, did not include attention checks within the task, as the experimenter was present in the room to ensure that participants were attending to the task. One participant had an acceptance rate below 10%; this participant also failed the QCAE attention check. In total, 54 participants were included in the final sample (aged 18–32 years, *M* (*SD*) = 21.9 (3.2), self-reported gender: 39 women, 15 men).

Prosocial ecology task

Participants watched an episode of the nature documentary *Blue Planet II* (BBC Studios, 2017) during which opportunities to earn rewards appeared on the screen (**Figure 1**). Opportunities were presented as coloured ovals with dots inside. The colour of the oval and dots represented the magnitude of the potential reward (5, 10, or 20 credits) and the number of dots represented the probability of being given the reward (0 – 100%; **Figure 1b**). The colour–magnitude combinations were randomized between participants. If the participant chose to accept the opportunity, they did so by pressing the space bar on the computer's keyboard. Doing so would mute and hide the video while an effort task appeared on screen. Crucially, the movie continued to play while hidden, so deciding to act on the opportunity meant that the participant would miss part of the movie. For the effort task in studies 1 and 2, participants had 6 seconds to rapidly press an on-screen button until they reached 60% of their maximum number of presses (see Procedure section). For study 3, participants needed to squeeze and maintain a handheld dynamometer to at least 50% of their maximum voluntary contraction (MVC; see Procedure section). If participants failed to exert enough effort within 3 seconds, they failed the effort task and did not receive any reward. If participants exerted enough effort, they were given the reward based on its probability (i.e., the number of dots in the offer).

The task was divided into 4 separate blocks (8 blocks in study 3) that differed in environments and the recipient of the rewards (each unique block was presented twice in study 3). In half of the blocks, participants could earn rewards for themselves and in the other half they could earn rewards for an anonymous other person. Additionally, in half of the blocks, opportunities appeared in a poor environment and in the other half they appeared in a rich environment. Importantly, both environments saw the same types of opportunities. For example, high magnitude/high probability rewards appeared in the poor environment and low magnitude/low probability rewards appeared in the rich one. The average frequency of these opportunities differed between environments (**Figure 1c**), such that in poor environments, the expected value of the reward (magnitude*probability) was on average lower compared to the rich environment.

At the start of each block, the task displayed the type of environment and who would receive the rewards. Each block consisted of 36 trials ('opportunities') to earn rewards. Block orders were randomized between participants and trial orders were pseudorandomized. When an opportunity appeared, participants had 1.5 seconds to act upon it. If they accepted the offer, the video was hidden and muted while the effort task appeared, otherwise the video continued to play. The duration the video played was the same whether participants accepted the opportunity or not. Finally, between trials there was a 1–4 second delay before the next opportunity appeared. For studies 1 and 2, there were a total of 4 attention checks throughout the task. For this, participants simply needed to press an on-screen button once within 3 seconds to pass the check. At the end of the session, bonus money was awarded based on the total number of credits earned during self trials. Online participant data were collected using Gorilla Experiment Builder (www.gorilla.sc). In-person participant data were collected using the Psychophysics Toolbox (version 3.0.11) for MATLAB (version 2012b).

Questionnaire measures

After completing the main task, participants completed a series of questionnaires and answered questions related to their experience in the task. We asked participants to rate how much they enjoyed watching the movie from 0 (*Not at all*) to 9 (*Very much*); they also indicated whether they had seen the movie before.

Apathy Motivation Index. We measured individual differences in apathy and motivation using the Apathy Motivation Index (AMI) (*72*). The AMI is an 18-item scale where participants are asked to indicate their agreement with each item using a 5-point Likert scale. The scale measures apathy in behavioural, social, and emotional domains as separate subscales. Items are scored such that higher scores indicate higher levels of apathy.

Questionnaire for Cognitive and Affective Empathy. We measured individual levels of empathy using the Questionnaire for Cognitive and Affective Empathy (QCAE) (*73*). The QCAE is a 31-item scale that measures cognitive and affective empathy as separate subscales. Participants are asked to rate their agreement with each item using a 4-point Likert scale. For each item, higher scores indicate higher levels of empathy in the given domain.

Depression and Anxiety Stress Scales. We used the shortened version of the Depression and Anxiety Stress Scales (DASS) to measure individual differences in anxiety and depression (*74*). The shortened DASS is a 21-item scale that measures stress, depression, and anxiety using different subscales. Participants are asked to rate how each item applies to themselves using a 4-point Likert scale. For each item, higher scores indicate higher levels of the given emotional state. For the present studies, we excluded questions from the stress subscale, as we were specifically interested in the effects of depression and anxiety.

Oxford Utilitarianism Scale. We measured individual differences in utilitarian beliefs using the Oxford Utilitarianism Scale (OUS) (*75*). The OUS is a 9-item scale that measures utilitarian beliefs in positive and negative dimensions using two separate subscales. Participants are asked to rate their level of agreement with each item using a 7-point Likert scale. For each item, higher scores indicate stronger utilitarian beliefs in the given dimension.

Procedure

Study 1 and study 2. Before completing the main task and before any instructions, participants completed an effort thresholding procedure. For this, participants repeatedly pressed an on-screen button as fast as possible for 6 seconds using the computer mouse. Each button press filled a coloured bar on screen to provide visual feedback. Participants repeated this procedure twice more and were encouraged to fill the coloured bar to a line that was 110% of their current maximum. This thresholding procedure was used to determine how much effort (i.e., number of button presses) was needed in the main prosocial ecology task after accepting an opportunity. Participants then received instructions on how to complete the main task and were told that they would be playing alongside another anonymous person online (Player 2), whose identity would not be revealed to them. In reality, this second player did not exist and participants simply completed the task on their own. We told participants that in the task they could sometimes earn credits that would be given to the other player, but that Player 2 would not be earning credits for the participant themselves. To reinforce the idea that Player 2 was a real person, we introduced them using a fake Prolific participant identifying number that was similar in resemblance to the participant's own number. No participants indicated disbelief that Player 2 was a real person in our debriefing questions at the end of the study. Participants completed 5 practice trials before performing the main task. After completing the main task, we measured participants' effort thresholds again using the same procedure from the beginning of the study. Finally, participants completed the questionnaires and answered questions related to the task.

Study 3. The procedure used in study 3 was nearly identical to that used in studies 1 and 2. The two key differences were as follows: (1) the modality of the effort task after accepting an opportunity to act, (2) how Player 2 was introduced. For the effort task, participants exerted force by squeezing the handle of a dynamometer rather than pressing an on-screen button. In the main task participants needed to exert force to at least 50% of their maximum voluntary contraction (MVC; determined using the same effort thresholding procedure as above, but instructing participants to squeeze as hard as they can) for a minimum of 1 second to succeed. This effort target was reduced relative to the online version of the task, as squeezing the grip-force device required more effort than repeatedly pressing a computer mouse button. To introduce Player 2, we used a role assignment procedure from earlier social decision-making studies to minimize social preferences of reciprocity (*17*, *18*, *53*). Participants were anonymously introduced to the other participant, who was a confederate, in person. To ensure that they remained anonymous, we instructed both participants to remain silent and wear gloves to hide physical characteristics when meeting. The real participant stood on one side of a door while a second experimenter instructed the confederate to stand on the other side. Both participants were instructed to wave to each other and acknowledge that they had seen the gloved hand of the other. To assign roles to each participant, the experimenter tossed a coin to determine who picked a ball out of box first. The colour of the ball determined who was Player 1 and who was Player 2. The procedure was fixed so that the real participant was always assigned the role of Player 1 and the confederate participant assigned the role of Player 2. After the roles were assigned, we emphasized to the real participant that Player 2 would be unaware of Player 1's tasks being performed, and that any rewards earned on their behalf would be anonymous. No participants indicated disbelief that Player 2 was a real person in our questions at the end of the study.

Statistical analysis

We analysed the behavioural data and fitted computational model parameters using R (v4.3.1). We used the 'glmmTMB' package (v1.17) to fit generalised linear mixed-effects models (GLMMs) to the data and fitted parameters; see Supplementary Methods for full details of the models. Our preregistration stated that we would use the 'lme4' package to fit GLMMs; instead, we chose to use glmmTMB for its similarity to lme4 statistically, yet the implementation of a higher speed of processing for larger datasets such as ours (*76*). Model estimates are supplemented with 95% confidence intervals and all significance tests were two-tailed with a threshold of 0.05. Paired *t*-tests were used to compare effort thresholds and are supplemented with Cohen's *d* effect sizes. Three participants in study 1, and one participant in study 2, did not complete the post-test thresholding procedure and were excluded from this comparison. The 'BayesFactor' package (v0.9.12-4.4) was used to calculate Bayes factors (BF_{01}) for non-significant comparisons using a uniform prior. For the continuous variables from the GLMMs (e.g., previous expected value), we calculated Bayes factors based on BIC scores (*77*). Traditionally, a BF_{01} larger than 3 (equivalent to a BF_{10} smaller than 1/3) is considered substantial evidence in favour of the null hypothesis, with the strength of the evidence increasing at higher BF values (*78*).

Computational modelling

We quantified the opportunity costs (o) and value sensitivity (β) for each recipient and environment by comparing multiple discounting models that differed in their shape and number of unique parameters. For all models, we tested for both o and β whether a single parameter applied across both recipients and environments, whether two parameters were specific to recipients (self vs. other), whether two parameters were specific to environments (poor vs. rich), or whether four parameters were specific to each condition (self/poor vs. self/rich vs. other/poor vs. other/rich). We compared variations on the shape of the discounting function including linear, parabolic, hyperbolic, and power functions (*54*, *56*),

Linear: $SV = (r * p) - o$

Parabolic: $SV = (r * p)^2 - o$

Hyperbolic: $SV = (r * p)/(1 + o)$

Power: $SV = (r * p)^\theta - o$

In these models, *SV* represents the subjective value that results from the reward's magnitude *r* and probability *p* after it has been discounted by the opportunity costs *o*. The opportunity cost parameter captures the value of alternative opportunities (continuing to watch the movie, avoiding the effort task, etc.) that a person could instead pursue. Higher values of *o* will generally make people more selective and thus less likely to pursue a given opportunity, as other high-value alternatives are more readily available (*1*, *3*, *6*). With lower values of *o*, for example in poor environments, suggest that people generally will be less selective. In the power function model, the free parameter θ individually scales the value of the expected reward (magnitude*probability). We also compared variations of the value and weighting functions from prospect theory (*55*, *58*) that separately adjusted the scaling of the reward's magnitude and probability,

Prospect: $SV = v(r) * w(p) - o$

where the value v and weighting w functions are defined as,

$$v(r) = r^\alpha$$

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1 - p)^\gamma)^{-\gamma}}$$

Here, α represents risk aversion and γ represents the weighting placed on the reward's probability. In total we tested 112 different models that varied in shape and in number of opportunity cost and decision noise parameters.

These models were fit to choices using a logistic function,

$$\Pr(accept) = \frac{1}{1 + e^{-(\beta * SV)}}$$

and estimated using an iterative maximum a posteriori (MAP) approach (*79*, *80*) in MATLAB (version 2022a). The probability of choosing to act, Pr(*accept*), is based on *SV* and a value sensitivity (inverse temperature) parameter β.

Model identifiability and parameter recovery

We used simulated data to ensure the validity of our model comparison and parameter fitting procedures (*81*). For model identifiability, we used each model to separately simulate choice data for 100 artificial agents. Simulated parameters were drawn from a uniform distribution with lower and upper bounds matched to the range of parameter values observed in the real participants. The simulated data were separately fit to each model using the same MAP procedure as was used on the real participants' data. This allowed us to create a confusion matrix of model exceedance probabilities, which showed good identifiability (**Figure 5a**). Exceedance probabilities were calculated using the 'spm_BMS' function from SPM 12 (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/). For parameter recovery, we used the winning model to simulate data for 5000 artificial agents, again drawing the parameters from a uniform distribution bounded by the range observed in the real participants. We fit the simulated data using the same MAP procedure as before and correlated the recovered parameter values with the 'true' simulated values. This showed that our winning model had good parameter recovery (rs > 0.80; **Figure 5b**).

Exploratory factor analysis

We conducted an exploratory factor analysis on the subscales of the questionnaires using the \`psych\` package (version 2.3.6) for R. We included all the subscales from the AMI and OUS, only the depression and anxiety subscales from the DASS, and the cognitive empathy and affective empathy subscales from the QCAE (**Figure 6a**). To extract the factor loadings, we used maximum likelihood and an oblique rotation (oblimin). Parallel analysis and inspection of the scree plot suggested a 3-factor solution. These 3 factors captured 54.15% of the variance in the set of measures and were minimally correlated (highest r = 0.12). Participant-level scores for each factor were computed using Thurstone's regression method. These scores were then correlated with the fitted parameters from the winning model using Pearson's r and p-values were FDR adjusted using the Benjamini–Hochberg procedure.

Data availability

The datasets analysed during the current study are available at: https://osf.io/dmfhq/?view_only=a4b4584e472c44acb943d755f1920643.

Code availability

The code used for data analysis and model fitting are available at: https://osf.io/dmfhq/?view_only=a4b4584e472c44acb943d755f1920643.

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Supplementary Methods

Statistical analysis

Generalised linear mixed-effects models (GLMM) were used to predict participants' choices (accept or reject offer) in the Prosocial Ecology Task and the fitted computational parameters. Our main analyses included environment (poor vs. rich), recipient (self vs. other), and expected value (reward magnitude*probability) as well as their interactions as fixed effects. Continuous variables were centred within subjects and categorical variables were recoded using effect coding. Random effects included participant-level random intercepts, and random slopes that were determined by first fitting the maximal model and then comparing against reduced models to trim away random effects that did not improve the fit of the model in terms of Akaike Information Criterion (AIC; *1*). This was done to reduce Type I error while maintaining power, and improve model convergence (*1*, *2*). Force data in study 3 were normalised as the proportion of their maximum force and calculated using the area under the curve for the 3-second window in which they exerted force. The R and MATLAB code used for data analysis and model fitting are available at: https://osf.io/dmfhq/?view_only=a4b4584e472c44acb943d755f1920643.

Model comparison

In addition to using exceedance probability to compare models, as described in the main manuscript, we also compared the computational models using the integrated Bayesian Information Criterion (BICint), which tends to favour smaller models over complex ones. We found that the model with the lowest summed BICint had distinct opportunity costs and value sensitivity parameters for each recipient (self vs. other) but not for each environment. This model however had an exceedance probability close to 0 (the winning model had an exceedance probability of 0.93) and explained less variance than our winning model (R^2 = 0.79; winning model R^2 = 0.83). See **Figure S3** for the BICint scores for all models.

Supplementary Results

Study 2

Examining the effect of environment, we found that participants were less likely to act in the rich compared to the poor environment (poor vs. rich: OR = 0.29 [0.22, 0.37], z = 9.59, p < 0.001), and that this difference in environments widened at higher expected reward values (environment × expected value: OR = 0.17 [0.13, 0.22], z = 14.28, p < 0.001). Participants also demonstrated that they were often willing to interrupt their behaviour to help others (M = 43.66%, SD = 22.77%, t-test comparing against 0%: $t_{(218)}$ = 28.37, p < 0.001, d = 1.92 [1.73, 2.14]), despite having the option to continue watching the movie. However, as in study 1, participants showed a self-bias where they chose to act to help others less than opportunities for themselves (self vs. other: OR = 0.10 [0.07, 0.13], z = 13.52, p < 0.001). This difference self-bias also increased at higher expected values (recipient × expected value: OR = 0.37 [0.29, 0.46], z = 8.45, p < 0.001).

When we examined reward magnitude and probability as separate predictors, we again found that participants were more likely to choose to act at higher reward magnitudes (OR = 2.31 [2.06, 2.61], z = 13.88, p < 0.001) and at higher probabilities (OR = 7.89 [6.81, 9.16], z = 27.44, p < 0.001). This model (see **Table S9** for full results) revealed a significant 4-way interaction between reward magnitude, reward probability, environment, and recipient (OR = 0.74 [0.58, 0.96], z = 2.31, p = 0.021), analogous to the findings described above where reward magnitude and probability were computed together as expected value.

Participants in study 2 were also highly successful when they performed the effort task for both self and other. On average they succeeded in 99.6% of the effort task trials, which further supports the notion that the effort task did not meaningfully increase the risk of choosing to act. Examining participants' effort thresholds before and after the main task showed again that thresholds were higher at the end of the study ($t_{(217)}$ = 9.32, p < 0.001, d = 0.63 [0.52, 0.75]), again suggesting that participants were not fatigued by the effort task. We also asked participants how much they enjoyed watching the movie and whether they had seen it previously. The majority of participants had not seen the movie before (175 *no* vs. 44 *yes*, $\chi^2_{(1)}$ = 78.36, p < 0.001) and overall enjoyment was high (M (SD) = 6.89 (2.05), 0 = *did not enjoy at all,* 9 = *very much enjoyed*; t-test against neutral rating: $t_{(218)}$ = 17.27, p < 0.001, d = 1.17 [0.94, 1.45]).

Comparing the number of credits earned we replicated the significant interaction between environment and recipient showing that, compared to themselves, participants earned relatively more credits for others when the environment was poor than when it was rich (recipient × environment: b = –43.09 [–51.00, –35.16], z = 10.69, p < 0.001). That is, although participants overall earned more credits for themselves than for others (self vs. other: b = –36.61 [–42.60, –30.62], z = 12.03, p < 0.001), and earned more credits in the rich blocks compared to the poor blocks (poor vs. rich: b = 141.36 [134.44, 148.27], z = 40.25, p < 0.001), the difference between credits earned for self and for other was smaller in the poor environment as compared to the rich one (**Figure S1**). Together, the findings from study 2 replicate our finding of robust ecological effects on prosocial decisions that are stronger than for the same decisions that benefit oneself.

Study 3

We also found that participants were again less likely to act to help the other person relative to themselves (self vs. other: OR = 0.20 [0.13, 0.31], z = 7.72, p < 0.001) and that this difference increased at higher expected values (recipient × expected value: OR = 0.32 [0.23, 0.43], z = 7.32, p < 0.001). There was also a significant effect of environment, replicating our findings from the studies described above. Overall, participants chose to act to benefit the other person 39.20% (SD = 16.57%) of the time (t-test comparing against 0%: $t_{(53)}$ = 17.39, p < 0.001, d = 2.37 [1.94, 3.07]). Participants were more likely to act on a given opportunity when it appeared in a poor environment compared to a rich one (poor vs. rich: OR = 0.24 [0.19, 0.30], z = 12.56, p < 0.001), and this difference increased at higher expected values (environment × expected value: OR = 0.20 [0.16, 0.24], z = 16.29, p < 0.001).

When we examined reward magnitude and probability separately we again found that participants were more likely to choose to act on opportunities with higher reward magnitudes (OR = 1.20 [1.17, 1.23], z = 15.49, p < 0.001) and with higher reward probabilities (OR = 7.40 [5.52, 10.04], z = 13.27, p < 0.001). Reward magnitude significantly interacted with both recipient (magnitude × recipient: OR = 0.93 [0.91, 0.95], z = 5.73, p < 0.001) and environment (magnitude × environment: OR = 0.89 [0.87, 0.91], z = 9.41, p < 0.001), showing that participants accepted high magnitude offers more often for themselves and more often in the poor environment. We also found that the reward probability interacted with environment (probability × environment: OR = 0.63 [0.44, 0.89], z = 2.64, p = 0.008) wherein participants were more likely to accept higher probability offers in the poor environment relative to the rich one, but we did not see any significant interaction between reward probability and recipient (probability × recipient: OR = 0.94 [0.63, 1.39], z = 0.32, p = 0.75). See **Table S10** for all results from the model.

Finally, as in studies 1 and 2, we found that participants were very successful in the effort task when they chose to act on the opportunity for both self and other (M = 98.7%). We found that participants' effort thresholds measured at the end of the study were lowered compared to those at the beginning ($t_{(53)}$ = 2.45, p = 0.018, d = 0.33 [0.08, 0.57]). We also replicated effects of an interaction between recipient and environment in the amount of credits earned (**Figure S1**). Specifically, participants earned more credits in rich blocks than in poor blocks (poor vs.

rich: b = 296.34 [275.71, 316.98], z = 28.59, $p < 0.001$) and more for themselves that for the other player (self vs. other: b = –58.66 [–73.60, –43.71], z = 7.74, $p < 0.001$). This self–other difference in credits earned was greater in the rich compared to the poor environment (recipient × environment: b = –74.72 [–104.61, –44.84], z = 4.93, $p < 0.001$). As in the other studies, the majority of participants in study 3 had not seen the movie before (45 *no* vs. 9 *yes*, $\chi^2_{(1)} = 24.00$, $p < 0.001$) and overall enjoyment was high (M (SD) = 7.59 (1.47), 0 = *did not enjoy at all,* 9 = *very much enjoyed*; t-test against neutral rating: $t_{(53)} = 15.51$, $p < 0.001$, d = 2.11 [1.59, 3.05]). Altogether, our findings from study 3 demonstrate that the effects of environment and recipient on decisions to act are robust across types of effort and the context in which participants meet another person.

Table S1. *GLMM predicting choices (study 1)*

Fixed effect	OR	CI low	CI high	*z*	*p*
(Intercept)	3.00	2.41	3.76	9.70	< 0.001
Environment (Poor vs. Rich)	0.50	0.40	0.62	6.36	< 0.001
Recipient (Self vs. Other)	0.14	0.10	0.19	12.94	< 0.001
Expected value	8.93	7.51	10.67	24.50	< 0.001
Environment × Recipient	1.24	0.88	1.77	1.22	0.22
Environment × Expected value	0.32	0.26	0.39	10.44	< 0.001
Recipient × Expected value	0.48	0.39	0.59	6.94	< 0.001
Environment × Recipient × Expected value	1.49	1.05	2.12	2.20	0.027

Note. GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound.

Table S2. *GLMM with covariates predicting choices (Study 1)*

Fixed effect	**OR**	**CI low**	**CI high**	***z***	***p***
(Intercept)	2.91	2.34	3.64	9.53	< 0.001
Trial number	0.52	0.48	0.57	15.07	< 0.001
Previous choice	1.21	1.09	1.35	3.53	< 0.001
Previous expected value	0.97	0.93	1.01	1.65	0.098
Environment (Poor vs. Rich)	0.56	0.47	0.68	5.88	< 0.001
Recipient (Self vs. Other)	0.15	0.11	0.20	12.59	< 0.001
Expected value	9.13	7.69	10.88	25.08	< 0.001
Environment × Recipient	0.98	0.76	1.25	0.20	0.84
Environment × Expected value	0.31	0.26	0.38	11.73	< 0.001
Recipient × Expected value	0.51	0.42	0.61	7.11	< 0.001
Environment × Recipient × Expected value	1.42	1.10	1.83	2.69	0.007

Note. This model added trial number, previous choice, and previous expected value as covariates to the main model (see Table S3). GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound; Previous choice: the accept/reject decision to act on the immediately preceding opportunity; Previous expected value: the expected value of the preceding opportunity.

Table S3. *GLMM with reward magnitude and probability as separate effects (study 1)*

Fixed effect	OR	CI low	CI high	*z*	*p*
(Intercept)	1.91	1.52	2.40	5.51	< 0.001
Magnitude	2.33	2.09	2.60	15.02	< 0.001
Probability	7.05	6.00	8.32	23.51	< 0.001
Recipient (Self vs. Other)	0.13	0.10	0.18	13.21	< 0.001
Environment (Poor vs. Rich)	0.73	0.60	0.89	3.16	0.002
Magnitude × Probability	1.02	0.96	1.09	0.71	0.47
Magnitude × Recipient	0.92	0.82	1.03	1.44	0.15
Probability × Recipient	0.83	0.71	0.97	2.29	0.022
Magnitude × Environment	0.95	0.85	1.06	0.88	0.38
Probability × Environment	1.02	0.87	1.18	0.21	0.84
Recipient × Environment	0.79	0.56	1.13	1.29	0.20
Magnitude × Probability × Recipient	0.89	0.79	1.00	1.95	0.052
Magnitude × Probability × Environment	1.09	0.96	1.23	1.37	0.17
Magnitude × Recipient × Environment	1.08	0.87	1.35	0.72	0.47
Probability × Recipient × Environment	1.13	0.85	1.52	0.85	0.39
Magnitude × Probability × Recipient × Environment	1.17	0.92	1.48	1.29	0.20

Note. Magnitude and probability represent the reward's number of credits and probability, respectively. GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound.

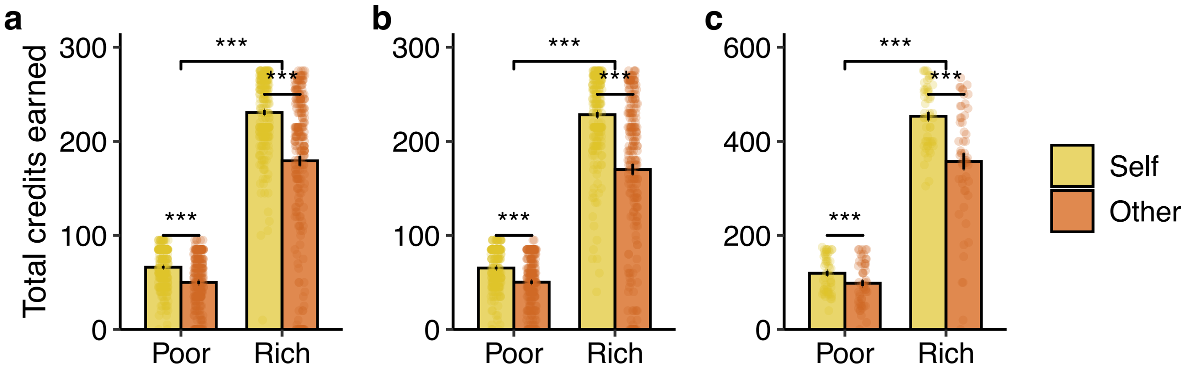

Figure S1. Total number of credits earned within the prosocial ecology task. Mirroring their choice behaviour, participants earned relatively more credits for others in poor environments compared to rich ones than they did for themselves. **(a)** Total number of credits earned in study 1. **(b)** Total number of credits earned in study 2. **(c)** Total number of credits earned in study 3.

Table S4. *GLMM predicting choices (study 2)*

Fixed effect	**OR**	**CI low**	**CI high**	***z***	***p***
(Intercept)	3.40	2.68	4.34	9.95	< 0.001
Environment (Poor vs. Rich)	0.29	0.22	0.37	9.59	< 0.001
Recipient (Self vs. Other)	0.10	0.07	0.13	13.52	< 0.001
Expected value	11.60	9.46	14.31	23.34	< 0.001
Environment × Recipient	2.27	1.49	3.54	3.74	< 0.001
Environment × Expected value	0.17	0.13	0.22	14.28	< 0.001
Recipient × Expected value	0.37	0.29	0.46	8.45	< 0.001
Environment × Recipient × Expected value	2.55	1.67	4.01	4.21	< 0.001

Note. GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound.

Table S5. *GLMM with covariates predicting choices (study 2)*

Fixed effect	OR	CI low	CI high	*z*	*p*
(Intercept)	3.35	2.64	4.28	9.88	< 0.001
Trial number	0.50	0.46	0.55	14.72	< 0.001
Previous choice	1.15	1.03	1.30	2.44	0.015
Previous expected value	0.95	0.91	0.99	2.38	0.017
Environment (Poor vs. Rich	0.32	0.25	0.40	9.68	< 0.001
Recipient (Self vs. Other)	0.10	0.07	0.14	13.56	< 0.001
Expected value	11.70	9.55	14.44	23.42	< 0.001
Environment × Recipient	1.83	1.25	2.74	3.02	0.002
Environment × Expected value	0.16	0.13	0.20	15.28	< 0.001
Recipient × Expected value	0.38	0.30	0.48	8.08	< 0.001
Environment × Recipient × Expected value	2.54	1.67	3.96	4.24	< 0.001

Note. This model added trial number, previous choice, and previous expected value as covariates to the main model (see Table S4). GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound; Previous choice: the accept/reject decision to act on the immediately preceding opportunity; Previous expected value: the expected value of the preceding opportunity.

Table S6. *GLMM predicting choices (study 3)*

Fixed effect	OR	CI low	CI high	z	p
(Intercept)	1.88	1.31	2.71	3.47	< 0.001
Environment (Poor vs. Rich)	0.24	0.19	0.30	12.56	< 0.001
Recipient (Self vs. Other)	0.20	0.13	0.31	7.72	< 0.001
Expected value	18.31	14.15	24.10	21.88	< 0.001
Environment × Recipient	1.75	1.36	2.26	4.31	< 0.001
Environment × Expected value	0.20	0.16	0.24	16.29	< 0.001
Recipient × Expected value	0.32	0.23	0.43	7.32	< 0.001
Environment × Recipient × Expected value	1.92	1.32	2.80	3.40	< 0.001

Note. GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound.

Table S7. *GLMM with covariates predicting choices (study 3)*

Fixed effect	**OR**	**CI low**	**CI high**	***z***	***p***
(Intercept)	2.09	1.37	3.23	3.44	< 0.001
Trial number	0.65	0.59	0.71	8.96	< 0.001
Previous choice	0.93	0.76	1.14	0.68	0.49
Previous expected value	0.86	0.79	0.92	4.09	< 0.001
Environment (Poor vs. Rich)	0.20	0.14	0.27	10.23	< 0.001
Recipient (Self vs. Other)	0.20	0.13	0.30	7.79	< 0.001
Expected value	22.28	16.18	31.22	18.91	< 0.001
Environment × Recipient	1.77	1.36	2.31	4.25	< 0.001
Environment × Expected value	0.12	0.08	0.18	11.25	< 0.001
Recipient × Expected value	0.33	0.24	0.44	7.44	< 0.001
Environment × Recipient × Expected value	2.05	1.41	3.01	3.70	< 0.001

Note. This model added trial number, previous choice, and previous expected value as covariates to the main model (see Table S7). GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound; Previous choice: the accept/reject decision to act on the immediately preceding opportunity; Previous expected value: the expected value of the preceding opportunity.

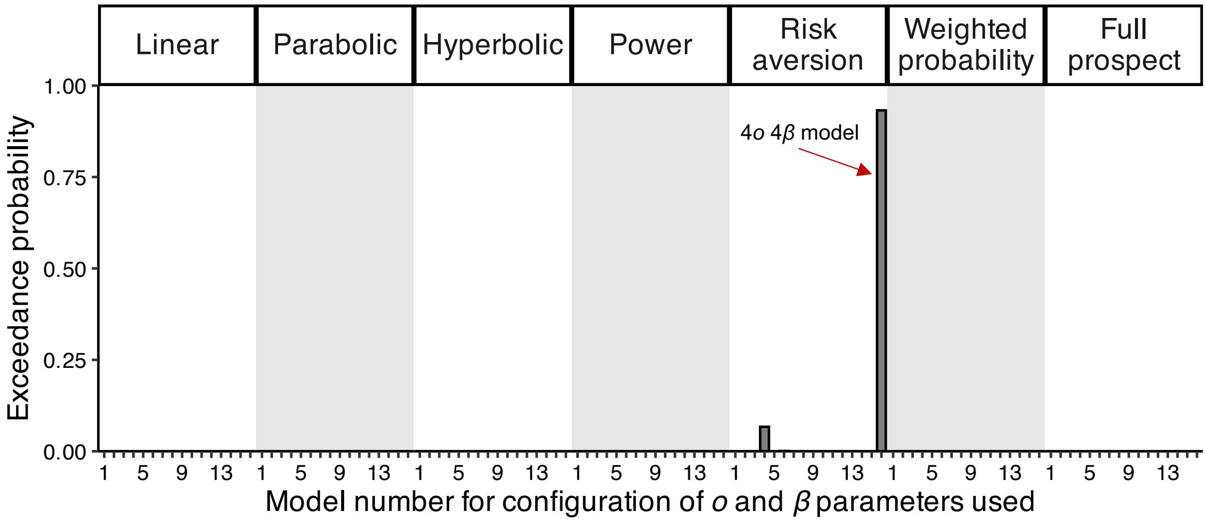

Figure S2. Exceedance probabilities for all 112 model combinations tested. The model which included 4 separate parameters for opportunity costs and for value sensitivity, in addition to a risk aversion parameter, had the highest exceedance probability (0.93). The model numbers 1-16 on the x-axis represent the following parameter combinations: **(1)** $1o$ 1β, **(2)** $2o_{s/o}$ 1β, **(3)** $2o_{p/r}$ 1β, **(4)** $4o$ 1β, **(5)** $1o$ $2\beta_{s/o}$, **(6)** $2o_{s/o}$ $2\beta_{s/o}$, **(7)** $2o_{p/r}$ $2\beta_{s/o}$, **(8)** $4o$ $2\beta_{s/o}$, **(9)** $1o$ $2\beta_{p/r}$, **(10)** $2o_{s/o}$ $2\beta_{p/r}$, **(11)** $2o_{p/r}$ $2\beta_{p/r}$, **(12)** $4o$ $2\beta_{p/r}$, **(13)** $1o$ 4β, **(14)** $2o_{s/o}$ 4β, **(15)** $2o_{p/r}$ 4β, **(16)** $4o$ 4β. The o and β parameters represent the opportunity cost and value sensitivity parameters, respectively. The s, o, p, and r subscripts represent the self, other, poor, and rich conditions, respectively.

Table S8. *Correlations between the factors and model parameters*

		Psychiatric traits	Empathy and Emotional Motivation	Utilitarianism
$o_{self/poor}$	r	0.02	–0.03	–0.06
	BF_{01}	15.59	14.35	8.06
$o_{self/rich}$	r	0.04	–0.01	–0.01
	BF_{01}	12.71	17.55	17.62
$o_{other/poor}$	r	0.03	–0.10	**–0.14****
	BF_{01}	15.00	1.38	0.16
$o_{other/rich}$	r	0.08	**–0.11***	**–0.18*****
	BF_{01}	3.41	0.95	0.00
$\beta_{self/poor}$	r	–0.03	0.06	–0.08
	BF_{01}	14.64	6.84	2.99
$\beta_{self/rich}$	r	–0.04	0.06	–0.09
	BF_{01}	11.24	6.35	2.55
$\beta_{other/poor}$	r	0.03	0.04	–0.08
	BF_{01}	14.10	13.48	4.15
$\beta_{other/rich}$	r	–0.08	–0.02	–0.10
	BF_{01}	4.69	16.43	1.71
α	r	0.04	–0.09	–0.08
	BF_{01}	12.06	2.26	2.96

Note. r values represent Pearson's correlation coefficient. Significant values are FDR-adjusted and bolded here for visualisation. BF_{01} represents the Bayes factor in favour of the null (i.e., no correlation between the variables). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

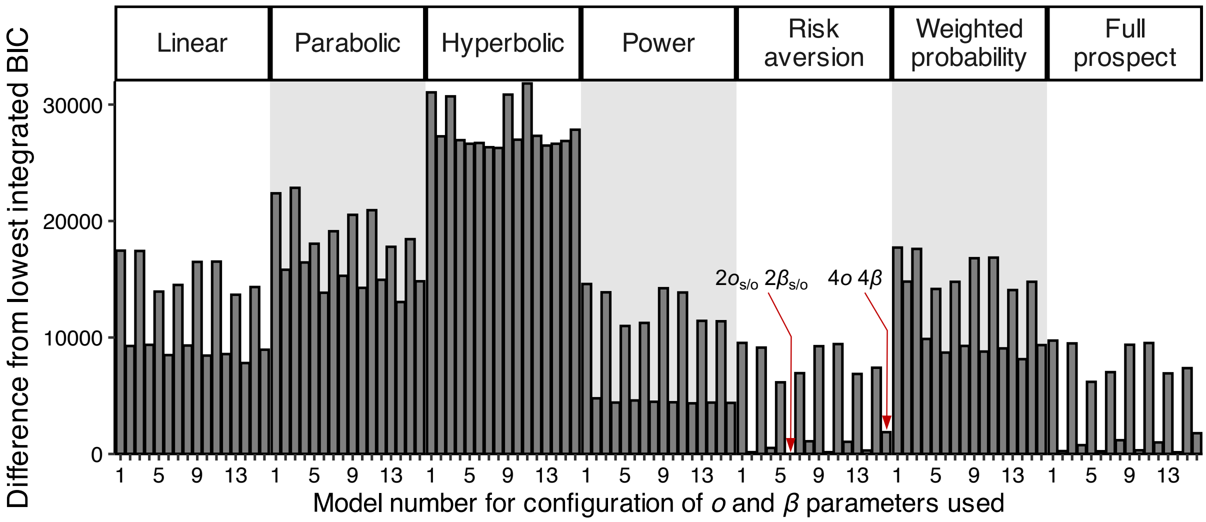

Figure S3. Summed integrated BIC scores for each model. Represented here are the differences in summed integrated BIC (BICint) scores from the model with the lowest summed BICint. The model that had separate opportunity cost and value sensitivity parameters for each recipient, but not each environment, as well as a risk aversion parameter had the lowest summed BICint. The model numbers 1-16 on the x-axis represent the following parameter combinations: **(1)** $1o$ 1β, **(2)** $2o_{s/o}$ 1β, **(3)** $2o_{p/r}$ 1β, **(4)** $4o$ 1β, **(5)** $1o$ $2\beta_{s/o}$, **(6)** $2o_{s/o}$ $2\beta_{s/o}$, **(7)** $2o_{p/r}$ $2\beta_{s/o}$, **(8)** $4o$ $2\beta_{s/o}$, **(9)** $1o$ $2\beta_{p/r}$, **(10)** $2o_{s/o}$ $2\beta_{p/r}$, **(11)** $2o_{p/r}$ $2\beta_{p/r}$, **(12)** $4o$ $2\beta_{p/r}$, **(13)** $1o$ 4β, **(14)** $2o_{s/o}$ 4β, **(15)** $2o_{p/r}$ 4β, **(16)** $4o$ 4β. The o and β parameters represent the opportunity cost and value sensitivity parameters, respectively. The s, o, p, and r subscript represent the self, other, poor, and rich conditions, respectively.

Table S9. *GLMM with reward magnitude and probability as separate effects (study 2)*

Fixed effect	**OR**	**CI low**	**CI high**	***z***	***p***
(Intercept)	1.89	1.17	1.23	5.38	< 0.001
Magnitude	2.31	5.52	10.04	13.88	< 0.001
Probability	7.89	0.25	0.74	27.44	< 0.001
Recipient	0.11	0.67	1.44	13.38	< 0.001
Environment	0.62	1.06	1.11	4.80	< 0.001
Magnitude × Probability	1.06	0.91	0.95	1.40	0.16
Magnitude × Recipient	0.98	0.63	1.39	0.38	0.70
Probability × Recipient	0.74	0.87	0.91	3.83	< 0.001
Magnitude × Environment	0.78	0.44	0.89	3.71	< 0.001
Probability × Environment	0.87	0.40	1.24	2.17	0.030
Recipient × Environment	0.80	0.93	0.98	1.30	0.19
Magnitude × Probability × Recipient	1.19	0.97	1.03	2.66	0.008
Magnitude × Probability × Environment	1.14	1.00	1.10	1.73	0.083
Magnitude × Recipient × Environment	0.79	0.47	1.71	1.91	0.056
Probability × Recipient × Environment	0.72	0.97	1.09	2.43	0.015
Magnitude × Probability × Recipient × Environment	0.74	1.17	1.23	2.31	0.021

Note. Magnitude and probability represent the reward's number of credits and probability, respectively. GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound.

Study 3

Table S10. *GLMM with reward magnitude and probability as separate effects (study 3)*

Fixed effect	**OR**	**CI low**	**CI high**	***z***	***p***
(Intercept)	0.12	0.08	0.19	9.17	< 0.001
Magnitude	1.20	1.17	1.23	15.49	< 0.001
Probability	7.40	5.52	10.04	13.27	< 0.001
Recipient	0.44	0.25	0.74	3.09	0.002
Environment	0.98	0.67	1.44	0.09	0.93
Magnitude × Probability	1.09	1.06	1.11	8.31	< 0.001
Magnitude × Recipient	0.93	0.91	0.95	5.73	< 0.001
Probability × Recipient	0.94	0.63	1.39	0.32	0.75
Magnitude × Environment	0.89	0.87	0.91	9.41	< 0.001
Probability × Environment	0.63	0.44	0.89	2.64	0.008
Recipient × Environment	0.71	0.40	1.24	1.20	0.23
Magnitude × Probability × Recipient	0.95	0.93	0.98	3.10	0.002
Magnitude × Probability × Environment	1.00	0.97	1.03	0.19	0.85
Magnitude × Recipient × Environment	1.05	1.00	1.10	1.90	0.058
Probability × Recipient × Environment	0.90	0.47	1.71	0.33	0.74
Magnitude × Probability × Recipient × Environment	1.03	0.97	1.09	0.90	0.37

Note. Magnitude and probability represent the reward’s number of credits and probability, respectively. GLMM: generalised linear mixed-effects model; OR: odds ratio; CI: 95% confidence interval lower/upper bound.