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Altruistic punishment in action: movement vigour in neuroeconomic choice

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Decision and action unfold in parallel, with movement vigour typically reflecting subjective value: the higher the subjective value assigned to an option, the greater the vigour in moving towards it. Here, we reveal a striking inversion of this classic vigour–value relationship in the context of altruistic punishment. In study 1, using a motor version of the Ultimatum Game, we found that vigour increased with offer amount when offers were accepted but decreased when offers were rejected (altruistic punishments). In study 2, we disentangled the factors driving this reversal using a social exchange task. We found that vigour during punishment was not determined by self-cost or other cost alone, but by the efficiency of punishment—the ratio of other cost to self-cost. These findings establish movement vigour as a dynamic read-out of social utility and demonstrate that social preferences can fundamentally reshape vigour–value mappings.

1. Introduction

How individuals move towards a choice option reveals their implicit preferences towards that option [1]. Both theoretical work and related experimental findings indicate that when making decisions, movement vigour—operationalized as response latency and movement speed—reflects the subjective value, or *utility*, assigned to a choice option [2]. For example, reaching movements performed towards an option which

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will deliver a reward exhibit both shorter response time and higher peak velocity as compared with movements towards a non-rewarded option [3–5]. Furthermore, when rewards are probabilistic, response time and velocity depend on expectation of reward at the conclusion of the movement. For example, in monkeys trained to make a saccade under reward uncertainty, saccade peak velocity increases with the probability of reward [6,7]. These findings suggest that movement vigour is shaped by the anticipated reward associated with a choice and thus may serve as a proxy for subjective economic utility [2].

However, real-world decisions rarely involve personal pay-offs alone. From punishing unfair behaviour to sacrificing one's own gain for others, humans routinely engage in decisions shaped by *social preferences*—decisions guided not just by personal reward, but also by the consequences for others [8–10]. Evidence across diverse societies [11] shows that individuals systematically deviate from choices that maximize their own material pay-offs to impact the pay-offs of others, either positively or negatively [12]. Altruistic costly punishment is a paradigmatic example of this phenomenon [13]: individuals willingly incur personal costs to sanction the unfair behaviour of others [14].

To date, whether movement vigour can capture social preferences remains unknown. While prior research has examined movement kinematics in social decision tasks (e.g. [15]), this work has concentrated on decoding social decisions, such as accepting or rejecting an offer, from movement patterns. Whether specific kinematic parameters, and movement vigour in particular, reflect the computation of social utility during the decision-making process itself remains unaddressed.

We reasoned that if movement vigour reflects a narrow utility function tied to subjective economic utility, it should scale only with anticipated self-pay-offs. Conversely, if it reflects a broader utility function that incorporates expectations about outcomes for others, it should vary as a function of both anticipated self- and other-pay-offs. To test these hypotheses, we combined behavioural analysis and movement kinematics across two studies to measure movement vigour in well-structured social decision tasks derived from economic game theory [16].

In study 1, we examined how self- and other-pay-off expectations are mapped onto the vigour of motor responses in the context of accepting and rejecting offers in an Ultimatum Game. In this game, a proposer is given a sum of money to be divided with a responder. The proposer makes an offer to the responder, who in turn must either accept or reject it. If the offer is accepted, the sum is divided as proposed. If it is rejected, neither player receives anything. In either event, the interaction is then over. In rejecting an offer, the responder punishes the proposer for their (presumably) unfair proposal, though this act comes at a personal cost. By analysing the kinematics of responders, we found a striking reversal in the typical vigour–value mapping: movement vigour increased with the offered amount for accepted offers (joint pay-offs) but decreased with the offered amount for rejected ones (costly punishments).

Study 2 was designed to reveal the factors driving this reversal. Specifically, we tested three hypotheses: during punishment, movement vigour reflects (i) the self-cost incurred to punish the other, (ii) the cost inflicted on the other, or (iii) the relationship between the two. The results clearly supported the third hypothesis: vigour systematically scaled with the efficiency of punishment, that is, the reduction in the partner's pay-off per unit of self-cost.

Taken together, these findings establish movement vigour as a continuous read-out of social utility in action and demonstrate that social preferences can fundamentally reshape vigour–value mappings.

2. Methods

2.1. Experimental model and subject details

Data included in study 1 were acquired from 21 participants (10 females; mean age ± s.d., 23.14 years ± 2.01 years). Data included in study 2 were acquired from 24 participants. Two participants in study 2 made 15 consecutive decisions not to punish, and their data were not analysed (see §2.2.2). Thus, the final sample in Study 2 consisted of 22 participants (11 females; mean age ± s.d., 22.77 ± 3.85). All participants were naive, right-handed and with either normal or adequately corrected vision. None had a history of neurological or psychiatric conditions. Written informed consent was obtained from each participant before the study, and all participants were debriefed at the end of the experiments due to deception. The study was conducted in compliance with the revised Helsinki Declaration (World Medical Association General Assembly, 2008) and received approval from the local ethics committee of Azienda Socio-Sanitaria Ligure 3 (ASL3 Genovese), Genoa, Italy. Participants received monetary compensation proportional to their earnings throughout the experiment.

2.2. Experimental design and procedures

2.2.1. Study 1

Study 1 represents an independent analysis of data from Turri *et al.* [15] and was designed to investigate how vigour varies as a function of the offer level for accepting and rejecting (punishments) decisions, in a motor version of the Ultimatum Game. A summary of the experimental design and procedures is provided below. We refer to Turri *et al.* [15] for full details.

Participants played a one-shot Ultimatum Game in the role of responders. They were informed that on each trial, a new proposer would receive 10 tokens and could offer 1, 2, 3, 4 or 5 tokens. Instructions made clear that if they accepted the offer, tokens would be split as proposed; if they rejected the offer, neither player would receive anything. Unbeknownst to participants, proposers were, in fact, computer-simulated and all participants received the same set of offers. Debriefing at the end of the experimental session revealed that only one participant (S008) suspected that the proposers were not real. We verified that excluding this participant does not influence any of the results.

Each participant completed two sessions, separated by a short break. Each experimental session comprised 12 control trials (six rightward, six leftward), followed by 68 Ultimatum Game trials. The set of offers included 12 one-token offers, 12 two-token offers, 12 three-token offers, 16 four-token offers and 16 five-token offers, emulating the offering patterns of human proposers [14]. The trials order was fully randomized for each participant. Participants responded by reaching, grasping and lifting one of the two cylinders labelled 'accept' and 'reject', located to the left and to the right of their body midline. The assignment of 'accept' and 'reject' labels to the cylinders was alternated between sessions for each participant, and their order was balanced across participants.

2.2.2. Study 2

Study 2 was designed to investigate how self-cost, other cost and their relationship (efficiency of punishment) influence the vigour of punishing decisions. Participants played an adaptation of an economic task designed to elicit costly punishment acts [17] in the role of trustors. On each trial, they were given 10 tokens and had to decide whether to keep their endowment (not to trust) or transfer it to a trustee (to trust). Transferring the endowment quadrupled the amount sent. The trustee who received the endowment then had the choice of sending back half (i.e. acting trustworthily) or retaining the entire amount (i.e. acting untrustworthily). Participants were told that they interacted with a different trustee in each trial, although the trustee was in fact computer-simulated and acted untrustworthily in 60% of the trials. They were informed that in trials in which the trustee acted untrustworthily, they would receive five additional tokens and would have the option to use part of these tokens to punish the trustee according to one of four different punishment conditions:

- Use two tokens to take 10 tokens from the trustee
- Use two tokens to take 20 tokens from the trustee
- Use four tokens to take 20 tokens from the trustee
- Use four tokens to take 40 tokens from the trustee

The allocation of these conditions was pseudo-randomized into trial sets, ensuring each condition appeared an equal number of times every 20 trials, to maintain a consistent proportion of conditions across all participants. These conditions generate the contrasts necessary to disentangle the effect of self-cost, other cost and efficiency of punishment (see table 1). In trials in which a trustee behaved trustworthily, no additional tokens were provided and no punishment option was available. Stimuli presentation and trial randomization were managed using E-Prime software.

Participants responded by reaching out, grasping a cylinder and moving it to one of two squared areas (15 × 15 cm), 'punish' (right) or 'do not punish' (left). The total number of trials was based on transfer (trusting) decisions, ensuring that each participant completed 100 transfer decisions. The experimental session was terminated earlier when participants reached 50 instances of choosing not to trust or made 15 consecutive decisions not to punish. We verified that punishment rates did not

Table 1. Punishment conditions.

self-cost	other cost	efficiency of punishment
2	10	5 : 1
2	20	10 : 1
4	20	5 : 1
4	40	10 : 1

differ between participants for whom the experiment was terminated early due to choosing not to trust and those who completed the session by choosing to trust ($t(20) = -0.35$, $p = 0.7305$). At the end of the experimental session, participants completed a series of test questions designed to assess their understanding of how decisions in the game influenced pay-offs (adapted from de Quervain *et al.* [17]; see electronic supplementary material, Supplemental Information). Before analysing the data, we verified their comprehension of the experimental procedures by reviewing their responses. Of the 22 participants, 6 made minor calculation errors. However, these errors did not indicate a misunderstanding of the instructions, supporting their inclusion in the subsequent analyses.

Finally, participants filled out a questionnaire adapted from de Quervain *et al.* [17] evaluating their response to the trustee's breach of trust (electronic supplementary material, Supplemental Information, Questionnaire). Using a seven-point Likert scale, participants rated their irritation (M = 4.64, s.d. = 1.59), disappointment (M = 4.73, s.d. = 1.64), desire to punish (M = 3.95, s.d. = 1.29), perceived unfairness (M = 4.95, s.d. = 1.53) and unkindness (M = 4.23, s.d. = 1.97). Internal consistency was good (Cronbach's $\alpha = 0.73$; electronic supplementary material, table S1), with all items contributing significantly except desire to punish, which showed lower item–total correlation. Given this, we computed a composite score indexing response to abuse of trust, excluding desire to punish and analysed desire to punish as a separate variable.

2.2.3. Kinematic data acquisition and preprocessing

We recorded movement kinematics using a near-infrared motion capture system equipped with eight cameras (acquisition frequency = 100 Hz; Motion Capture Vicon system). Participants sat on a height-adjustable chair, with their right hand resting on a table in a semi-prone position and the tips of the thumb and index finger touching as the initial position. The participant's right hand was outfitted with retro-reflective markers (4 mm in diameter). Cameras were positioned at about 1.5 m from the participant's location. Each trial was individually inspected for correct marker identification and then ran through a low-pass Butterworth filter with a 6–8 Hz cut-off. Wrist velocity was computed using custom software (Matlab; MathWorks, Natick, MA) as the module of the three-dimensional velocity vector for the marker placed on the radius (mm s^{-1}), from reach onset to reach offset. Reach onset was defined as the first time point at which wrist velocity exceeded 20 mm s^{-1}. Reach offset was defined as the time point closest to the target at which wrist velocity decreased below 20 mm s^{-1}. On trials in which velocity did not decrease below 20 mm s^{-1} towards target, the local minimum was used to define reach offset. Wrist peak velocity (PV) was calculated as the maximum wrist velocity (mm s^{-1}) attained during the reach-to-grasp phase for each movement. Response time (RT) was calculated as the interval between the presentation of the prompt (in study 1, e.g. 'Laura's offer is two tokens'; in study 2, e.g., 'You have been assigned five additional tokens. Do you want to give up four tokens to make 20 tokens be lost by LM?') and reach onset, in milliseconds.

2.3. Quantification and statistical analysis

2.3.1. Data screening and removal of outliers

Based on visual inspection of the kinematic profiles, 2.5% of trials in study 1 and 2.8% of trials in study 2 were excluded from RT and PV analysis due to anomalies in velocity profiles, buttons malfunctioning and execution errors (such as wrong fingers or left-hand usage). In both studies, measurements that fell outside the 1.5 interquartile range were removed for each subject (study 1: 3.92% of trials for

RT analysis, 1.31% of trials for PV analysis; study 2: 4.49% of trials for RT analysis, 2.13% of trials for PV analysis).

2.3.2. Logistic mixed-effect models for assessing statistical differences in the distribution of acceptance rates and punishment rates

To investigate the statistical differences in the distribution of acceptance rates (study 1) and punishment rates (study 2), we used logistic mixed-effect models (LMEM), that is, mixed models with a binomial distribution and a logit link function, as they are established tools to model binary stochastic decision variables (0/1) in each trial. In study 1, we considered single-trial decisions to accept or reject as dependent variable, offer level as fixed effect, and subject (random intercepts) as random effect. In Study 2, we considered single-trial choice to punish or not punish as the dependent variable, self-cost, efficiency of punishment and their interaction as fixed effects. The random-effects structure included subject-specific random intercepts and slopes for each trial set.

2.3.3. Generalized linear mixed models for assessing statistical differences in response time and peak velocity

To assess statistical differences in RT and PV, we used generalized linear mixed models (GLMMs). For RT, we used gamma mixed-effects models with a log-link function, which is well-suited for modelling positively skewed, non-negative data [18]. For PV, we fit our mixed models with a Gaussian distribution with an identity link function [19]. In both studies, RT and PV were analysed as dependent variables in separate models. In study 1, we considered the decision (accept, reject), the offer level and their interaction as fixed effects, movement direction as covariate and subjects (random intercepts) as random effects. Because in the Ultimatum Game, responders are explicitly informed that proposers can offer between one and five tokens—and because five tokens represent the maximum possible and therefore a fully fair offer—a rejection of a five-token offer cannot be interpreted as costly punishment of unfairness. For this reason, five-token rejections (less than 1% of the dataset) were not included in these analyses. To ensure robustness, we verified that including these trials did not change the pattern of results. The results of these supplementary analyses are provided in electronic supplementary material, tables S12 and S13. In study 2, we considered self-cost, efficiency of punishment and their interaction as fixed effects, and subject random intercepts and slopes for trial sets as random effects.

2.3.4. Selection of random-effects structure and significance of fixed effects in mixed-effect models

First, we determined the random-effects structure by comparing the Bayesian information criterion (BIC) values from the most complex to the null model and selecting the one with the lowest BIC (see random effect structure selection in electronic supplementary material, tables S2–S11). Next, we assessed the significance of all fixed effects using likelihood-ratio tests (LRT) between models that differed by only one predictor at a time [20,21] (see fixed effects significance in electronic supplementary material, tables S2–S11). The effects of response to abuse of trust and desire to punish were tested separately by including them as fixed effects interacting with effectiveness of punishment in our GLMMs for both RT and PV. Model fitting was performed using the *lmer* and *glmer* functions from the R package *lme4* [22], 2015), using the *BOBYQA* optimizer. All the categorical factors were encoded by using the *sum contrasts* method to simplify comparisons between two levels of each factor [23]. All continuous variables were centred to reduce collinearity and enhance convergence and interpretability [24]. Statistical comparisons against chance and across levels were conducted using the R package *emmeans*.

2.3.5. Significance of correlations

We assessed the significance of correlation coefficients applying two-sided parametric Student's t-tests for Pearson correlations and the asymptotic t approximation for Spearman correlations. We used the *cor.test* built-in function in R to perform these calculations.

2.3.6. Conventions for p values

All statistical comparisons report two-sided, Holm–Bonferroni corrected p-values. Electronic supplementary material, tables S2–S11, provides the details of the mixed-effects models (BICs for the random structure selection, LRTs for significance of main effects and interactions, *post hoc* analyses and final model summaries including fixed effect estimates (est), s.e., z-values (for GLMMs), t-values (for LMMs) and p-values derived from Wald tests).

3. Results

3.1. Costly punishment in the Ultimatum Game

In study 1, participants played a motor version of the Ultimatum Game in the role of responder [15]. We first examined behavioural choices. Consistent with what is typically found in previous studies [14], acceptance rates—defined as the number of accepted offers divided by the number of proposed offers across each offer amount—increased significantly with higher offer amounts ($\beta = 1.95$, s.e. = 0.08, $\chi^2(1) = 1691.4$, $p < 0.001$) (figure 1c and electronic supplementary material, table S2).

3.2. Costly punishment reverses the relationship between offered amount and movement vigour

Participants accepted or rejected the proposed offer by reaching, grasping and then lifting one of two objects. To examine the vigour of response to both accepted and rejected offers, we next analysed the RTs and PVs of reach-to-grasp actions. For accepted offers, we hypothesized, consistent with previous work [2], that movement vigour would increase as a function of the offered amount (figure 1a). For rejected offers, we considered three hypotheses (figure 1a). If vigour scales with the offered amount irrespective of the decision to accept or reject, then the relationship between vigour and offer level for rejected offers should mirror that for accepted offers. In this scenario, we would expect vigour to increase with offer amount even when offers are rejected (H1). Alternatively, if vigour scales with the negative consequences (self-cost) associated with rejecting an offer, then the patterns should reverse: vigour should decrease as the rejected offer amount increases (H2). Finally, it is possible that rejecting the offer simply destroys the relationship between movement vigour and utility. Under this hypothesis (H3), variations in offer amount should not be predictive of variations in movement vigour.

GLMMs revealed a significant interaction between decision (accept, reject) and offer amount (from 1 to 5) for both RT ($\beta = -0.05$, s.e. = 0.01, $\chi^2(1) = 86.05$, $p < 0.001$) and PV ($\beta = 5.43$, s.e. = 1.56, $\chi^2(1) = 12.08$, $p < 0.001$) (figure 1d and electronic supplementary material, tables S3 and S4). Specifically, for accepted offers, higher offered amounts resulted in faster RTs and higher PVs; for rejected offers, higher offered amounts resulted in slower RTs (est = −0.09, s.e. = 0.01, z = −9.30, $p < 0.001$) and lower PVs (est = 10.9, s.e. = 3.13, $t = 3.48$, $p < 0.001$). These results suggest a reversal in the mapping between offer amount and vigour for rejected offers: whereas movement vigour increased with offer amount for accepted offers, it decreased with offer amount for rejected offers. Rejecting a higher offer is subjectively more costly than rejecting a lower one. Consistent with H2, one possible explanation of this reversal is therefore that, for rejected offers, movement vigour decreases as self-cost increases. There are, however, alternative explanations to consider. Study 2 was designed to disentangle these competing explanations.

3.3. A design to dissociate self-cost, other cost and efficiency of punishment

In each round of the Ultimatum Game, the cost incurred by the responder to punish the proposer (self-cost) is always complementary to the cost inflicted on the proposer (other cost). For instance, if the responder rejects an offer of 1, the proposer loses 9 (1,9), if the responder rejects an offer of 2, the proposer loses 8 (2,8) and so on up to an equal split (5,5). This structure makes it impossible to dissociate the influence of self-cost from that of other cost. The negative dependency of vigour on offer amount observed in study 1 could reflect the increasing self-cost (from 1 to 5), the decreasing cost inflicted on the other (from 9 to 5), or the relationship between the two. This last possibility is captured by the concept of efficiency of punishment, defined as the ratio of other cost to self-cost (impact-to-cost ratio) [25–27]. From this perspective, movement vigour would not track self-cost or other cost *per se*,

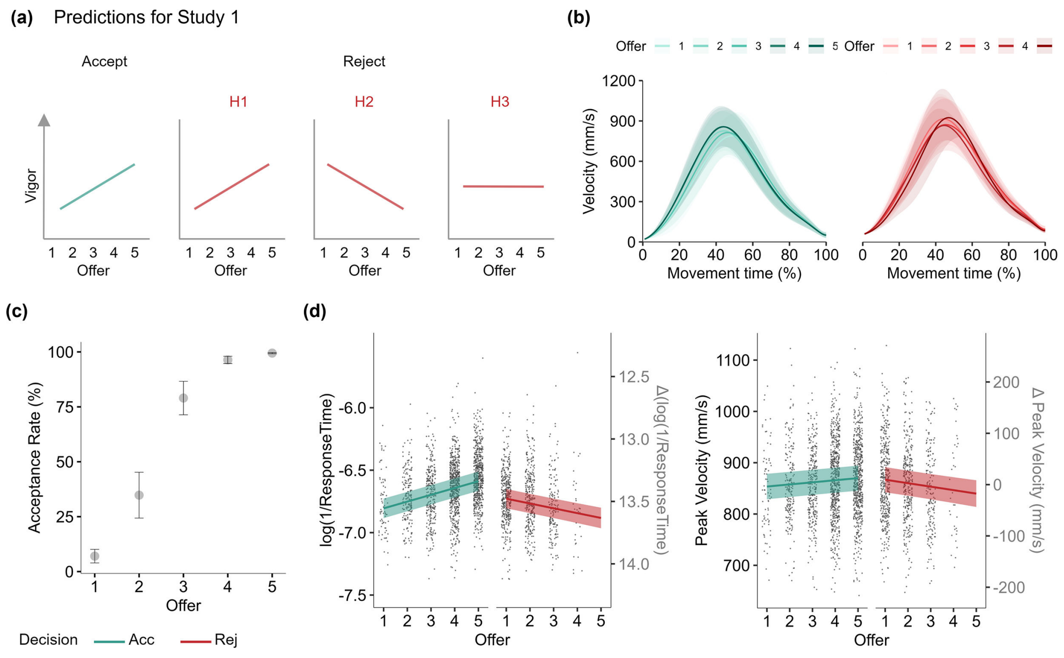

Figure 1. Vigour reflects offer amount differently for accepted and rejected offers in the Ultimatum Game (study 1). (a) Hypotheses on the relationship between movement vigour and offer amount depending on the choice. For accepted offers, we hypothesized that vigour would increase with offer amount. For rejected offers, we considered three hypotheses: vigour increases with offer amount (H1); vigour decreases with offer amount (H2); vigour is not influenced by offer amount (H3). (b) Velocity profiles of reaching movements for accepted and rejected offers across all participants. Lines show across-subject mean velocity for each offer level (colour shades), and shaded ribbons indicate s.d. (c) Acceptance rates (%) as a function of offer amount in the Ultimatum Game. Data are represented as estimated marginal means ± s.e.m. over trials and participants. (d) Log of inverse response time (RT) and peak velocity (PV) for accepted and rejected offers by offer amount. Mean lines and shaded areas represent estimated marginal means ± s.e.m. at the population level (left *y* axis). Grey dots represent individual trial data points referenced to the subject-specific intercept, aligned with the general intercept (0 of the right y axis). Since PV reflects vigour directly and RT inversely, RT is plotted as the log of inverse RT to align with hypotheses in (a).

but rather the expected efficiency of the punitive action. Under this account, the pattern observed in study 1 would reflect the efficiency of punishing actions: rejecting an offer of 1 is highly efficient (9 : 1 impact-to-cost ratio) and elicits greater vigour, whereas rejecting fairer offers becomes progressively less efficient (5 : 5 ratio for an offer of 5) and is associated with reduced vigour.

To disentangle between these hypotheses, in study 2, we designed a social economic exchange task based on a modified Trust Game [17] to elicit costly punishment under separate manipulations of self-cost, other cost and efficiency of punishment. In this task, after participants chose to trust a trustee by transferring their money, the trustee could break this trust by keeping the entire amount instead of splitting it equally. Consistent with previous research [17], we expected that receiving nothing back would evoke in the trustor a desire to punish the trustee. The trustor received five additional tokens and, depending on the condition, could use either two or four of these to punish the trustee. We manipulated the efficiency of punishment by adjusting the ratio of tokens deducted from the trustee to tokens spent by the trustor, using either a 5 : 1 or 10 : 1 ratio. Consequently, spending two or four tokens resulted in a cost to the other player of 10, 20 or 40 tokens.

By orthogonalizing self-cost and efficiency of punishment, this design enabled us to generate the contrasts necessary to disentangle the influence of self-cost, other cost and efficiency of punishment (figure 2a and table 1). Specifically, if self-cost underlies the vigour of costly punishments, we would expect participants to move more vigorously when self-cost is lower (main effect of self-cost; H1) (figure 2a). If other costs underlie vigour, we would expect vigour to increase linearly with other costs, as reflected by the interaction between self-cost and efficiency of punishment (H2). Finally, if the efficiency of punishment underlies vigour, we would expect participants to move more vigorously when punishing with high efficiency compared with low efficiency (main effect of efficiency of punishment; H3).

Behavioural analysis of punishment rates—defined as the percentage of punishment decisions relative to the total of opportunities to punish—revealed a main effect of efficiency of punishment,

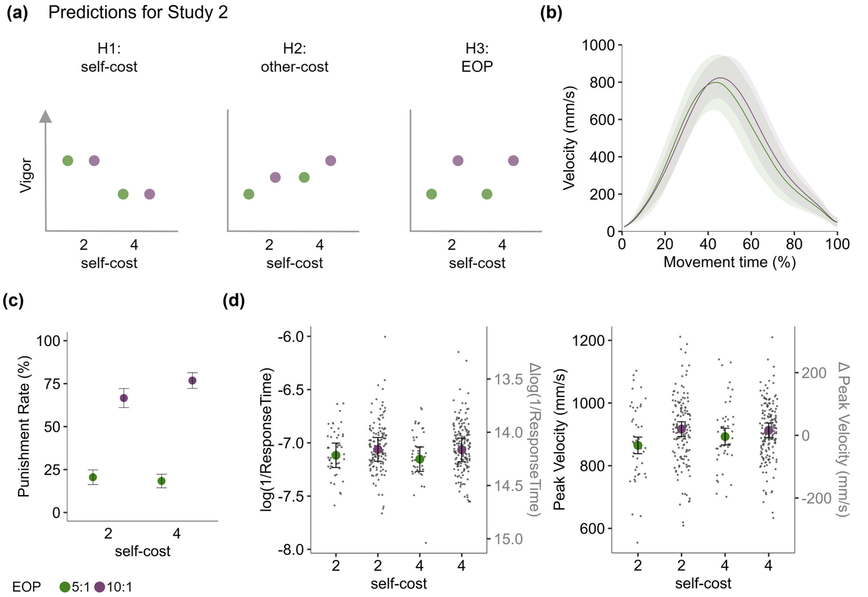

Figure 2. Predictions and results for the vigour of costly punishment under orthogonal manipulations of self-cost and efficiency of punishment (Study 2). (a) Hypotheses derived from manipulations of self-cost and efficiency of punishment. These manipulations enabled us to generate the contrasts necessary to disentangle the effect of self-cost (H1), other cost (H2) and efficiency of punishment (EOP) (H3). (b) Velocity profiles of reaching movements to costly punish unfair trustees coloured by EOP. Lines show the across-subject mean velocity for low and high EOP, and shaded ribbons indicate s.d. (c) Punishment rates (%) under orthogonal manipulations of self-cost (2,4) and EOP (5 : 1, 10 : 1). Data are represented as estimated marginal means ± s.e.m. over trials and participants. (d) Log of inverse RT and PV under orthogonal manipulations of self-cost and EOP. Coloured dots and error bars represent estimated marginal means ± s.e.m. at the population level (left y axis). Grey dots represent individual trials referenced to the subject-specific intercept, centred to the general intercept that is set as zero (right y axis). The y axes show the log of inverse response time to facilitate direct interpretation in line with the hypotheses in (a).

with higher punishment rates observed when the efficiency of punishment was higher (10 : 1) (β = −1.18, s.e. = 0.08, $\chi^2(1)$ = 243.82, $p < 0.001$). This effect was further qualified by an interaction with self-cost (β = 0.16, s.e. = 0.08, $\chi^2(1)$ = 4.15 , p = 0.042), with punishment rates peaking when the cost inflicted on the trustee was highest (4 self-cost, 10 : 1 efficiency of punishment) (est = 0.10, s.e. = 0.04, z = 2.35, p = 0.038) (figure 2c and electronic supplementary material, table S5). In this condition, trustors using four tokens impose a loss of 40 tokens on trustees. As expected, participants who reported a stronger desire to punish in the post-experiment questionnaire exhibited higher punishment rates (r = 0.51, p = 0.014, adjusted p = 0.029), whereas no such relationship was found for those reporting a higher response to abuse of trust (r = −0.21, p = 0.34, adjusted p = 0.34).

3.4. Efficiency of punishment controls movement vigour

Tracking movement vigour under orthogonal manipulations of self-cost and efficiency of punishment revealed a main effect of efficiency of punishment on both RT (β = 0.04, s.e. = 0.01, $\chi^2(1)$ = 6.19, p = 0.013) and PV (β = −17.98, s.e. = 6.45, $\chi^2(1)$ = 7.61, p = 0.006). As shown in figure 2d, participants responded with faster RTs and higher PVs when punishing with higher efficiency (10 : 1) compared with lower efficiency (5 : 1) (electronic supplementary material, tables S6 and S7). Neither the main effect of self-cost (RT: β = −0.01, s.e. = 0.01, $\chi^2(1)$ = 0.59, p = 0.444; PV: β = −6.04, s.e. = 5.92, $\chi^2(1)$ = 0.04, p = 0.308) nor the interaction between self-cost and efficiency of punishment (RT: β = 0.01, s.e. = 0.01, $\chi^2(1)$ = 0.37, p = 0.545; PV: β = −7.94, s.e. = 5.87, $\chi^2(1)$ = 1.84, p = 0.175) approached significance. Together, these results indicate a direct influence of efficiency of punishment on movement vigour and suggest that efficiency of punishment rather than self-cost or other cost is the primary factor controlling the vigour of costly punishment.

We further examined whether self-reported desire to punish and response to abuse of trust, as measured in the post-experiment questionnaire, modulated the effect of efficiency of punishment on movement vigour. Desire to punish significantly interacted with efficiency of punishment (EOP) for PV (β = 15.40, s.e. = 4.88, $\chi^2(1)$ = 9.69, p = 0.002). Specifically, a stronger desire to punish was associated with higher PVs under lower efficiency of punishment (5 : 1), but not under higher efficiency (10 : 1) (est = 30.8, s.e. = 9.8, t = 3.14, p = 0.002) (electronic supplementary material, table S9), suggesting that desire to punish amplified movement vigour particularly when punishment was less effective. For RTs, the interaction between desire to punish and EOP did not approach significance (β = −0.02, s.e. = 0.01, $\chi^2(1)$ = 2.35, p = 0.125) (electronic supplementary material, table S8). Response to abuse of trust did not significantly modulate the effect of EOP on either RT (β = −0.00, s.e. = 0.01, $\chi^2(1)$ = 0.00, p = 0.976) or PV (β = 4.10, s.e. = 5.34, $\chi^2(1)$ = 0.58, p = 0.447) (electronic supplementary material, tables S10 and S11).

4. Discussion

Decision and action are increasingly understood to unfold in parallel, with motor parameters reflecting cognitive evaluations in real time [2]. Our findings offer new insight into how social preferences are expressed through action. While previous research has shown that movement vigour increases with subjective utility in self-regarding decisions [1], it remained unknown whether—and how—such mappings extend to other-regarding decisions. Here, we introduce a novel framework to investigate this question.

Using costly punishment as a model for other-regarding decisions, Study 1 showed that in a motor version of the Ultimatum Game, movement vigour increased with offer amount when participants accepted these offers but decreased with offer amount when they rejected them. This motor reversal indicates that social preferences can fundamentally reshape the standard reward–vigour mapping observed in self-regarding decisions.

Study 2 was designed to disentangle the mechanisms driving this remapping. In the Ultimatum Game, the cost incurred by the responder to punish the proposer is inherently coupled with the cost inflicted on the proposer, making it impossible to disentangle whether self-cost, other cost or their ratio governs the vigour–offer relationship. To dissociate these factors, in study 2, we used a modified socio-economic exchange task. Results showed that the vigour of altruistic punishment was not driven by self-cost or other cost in isolation but by their ratio—the efficiency of punishment. Higher punishment efficiency elicited more vigorous responses, whereas lower efficiency led to reduced vigour.

Critically, the kinematic pattern dissociated from the pattern of punishment rates, which were highest when the absolute cost to the other was greatest (40 other cost). This dissociation suggests that the decision to punish and the vigour with which the punishment is enacted rely on partially distinct computations. Whereas the decision to punish is primarily driven by the other cost, the vigour with which the decision is enacted reflects a computation that weighs other cost against self-cost. This interpretation aligns with prior work suggesting a dynamic interplay between emotional and cognitive processes in altruistic punishment [9]. Emotional processes such as resentment [14], physiological arousal [28], anticipated satisfaction from punishing defectors [17] and impulsiveness [29] motivate the initial decision to punish. In implementing this decision, however, the motor system integrates the costs inflicted on the other with the cost they must bear themselves. Movement vigour—quantified through response times and peak movement velocities—provides a continuous read-out [2] of how participants implicitly balance these costs. A methodological advantage of estimating punishment efficiency from vigour is that vigour, unlike aggregate measures such as punishment rate, can be measured at the single-trial level. This enables direct linking of efficiency computations to single-trial neural activity [30,31].

A plausible neural substrate for these computations lies in corticostriatal circuits modulated by dopamine. Converging evidence shows that dopamine signalling in these circuits influences both how rewards and effort costs are weighted during action selection [32] and how vigorously the resulting actions are executed [33–35]. These circuits also support altruistic punishment, specifically the trade-off between the satisfaction of punishing norm violators and the monetary cost incurred to do so: dorsal striatal activity tracks the anticipated reward of punishing, whereas prefrontal regions are engaged in weighing emotional satisfaction against financial costs incurred to punish [17]. Further support for a role of dopaminergic modulation, dopamine depletion in Parkinson's disease (PD) gives rise to alterations in both movement vigour [1] and altruistic punishment [36]. Our approach could be used to reveal the specific computations influenced by dopamine signalling. For example, it could help determine whether changes in altruistic punishment in PD stem from altered representations of self-costs, reduced sensitivity to other costs or disruptions in integrating these quantities into a single social utility signal.

The efficiency of punishment is a key determinant of punishment behaviour and a crucial parameter for the maintenance of cooperation [25–27]. While some individuals engage in punishment even when it is inefficient (e.g. when self-cost is equal to other cost, such as in a 1 : 1 efficiency ratio) [27], punishment rates generally increase with efficiency of punishment [26]. Crucially, the efficiency of punishment directly influences the threshold level at which people decide to punish [25]: when punishment is more efficient, individuals are willing to sanction even minor deviations from cooperation, whereas when it is less efficient, they tolerate greater free-riding. This directly impacts the stability of cooperative behaviour [25], which requires that sufficiently many individuals are willing to pay a cost to punish defectors [37]. Movement vigour externalizes the computation of punishment efficiency [30,38], raising the possibility that vigour may serve as a communicative signal [39]. This aligns with theories of costly signalling [40,41] and more generally with the notion that people expect punishment to be constructed and interpreted as a communicative act [39]. Future research should investigate whether and how observers do indeed perceive and interpret the vigour of others' actions, and to what extent individuals may strategically alter their movement vigour to amplify the communicative intent embedded in punishment acts.

Taken together, these findings extend theories of reward-based vigour modulation beyond self-regarding contexts, demonstrating that vigour reflects not just subjective utility, but a broader function that incorporates social preferences. A long-standing tradition in economic theory holds that preferences are impossible to measure directly [12]. Our results challenge this assumption of unobservability [42,43], demonstrating that movement vigour captures how individuals implicitly balance self-costs against the consequences for others. Replicating this effect in larger samples, across different cultural contexts and age ranges, will be essential to establish movement vigour as a direct, continuous measure of socially weighted preferences.

Ethics. The study was conducted in compliance with the revised Helsinki Declaration (World Medical Association General Assembly, 2008) and received approval from the ASL 3 Genovese ethical committee.

Data accessibility. Data and R Code for the main analyses are available via the github link https://github.com/opansardi/vigor.

Supplementary material is available online [44].

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. O.P.: conceptualization, formal analysis, investigation, writing—original draft; A.C.: conceptualization, methodology, writing—review and editing; G.T.: methodology; S.P.: formal analysis, methodology, supervision, writing—review and editing; A.G.S.: conceptualization, writing—review and editing; C.B.: conceptualization, funding acquisition, supervision, writing—original draft, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

Conflict of interest declaration. We declare we have no competing interests.

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References

1. Shadmehr R, Reppert TR, Summerside EM, Yoon T, Ahmed AA. 2019 Movement vigor as a reflection of subjective economic utility. *Trends Neurosci.* **42**, 323–336. (doi:10.1016/j.tins.2019.02.003)
2. Shadmehr R, Ahmed AA. 2021 Précis of vigor: neuroeconomics of movement control. *Behav. Brain Sci.* **44**, e123. (doi:10.1017/S0140525X20000667)
3. Sackaloo K, Strouse E, Rice MS. 2015 Degree of preference and its influence on motor control when reaching for most preferred, neutrally preferred, and least preferred candy. *OTJR* **35**, 81–88. (doi:10.1177/1539449214561763)
4. Summerside EM, Shadmehr R, Ahmed AA. 2018 Vigor of reaching movements: reward discounts the cost of effort. *J. Neurophysiol.* **119**, 2347–2357. (doi:10.1152/jn.00872.2017)
5. Summerside EM, Courter RJ, Shadmehr R, Ahmed AA. 2024 Slowing of movements in healthy aging as a rational economic response to an elevated effort landscape. *J. Neurosci.* **44**, e1596232024. (doi:10.1523/JNEUROSCI.1596-23.2024)
6. Korbisch CC, Apuan DR, Shadmehr R, Ahmed AA. 2022 Saccade vigor reflects the rise of decision variables during deliberation. *Curr. Biol.* **32**, 5374–5381. (doi:10.1016/j.cub.2022.10.053)
7. Seideman JA, Stanford TR, Salinas E. 2018 Saccade metrics reflect decision-making dynamics during urgent choices. *Nat. Commun.* **9**, 2907. (doi:10.1038/s41467-018-05319-w)
8. Fehr E, Schmidt KM. 1999 A theory of fairness, competition, and cooperation. *Q. J. Econ.* **114**, 817–868. (doi:10.1162/003355399556151)
9. Sanfey AG. 2007 Social decision-making: insights from game theory and neuroscience. *Science* **318**, 598–602. (doi:10.1126/science.1142996)

10. Vahed S, Galván EP, Sanfey AG. 2024 Computational modeling of social decision-making. *Curr. Opin. Psychol.* **60**, 101884. (doi:10.1016/j.copsyc.2024.101884)
11. Henrich J *et al*. 2005 'Economic man' in cross-cultural perspective: behavioral experiments in 15 small-scale societies. *Behav. Brain Sci.* **28**, 795–815. (doi:10.1017/S0140525X05000142)
12. Fehr E, Camerer CF. 2007 Social neuroeconomics: the neural circuitry of social preferences. *Trends Cogn. Sci.* **11**, 419–427. (doi:10.1016/j.tics.2007.09.002)
13. Fehr E, Gächter S. 2002 Altruistic punishment in humans. *Nature* **415**, 137–140. (doi:10.1038/415137a)
14. Sanfey AG, Rilling JK, Aronson JA, Nystrom LE, Cohen JD. 2003 The neural basis of economic decision-making in the ultimatum game. *Science* **300**, 1755–1758. (doi:10.1126/science.1082976)
15. Turri G, Cavallo A, Romeo L, Pontil M, Sanfey A, Panzeri S, Becchio C. 2022 Decoding social decisions from movement kinematics. *iScience* **25**, 105550. (doi:10.1016/j.isci.2022.105550)
16. Rilling JK, Sanfey AG. 2011 The neuroscience of social decision-making. *Annu. Rev. Psychol.* **62**, 23–48. (doi:10.1146/annurev.psych.121208.131647)
17. de Quervain DJF, Fischbacher U, Treyer V, Schellhammer M, Schnyder U, Buck A, Fehr E. 2004 The neural basis of altruistic punishment. *Science* **305**, 1254–1258. (doi:10.1126/science.1100735)
18. Ng VKY, Cribbie RA. 2017 Using the gamma generalized linear model for modeling continuous, skewed and heteroscedastic outcomes in psychology. *Curr. Psychol.* **36**, 225–235. (doi:10.1007/s12144-015-9404-0)
19. Lo S, Andrews S. 2015 To transform or not to transform: using generalized linear mixed models to analyse reaction time data. *Front. Psychol.* **6**, 1171. (doi:10.3389/fpsyg.2015.01171)
20. Agresti A. 2007 Generalized linear models. In *An introduction to categorical data analysis* (ed. A Agresti), pp. 65–98. Hoboken, NJ: John Wiley & Sons. (doi:10.1002/0470114754)
21. Schwarz G. 1978 Estimating the dimension of a model. *Ann. Statist.* **6**, 461–464. (doi:10.1214/aos/1176344136)
22. Bates D, Mächler M, Bolker B, Walker S. 2015 Fitting linear mixed-effects models using lme4. *J. Stat. Soft* **67**, 1–48. (doi:10.18637/jss.v067.i01)
23. Schad DJ, Vasishth S, Hohenstein S, Kliegl R. 2020 How to capitalize on a priori contrasts in linear (mixed) models: a tutorial. *J. Mem. Lang.* **110**, 104038. (doi:10.1016/j.jml.2019.104038)
24. Dalal DK, Zickar MJ. 2012 Some common myths about centering predictor variables in moderated multiple regression and polynomial regression. *Organ. Res. Methods* **15**, 339–362. (doi:10.1177/1094428111430540)
25. Egas M, Riedl A. 2008 The economics of altruistic punishment and the maintenance of cooperation. *Proc. R. Soc. B* **275**, 871–878. (doi:10.1098/rspb.2007.1558)
26. Falk A, Fehr E, Fischbacher U. 2005 Driving forces behind informal sanctions. *Econometrica* **73**, 2017–2030. (doi:10.1111/j.1468-0262.2005.00644.x)
27. Weber TO, Weisel O, Gächter S. 2018 Dispositional free riders do not free ride on punishment. *Nat. Commun.* **9**, 2390. (doi:10.1038/s41467-018-04775-8)
28. van 't Wout M, Kahn RS, Sanfey AG, Aleman A. 2006 Affective state and decision-making in the Ultimatum Game. *Exp. Brain Res.* **169**, 564–568. (doi:10.1007/s00221-006-0346-5)
29. Crockett MJ, Clark L, Lieberman MD, Tabibnia G, Robbins TW. 2010 Impulsive choice and altruistic punishment are correlated and increase in tandem with serotonin depletion. *Emotion* **10**, 855–862. (doi:10.1037/a0019861)
30. Becchio C, Pullar K, Scaliti E, Panzeri S. 2024 Kinematic coding: measuring information in naturalistic behaviour. *Phys. Life Rev.* **51**, 442–458. (doi:10.1016/j.plrev.2024.11.009)
31. Sanchez Jimenez A, Fernández Serra E, Quian Quiroga R. 2025 A new approach to quantify information in real-life, complex neuroscience processes. *Phys. Life Rev.* **53**, 236–238. (doi:10.1016/j.plrev.2025.03.014)
32. Treadway MT *et al*. 2012 Dopaminergic mechanisms of individual differences in human effort-based decision-making. *J. Neurosci.* **32**, 6170–6176. (doi:10.1523/JNEUROSCI.6459-11.2012)
33. da Silva JA, Tecuapetla F, Paixão V, Costa RM. 2018 Dopamine neuron activity before action initiation gates and invigorates future movements. *Nature* **554**, 244–248. (doi:10.1038/nature25457)
34. Manohar SG, Chong TTJ, Apps MAJ, Batla A, Stamelou M, Jarman PR, Bhatia KP, Husain M. 2015 Reward pays the cost of noise reduction in motor and cognitive Control. *Curr. Biol.* **25**, 1707–1716. (doi:10.1016/j.cub.2015.05.038)
35. Mazzoni P, Hristova A, Krakauer JW. 2007 Why don't we move faster? Parkinson's disease, movement vigor, and implicit motivation. *J. Neurosci.* **27**, 7105–7116. (doi:10.1523/JNEUROSCI.0264-07.2007)
36. Djamshidian A, O'Sullivan SS, Doherty K, Lees AJ, Averbeck BB. 2011 Altruistic punishment in patients with Parkinson's disease with and without impulsive behaviour. *Neuropsychologia* **49**, 103–107. (doi:10.1016/j.neuropsychologia.2010.10.012)
37. Boyd R, Gintis H, Bowles S, Richerson PJ. 2003 The evolution of altruistic punishment. *Proc. Natl Acad. Sci. USA* **100**, 3531–3535. (doi:10.1073/pnas.0630443100)
38. Scaliti E, Pullar K, Borghini G, Cavallo A, Panzeri S, Becchio C. 2023 Kinematic priming of action predictions. *Curr. Biol.* **33**, 2717–2727. (doi:10.1016/j.cub.2023.05.055)
39. Sarin A, Ho MK, Martin JW, Cushman FA. 2021 Punishment is organized around principles of communicative inference. *Cognition* **208**, 104544. (doi:10.1016/j.cognition.2020.104544)
40. Zahavi A. 1975 Mate selection—a selection for a handicap. *J. Theor. Biol.* **53**, 205–214. (doi:10.1016/0022-5193(75)90111-3)

41. Grafen A. 1990 Biological signals as handicaps. *J. Theor. Biol.* **144**, 517–546. (doi:10.1016/s0022-5193(05)80088-8)

42. Becchio C, Koul A, Ansuini C, Bertone C, Cavallo A. 2018 Seeing mental states: an experimental strategy for measuring the observability of other minds. *Phys. Life Rev.* **24**, 67–80. (doi:10.1016/j.plrev.2017.10.002)

43. Gordon J, Maselli A, Lancia GL, Thiery T, Cisek P, Pezzulo G. 2021 The road towards understanding embodied decisions. *Neurosci. Biobehav. Rev.* **131**, 722–736. (doi:10.1016/j.neubiorev.2021.09.034)

44. Pansardi O, Cavallo A, Turri G, Panzeri S, Sanfey AG, Becchio C. 2026 Supplementary material from: Altruistic punishment in action: movement vigor in neuroeconomic. Figshare. (doi:10.6084/m9.figshare.c.8351256)