Title

Think green: Investing cognitive effort for a pro-environmental cause

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Abstract

Despite the overwhelming evidence and recommendations to respond to the global climate challenges, the implementation of pro-environmental behavior (PEB) remains difficult for many individuals. One key notion in this context is that the reconfiguration of behavior generally requires cognitive effort. In a preregistered study entailing both laboratory and online samples we tested in how far participants are willing to invest cognitive effort for a pro-environmental cause (eco reward) and how this differs from cognitive effort for personal outcomes (own reward). Both eco and own reward led to response speeding and reduction of interference compared to no reward trials in a cognitive control task. However, the speeding effect was significantly smaller for eco reward trials, resonating with the notion that pro-environmental outcomes have a lower motivational value than personal ones – despite equal probability and magnitude of the associated monetary incentive. While present in the full sample, this difference was most pronounced in the online sample, which might reflect a weaker contribution of social desirability in this context. By singling out cognitive effort and the inherent costs thereof (rather than temporal and/or financial costs), the current paradigm can be used to test which factors and interventions might increase or decrease the willingness to allocate cognitive resources towards pro-environmental goals – which is key for initiating and also maintaining behavioral change.

Keywords: Cognitive effort, pro-environmental behavior, Reward, Stroop task, Inter-individual differences

Introduction

The climate crisis is a major focus not only in the political and public arenas, but also in different research fields, ranging from engineering and agriculture to economics and psychology. Large-scale contextual factors play an important role in addressing the crisis and providing sustainable solutions, such as financial resources and necessary infrastructure, access to relevant information and ecological alternatives, as well as social identity (Amel, Manning, Scott, & Koger, 2017; Fritsche, Barth, Jugert, Masson, & Reese, 2018; Nielsen et al., 2021). However, there is also the room and necessity for individual behavioral change, which in turn can contribute to wide-reaching changes, as the societal consensus shifts. One intriguing observation in pro-environmental behavior (PEB) research in cognitive psychology and related fields is the dissonance between knowledge and awareness of problems like global warming, shortage of fossil energy sources, and shrinking biodiversity on the one hand, and changes in individual behavior (as well as broader policies) that are needed to counteract the negative development on the other hand. So the question arises why some people do engage in PEB or promote pro-environmental goals, while others do not – despite a similar level of knowledge.

One factor that is embedded more or less explicitly in several frameworks of PEB is how *costly* certain behaviors are perceived. In one of the most prominent frameworks of PEB, the Theory of Planned Behavior (Ajzen, 1991), costs are implicitly reflected in the factor of perceived behavioral control, in that different behaviors appear to be more or less hard to implement. Diekmann and Preisendoerfer (1992) investigated the effect of differential expected costs directly showing that that the correlative relationship between pro-environmental attitudes and pro-environmental actions is highest for low-cost actions such as recycling and decreases for more effortful ones (Diekmann & Preisendoerfer, 1992). However, this specific relationship has been challenged for instance by the work Kaiser and colleagues (Campbell's paradigm, Kaiser, 2021; Taube, Kibbe, Vetter, Adler, & Kaiser, 2018), where behavior-specific costs (such as time, money, exertion) as well as the actor's attitude are independent predictors of PEB. Costs have also been manipulated in other experimental work on PEB, in form of financial costs (e.g., foregoing incentives to support a pro-environmental goal, Dorner, 2019; Wyss, Knoch, & Berger, 2022) or temporal costs (e.g., waiting time or task duration, Gulliver, Chapman, Solly, & Schultz, 2020; Lange & Dewitte, 2022; Lange, Steinke, & Dewitte, 2018; Taube et al., 2018). Without elaborating on the different nuances, a common pattern is that increasing the (expected) costs will diminish the probability of PEB.

In the present study, we focus on a specific form of costs that has – to the best of our knowledge - not yet been studied systematically in the context of PEB, namely the cost that is inherent to *cognitive effort*. Specifically, in addition to financial investments (e.g., buying solar panels) and physical effort (e.g., using the bike vs. the car), implementing actions that are environmentally relevant entails the allocation of cognitive resources at some point in the process. Even if the action itself is equally effortful as the environmentally unfriendly option (e.g., selecting the organic version of a product from the same shelf) or even less effortful (e.g., not buying the third pair of shoes in one year), it might come with associated cognitive costs such as making an informed decision in advance, or inhibiting a habitual action in the moment. More generally, the initiation and maintenance of behavioral change (and in particular breaking habits) is most often effortful.

Here we conceptualize cognitive effort as *the deliberate allocation of cognitive resources to carry out a certain task or obtain a certain goal*. Key elements of contemporary cognitive effort theories are that the process is goal-directed and voluntary (see Massin, 2017; Westbrook

& Braver, 2015). Although investing cognitive effort is an omnipresent necessity in modern every-day life, humans typically tend to follow the law of least effort wherever possible (Hull, 1943). Since cognitive effort is considered costly in most contexts, the willingness to allocate effort depends on the expected outcomes (Hughes, Yates, Morton, & Smillie, 2015; Krebs, Boehler, Roberts, Song, & Woldorff, 2012; Schevernels, Krebs, Santens, Woldorff, & Boehler, 2014; Treadway, Buckholtz, Schwartzman, Lambert, & Zald, 2009; Westbrook & Braver, 2015). The relationship between expected cognitive effort and outcome has been formalized in the Expected Value of Control framework (Shenhav, Botvinick, & Cohen, 2013). It posits that cognitive control (which is directly associated with effort) depends on the expected value of the control, the amount of control required, and the costs of control. More recently, the instrumental relationship between effort and outcome, also termed efficacy, has been identified as key moderator of this calculation (Frömer, Lin, Dean Wolf, Inzlicht, & Shenhav, 2021)[1].

The present study builds on the notion that decisions and actions that are environmentally relevant often entail cognitive effort, and hence cognitive costs. As they most often do not yield immediate and visible outcomes, the willingness to invest the cognitive effort is likely diminished compared to the canonical context of effort investment studied in effort-based decision making, which typically yields direct personal outcomes. We tested this basic assumption in a pre-registered behavioral study. Specifically, personal outcomes (own rewards) as well as pro-environmental outcomes (eco rewards) were embedded in a conflict task that probes cognitive effort (i.e., counting Stroop, Bush, Whalen, Shin, & Rauch, 2006). Task

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[1] *While there are certainly parallels, the present study is not framed in terms reinforcement learning. The most important reason being that the present (and related paradigms in the effort-based decision-making domain) do not rely on learning or conditioning, but use instructed behavior-outcome contingencies. Moreover, outcomes in the present task are not linked to specific responses (like the frequency of a lever press), but the completion of a cognitive task that is independent of the reward dimension.*

performance in eco reward trials was directly linked to monetary donations to a pro-environmental organization. By comparing the eco reward condition to a no reward and to the own reward condition, we were able to test in how far pro-environmental outcomes are promoting cognitive effort at all (above baseline performance) and whether they have a smaller effect compared to personal outcomes, respectively. Our motivation to use donations to pro-environmental organizations as incentive (instead of reduction of carbon emissions via behavioral adjustments or financial offsets, e.g., Lange et al., 2018; Wyss et al., 2022) is two-fold. Given that such incentives are not associated with a particular behavior (like e.g., cycling), these are especially valuable when studying cognitive effort – which is an inherent part of various behaviors and decisions. At the same time, this manipulation allowed us to increase personal relevance in that we let participants choose the target organization in advance. Regardless of the type of organization they chose, having a choice itself should encourage participants to internalize the pro-environmental goal.

To relate our findings to previous work in the domain of PEB, but also research on cognitive effort and motivation in general, we assessed inter-individual differences in self-reported pro-environmental attitudes and behavior, as well as the need for cognition (index of inherent tendency to engage in effortful tasks) and reward sensitivity (index of dependency on external rewards). We expected that participants with high scores on the pro-environmental attitude and behavior scales will display larger performance modulations in eco reward trials as compared to participants with lower scores (Lange et al., 2018). Moreover, participants with high reward sensitivity are expected to modulate their performance especially in own reward trials (e.g., Simon et al., 2010). With respect to need for cognition, we predicted a negative relationship with performance modulation in own reward trials based on previous research (Sandra & Otto, 2018), but had no specific prediction for the eco-reward trials.

We consider the experimental approach complementary to existing assessments of PEB that entail cost (or effort) components that are discussed above. The main distinguishing features are that we focus on *cognitive effort* (and the associated costs) exclusively, instead of temporal and/or financial costs. Here, cognitive effort (i.e., the allocation of cognitive resources) itself is the target behavior, which is different from assessing the choice of an action based on its expected costs. In the latter case, the costs are only experienced after the choice has been made (or remain hypothetical). Moreover, the use of the Stroop task as probe of effortful cognitive operations (including shielding from irrelevant information and suppressing predominant responses, Miller & Cohen, 2001) accommodates the observation that real-life pro-environmental decisions are hardly ever relying on a single input but involve noise and interference. Above and beyond these specific features, the present task might provide another tool to assess PEB in a controlled laboratory setting which ameliorates some of the issues associated with self-report measures, hypothetical scenarios, and field research (for a discussion see, Lange & Brick, 2021).

Materials and methods

Participants. This study was pre-registered via the Open Science Framework (OSF, https://osf.io/pvrza/). We recruited students between 18 and 35 years of age (right-handed, normal or corrected-to-normal vision, (no history) of diagnosed mental disorders) via the local University online recruiting website. The term *pro-environmental behavior* was not mentioned in the study announcement to avoid biased pre-selection. In total, we recruited 120 participants (pre-registered[2]). The first 60 participants were tested in the laboratory (age 19.1, SD 2.3; 55 female). Due to covid-19 restrictions, we switched to online testing for the second set of 60 participants (age 18.6, SD 2.4; 52 female). The dual testing (laboratory and online) was pre-registered, and the design and procedure was identical in both contexts. Participants received 1 course credit for participating in the 60-minute experiment, and an average of 9.7 (laboratory) and 9.5 euro (online) as a bonus (the sum of own and eco reward, details below). The experimental procedure was approved by the Ethical Committee at the Psychology Faculty (approval number 2020/90) and in line with the Declaration of Helsinki 1964 and its later amendments. Participants gave their written informed consent form before starting the experiment.

Experimental procedure. Instructions, stimulus presentation, and response collection was controlled by PsychoPy Builder 3.1.5 for the laboratory sample (Peirce et al., 2019) and JsPsych 6.1.0 for the online sample (de Leeuw, 2014). In the laboratory version, participants performed the task on a desktop PC. The online experiment was conducted using the Pavlovia research platform (www.pavlovia.org), and participants were asked to use the Chrome browser.

Participants performed a cued conflict task (counting Stroop, Bush et al., 2006), in which they could win monetary rewards (see Fig. 1). Each trial started with one of three cues (presented for 1000ms), indicating whether correct performance on this trial would lead to own reward (hand icon), eco reward (bin icon), or no reward (diamond shape). After a variable interval (500-900ms), one of four possible counting Stroop targets were presented (congruent: the word ONE

[2] *Sample size was based on a previous experimental study of PEB (Lange et al., 2018). In keeping with their a priori considerations (i.e., aiming at detection of medium size corrections (r = .3) with good statistical power at alpha = .05 and sufficient power at alpha = .0125 (multiple comparisons correction), G*Power 3.1 unveiled a minimum sample size of 111, which was rounded up to 120. Number of observations per cell in the design is 5760 for each reward condition (48 x 120) and twice as high for the no reward condition (96 x 120).*

presented once, the word TWO presented twice; incongruent: the word ONE presented twice, the word TWO presented once). The words were written in Dutch (ONE = EEN, TWO = TWEE). In single-word trials, word location was random (50% in above and 50% below the fixation cross). The participants' task was to indicate the number of words on the screen while ignoring the meaning of the words via pressing one of two buttons on the keyboard ('O' for one word or 'P' for two words). These buttons are at the same location on QWERTY and AZERTY keyboards. Note that the mapping between number and word were not counterbalanced as this would interfere with the inherent mental number line (increasing from left to right). The target remained on screen for a maximum of 800ms. If the response was given before the offset, the target was directly replaced by a feedback screen. For responses later than 800ms, the target was first replaced by the fixation cross until the response was registered, followed by the feedback screen. In case responses were not given within 1200ms (maximal response window), the feedback screen was displayed automatically. The feedback screen (1000ms) included the respective cue again, together with a check mark (response correct), or a cross (response incorrect), or a clock (response too late), depending on their performance. In correct reward trials (own and eco reward), a coin symbol was visible in the display symbolizing the bonus. In all other cases (incorrect/too late reward trials and all no reward trials) a zero was embedded in the display to indicate no gain). In order to increase general motivation for the task, participants were told that responses after target offset (after 800ms) would be considered as too late and hence be followed by a too-late feedback. Even though a time out of 800ms may not seem very strict for a counting Stroop task with two responses, it ensures that participants try their best on every trials (thereby increasing reward probability), while at the same time counteracting a potential speed-accuracy trade off (such as strategic response slowing). Regardless of this instructed time out, all responses up to a predefined time out of 1200ms after target onset were included in the analysis. The next cue followed after a variable interval of 1000-1900ms. After a block of 96 trials, participants received feedback about their performance (total % correct) and earnings (euro for own and eco condition separately) in the respective block.

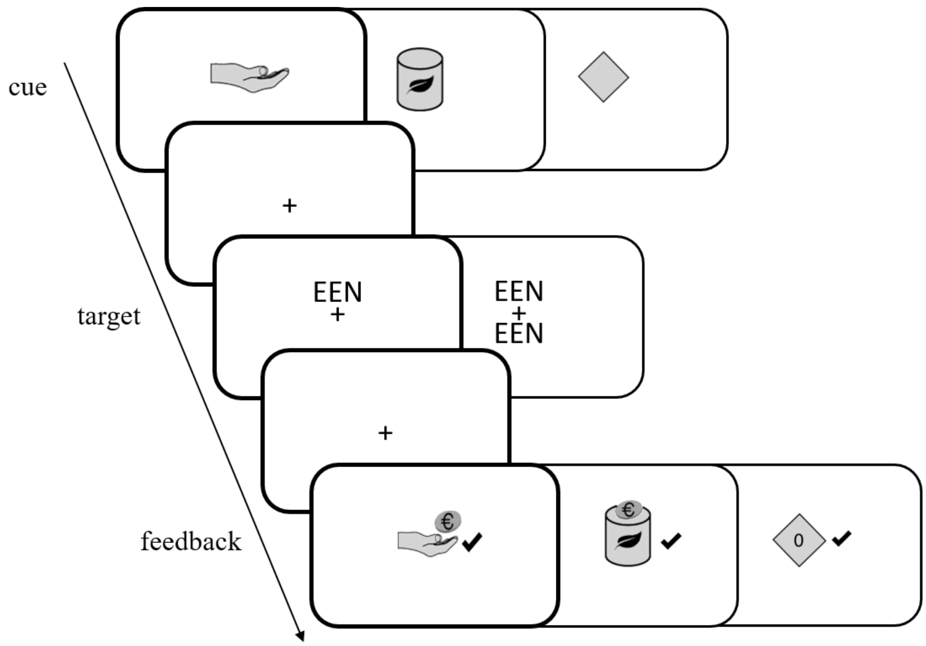

Figure 1. Schematic representation of the task. In each trial, participants were first presented with a symbolic cue indicating the reward type (from left to right: own reward, eco reward, no reward). The subsequent target (counting Stroop task) could be congruent (left example) or incongruent (right example). In this illustration, only two target types are shown (EEN = ONE in Dutch). The feedback screen included the reward type of the respective trial and indicated whether the response was correct and in-time (i.e., coin and check mark), incorrect (i.e., cross), or too late (i.e., clock). Here, only correct feedback is shown.

The design entailed two within-subject factors, Reward (own reward, eco reward, no reward) and Conflict (congruent, incongruent), resulting in six conditions. The number of no reward trials

(50%) equaled the sum of own reward and eco reward trials (25% each) to prevent for strategic effects (e.g., when the probability of seeing a reward trial is higher than 50%, participants might find it more efficient to ignore the cue meaning, see Hoofs, Boehler, & Krebs, 2019). All experimental conditions were randomly intermixed within blocks, with equal distribution across blocks. In total, participants performed four blocks of 96 trials each, amounting to a total of 48 trials per conflict condition for the reward trials (own and eco), and 96 trials per conflict condition for the no reward trials. Before the main task, participants performed 30 practice trials with equal distribution of conditions. All stimuli were presented on a white background. A fixation cross was present in the center of the screen throughout the trial.

Before the experiment, participants were instructed about the cue meaning and reward contingencies. In both the own reward and eco reward trials, participants would win a bonus for each correct trial (correct and within the response window). The maximum total reward for each of these conditions was 5 euro (each reward trial was worth about 5 cents). In the no reward trials, correct performance would not lead to any outcome. Participants were informed that the rewards earned during the task will be either transferred to their personal bank account (own reward trials) or to a pro-environmental organization (eco reward trials). To accommodate personal preferences for the type of organization, participants could choose between three existing ones (one acting on the international level, one on the national, and one on the local), by checking one of three boxes on the screen. Each of the organizations was briefly described on the screen.

At the very end of the experiment, participants were (truthfully) informed that it was not possible for the researchers to directly donate the obtained eco reward to the pro-environmental organization based on University regulations on scientific integrity. Hence, participants would receive both the own and eco rewards on their account (in total around 9.6 euro), and were free to donate any amount themselves if they wish to. They could then indicate whether they were planning to donate any money (yes/no). It was emphasized that this was entirely voluntary and that the information will be collected anonymously (like all other information in the study). If they indicated yes, they would receive the information on how to donate via email. Further, participants were asked not to communicate details about the donation procedure to other students. Please see detailed information on instructions, pro-environmental organizations, and debriefing in the Supplementary Material. After the experimental task and before the debriefing regarding the donations, participants filled out four trait scales: the Recurring Environmental Behavior Scale (REBS, Brick, Sherman, & Kim, 2017), the New Ecological Paradigm (NEP, Dunlap, Van Liere, Mertig, & Jones, 2000), the Need for Cognition scale (NFC, Cacioppo, Petty, & Kao, 1984), the Behavioral inhibition/Activation System scale (BIS-BAS, Carver & White, 1994). Questionnaires and donation intention were filled in via Excel sheets (laboratory) or within the program (online).

Data analysis. Performance data were analyzed in SPSS (Statistical Package for the Social Sciences, version 28). Questionnaire coding was performed in RStudio (version 1.4.1106). In the main analysis (pre-registered), response times (mean RT in ms) of correct trials (within the predefined time out of 1200ms), as well as error rates (mean ER in %) were submitted to repeated-measures analyses of variance (rANOVA), with within-subject factors Reward (own reward, eco reward, no reward) and Conflict (congruent/incongruent). To assess the effect of the task context, Context (laboratory, online) was included as between-subject factor in the rANOVAs of the RT and ER data (pre-registered exploratory). Greenhouse-Geisser corrections were applied to the degrees of freedom and p-values in case sphericity assumptions were violated. Trends are reported for completion but not further discussed. Significant main effects of factors with more than two levels and significant interactions are followed by post-hoc t-tests (two-sided). Effect sizes are reported for main effects and interactions (eta squared partial, η^2p) and for the t contrasts (Cohen's d). Confidence intervals (CI) are reported for significant t contrasts, expressed in the unit of measurement, i.e., ms and % ($_{\text{lower bound}}$ mean difference $_{\text{upper bound}}$).

The above performance measures were related to inter-individual differences in four trait measures, i.e., the REPS, NEP, NFC, and the reward sensitivity subscale of the BIS-BAS (referred to as Inter-individual difference analysis). To this end we created RT and ER different scores reflecting differences between the reward conditions (own minus no reward, eco minus no reward, own minus eco reward), and correlated those with the scale scores (Pearson's r, two-sided test). We applied Bonferroni correction for multiple comparisons (p divided by the number of scales). This approach was pre-registered, and only applied to the main correlational analysis (scale-behavior correlations in the full sample). In addition, we tested inter-scale correlations to explore potential relationships between pro-environmental traits on the one hand and need for cognition and general reward sensitivity on the other hand (pre-registered). Correlations between behavioral measures are merely reported for completion. Due to the differential performance modulations in the laboratory and online context, the above correlational analyses were also performed considering both samples separately (pre-registered exploratory).

We performed additional analyses that are all reported in the Supplementary Material. First, we tested in how far performance patterns changed over time-on-task by including Time (first half, second half) as within-subject factor in the analysis (pre-registered exploratory). Second, to explore the robustness of the main findings across different statistical approaches, we performed (Generalized) Linear Mixed Model analyses on the RT and ER data (pre-registered exploratory). Third, we conducted three analyses to test for systematic differences in data reliability between the laboratory and the online sample based (follow-up analyses, not pre-registered).

Results

Task performance full sample (pre-registered main analysis). The condition means of the full sample (N=120) are illustrated in Figure 2 (RT left panel; ER right panel). The rANOVA of RTs revealed main effect of Conflict ($F(1,119) = 293.529$, $p < .001$, $\eta^2p = .712$), with faster responses in congruent as compared to incongruent trials, as well as a main effect of Reward ($F(1.706,203.07) = 34.587$, $p < .001$, $\eta^2p = .225$), with fastest responses in the own reward and slowest responses in the no reward condition. Post-hoc comparisons of the latter effect revealed that all three Reward conditions differed significantly from one another (own < no reward: $t(119) = -7.74$, $p < .001$, $d = -.707$, CI = $_{-18.82}-14.99_{-11.15}$; eco < no reward: $t(119) = -6.058$, $p < .001$, $d = -.553$, CI = $_{-11.16}-8.41_{-5.66}$; own < eco reward: $t(119) = -3.243$, $p = .002$, $d = -.296$, CI = $_{-10.59}-6.58_{-2.56}$). There was no significant interaction between the two factors in the RT data ($p > .8$). The ER data featured a main effect of Conflict ($F(1,119) = 145.676$, $p < .001$, $\eta^2p = .55$), with higher ER in incongruent compared to congruent trials, as well as an interaction between Conflict and Reward ($F(2,238) = 3.341$, $p < .037$, $\eta^2p = .027$). This interaction resonated from a significantly reduced ER in incongruent eco reward as compared to no-reward trials ([incongruent minus congruent eco > no reward]: $t(119) = -2.221$, $p = .028$, $d = -.203$, CI = $_{-1.41}-.75_{-0.08}$), and a similar trending effect for own reward trials ([incongruent minus congruent own > no reward]: $t(119) = -1.715$, $p = .098$, $d = -.157$, CI = $_{-1.08}-.50_{.08}$). There was no difference in the interference effect between own and eco reward trials (p > .2). In contrast, ER in congruent trials was not differentially modulated by Reward (all p > .1). For completion, the main effect of Reward on ER was not significant (p > .2). An overview of the condition means and standard deviations (SD), as well as the performed statistical tests is provided in the Supplementary Material (Table S1 and S2).

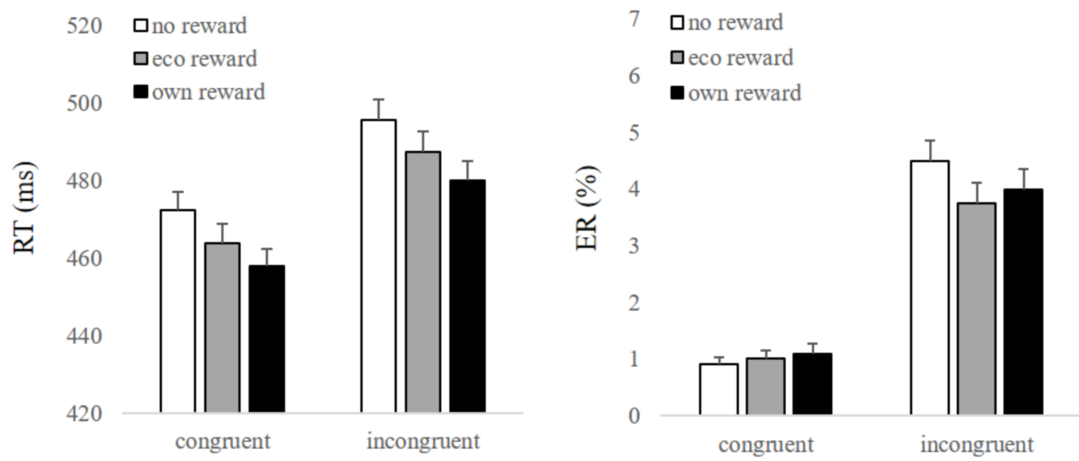

Figure 2. Performance full sample. Response times (RT in ms) and error rates (ER in %) for each condition are averaged across the full sample (N=120). Error bars indicate the within-subject standard error.

Task performance considering Context (pre-registered exploratory). To formally compare the data between laboratory (N=60) and online sample (N=60), we included Context as between-subject factor in the above rANOVAs. The condition means split by Context are illustrated in Figure 3 (RT left panel; ER right panel). In this analysis we are focusing on any effects that involve the Context factor, without reiterating the effects of the within-subject factors reported in the primary analysis. For RT, we found a main effect of Context ($F(1,118) = 36.18$, $p < .001$, $\eta^2p = .235$), with faster responses in the laboratory as compared to the online task (about 50ms).

Moreover, there was a significant interaction between Reward and Context ($F(2,236) = 4.898$, $p = .008$, $\eta^2p = .04$). Post-hoc comparisons revealed that in the online sample, all reward conditions differed significantly from one another, with own reward being the fastest and no reward being the slowest (own < no reward: $t(59) = -5.98$, $p < .001$, $d = -.508$, CI = $_{-24.06}$ -18.03 $_{-12.0}$; eco < no reward: $t(59) = -3.183$, $p = .002$, $d = -.772$, CI = $_{-9.61}$ -5.90 $_{-2.19}$; own < eco reward: $t(59) = -3.986$, $p < .001$, $d = -.515$, CI = $_{-18.22}$ -12.13 $_{-6.04}$). In contrast, in the laboratory sample, RTs were significantly faster in the own and eco reward conditions as compared no reward (own < no reward: $t(59) = -4.994$, $p < .001$, $d = -.645$, CI = $_{-16.72}$ -11.94 $_{-7.16}$; eco < no reward: $t(59) = -5.378$, $p < .001$, $d = -.694$, CI = $_{-14.98}$ -10.92ean $_{-6.85}$), with no difference between own and eco reward ($p > .6$). The remaining interactions between Context and the within-subject factors were non-significant (both $p > .2$). For ER, we observed a main effect of Context ($F(1,118) = 7.335$, $p = .008$, $\eta^2p = .059$), with a reduced number of errors in the laboratory compared to the online task, which is mirroring the RT data. Further, there was a trending interaction between Conflict and Context ($F(1,118) = 3.29$, $p = .072$, $\eta^2p = .027$). The remaining interactions involving Context were non-significant (both $p > .5$). A full overview of the condition means and standard deviations (SD), as well as the performed statistical tests is provided in the Supplementary Material (Table S1 and S4).

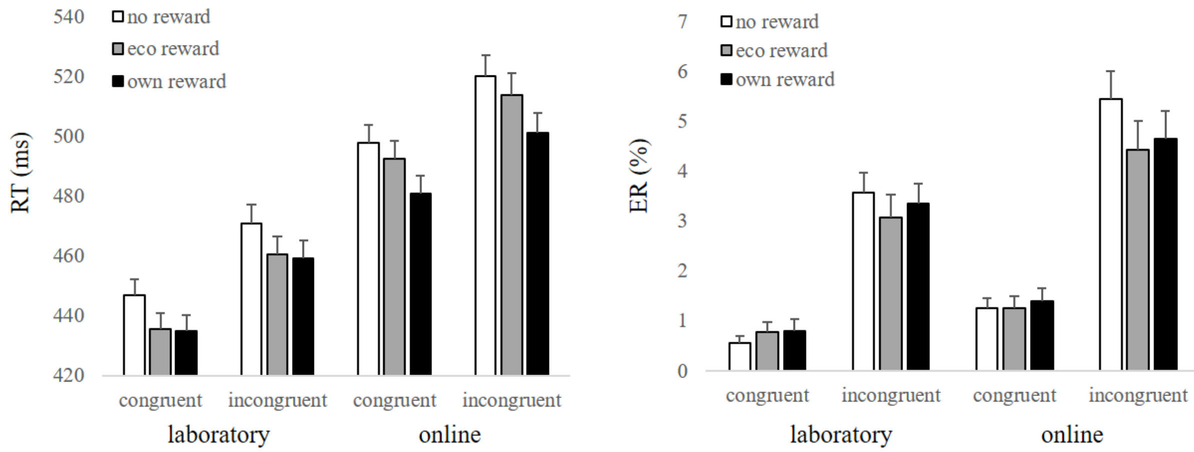

Figure 3. Performance considering task context. RT (in ms) and ER (in %) for each condition are shown for the laboratory (N= 60) and the (N= 60) online sample separately. Error bars indicate the within-subject standard error.

Inter-individual differences full sample (pre-registered main analysis). An overview of the correlations between performance and trait measures across the full sample is provided in the Supplementary Material (Table S3). Note that correlations were performed on performance difference measures (own minus no reward, eco minus no reward, own minus eco reward) rather than absolute values. In the full sample (pre-registered main analysis), only one significant correlation was observed at an uncorrected p-value of .05. Specifically, a high score in the REBS score was associated with relatively increased ER in own compared to eco reward trials ($r = .183$, $p=.046$). While this relationship is in line with our predictions, it did not survive Bonferroni correction for multiple comparisons ($p < .0125$). The remaining scale-behavior correlations in the full sample were non-significant.

Correlations between trait scales are reported at the bottom of Table S3. We found that both pre-environmental scales (REBS and NEP) were positively correlated ($r = .217$, $p = .017$) in the full sample (Table S3). Moreover, high REBS scores were related to high scores in NFC ($r = .248$, $p = .006$). All remaining scale-scale correlations were non-significant. Correlations between behavioral measures for the full sample are reported in Tables S3 for completion.

Inter-individual differences considering Context (pre-registered exploratory). When splitting the sample by task context (Table S5), the laboratory sample featured a significant correlation between REBS and ER resembling the pattern in the full sample ($r = .34$, $p=.008$), with higher REBS scores predicting higher relative ER in own compared to eco reward trials. Moreover, in line with our predictions, a high NEP score was associated with faster RTs in eco reward relative to no reward trials ($r = -.26$, $p= .042$). Moreover, a lower score in NFC was related to shorter RTs in own reward relative to both no reward trials ($r = .377$, $p = .003$) and eco reward trials ($r = .349$, $p = .006$). The remaining correlations between performance and trait measures in the laboratory sample were non-significant (see Table S5). In the online sample, only one correlation was significant, i.e., higher NEP scores were associated with faster RTs in own reward as compared to no reward trials ($r = -.264$, $p = .042$). All remaining correlations between performance and trait measures in the online sample were non-significant.

The inter-scale correlations split by task context are reported at the bottom of Table S5. The pattern in the laboratory sample mirrors the full sample, with a positive correlation between REPS and NEP ($r = .394$, $p = .002$), as well as between REBS and NFC ($r = .354$, $p = .005$). All remaining inter-scale correlations were non-significant. Correlations between behavioral measures split by context are reported in S5 for completion.

Additional measures (choice of organization and donation intention). Most participants chose the international organization as beneficiary before the experiment (laboratory: international = 40, national = 17, local = 3; online: international = 44, national = 11, local = 4). Due to the lop-sided distribution, we did not include choice in the above analyses. When being asked about their intention to donate (after the debriefing), the vast majority of participants answered with yes (89%). However, the number of *declined* donations was significantly smaller in the laboratory as compared to the online sample (3% vs. 18%; Fisher's exact test $p = .016$, two-sided).

Discussion

Performance modulations based on reward condition. Using a well-established paradigm to probe cognitive effort in anticipation of monetary outcomes, we show that participants are willing to invest cognitive resources for a pro-environmental cause. Specifically, this was indexed by overall reduced response speed (RT) as well as a differential reduction of Stroop interference (lower ER) in pro-environmental as compared to no reward trials. In direct comparison with personal outcomes, the RT benefit triggered by pro-environmental outcomes was significantly smaller, while the reduction of interference (ER) was of similar magnitude. The effect of personal outcomes replicates previous work using monetary reward cues in Stroop or related cognitive control tasks (Krebs, Boehler, & Woldorff, 2010; Krebs & Woldorff, 2017; Padmala & Pessoa, 2011; van den Berg, Krebs, Lorist, & Woldorff, 2014). In addition to overall speeding (across congruent and incongruent trials), we find a reduction of interference (incongruent minus congruent trials) in form of reduced ER in both pro-environmental and personal outcome trials. The combination of these two patterns is likely the result of increased attention building up before target presentation as well as cognitive control mechanisms during target processing (Braver et al., 2014; Krebs & Woldorff, 2017; Westbrook & Braver, 2015). While the present study does not distinguish between different underlying control mechanisms, the overall pattern can be framed in terms of increased cognitive effort in that these performance benefits qualify as voluntary and goal-directed. Specifically, participants adjust performance specifically in reward trials, and keep with the instruction to respond as fast as possible while maintaining high accuracy. Arguably, the present task is fairly easy and does not produce a large number of errors on average. However, the reward-induced reduction in ER is still meaningful in that it reflects superior interference resolution in even more trials in these conditions. This reduction of interference is indicative of goal-directed cognitive control to counteract the dominant response associated with the irrelevant word (Ridderinkhof, Forstmann, Wylie, & van den Wildenberg, 2010). As such, the observation that the reduction of interference is of similar magnitude in the pro-environmental reward condition confirms that participants are (on average) willing to invest their cognitive resources for a pro-environmental cause. That said, personal outcomes seem to be unique in the sense that they trigger additional response facilitation (regardless of conflict), which we tentatively interpret as the result of increased attention to personally relevant outcomes. Again, despite this discrepancy, there is no strategic trade-off between the two measures (i.e., ER benefits do not come at the cost of longer RTs). Note that the present study does not differentiate between specific reasons for the increased motivational value of personal outcomes (see further discussion below).

The present observations complement results of recent work by Lange and colleagues (2022), who manipulated PEB in an effort-based choice paradigm (Lange & Dewitte, 2022). Specifically, they found that participants' choice to engage in a more effortful task depended on the magnitude of the pro-environmental outcome. While conceptually related, the operationalization is different in that the present study does not capitalize on the choice component of PEB but the amount of cognitive effort invested ad-hoc in each trial, rendering cognitive effort the target behavior. Moreover, while the present task focuses on cognitive effort and its inherent costs, the more effortful task by Lange and colleagues (2021) entails an increased number of targets, hence also inducing a temporal cost. Finally, the tasks differ with regard to the outcome manipulation in that aforementioned study (Lange & Dewitte, 2022) compares pro-environmental outcomes associated with different payouts, while the present study compares pro-environmental and personal outcomes associated with identical per-trial payouts.

The effect of task context. While the benefit in response speed for the pro-environmental condition was observed across the entire sample, it was much larger in the laboratory sample, and in fact comparable to the personal outcome condition. The reason for this might be related to effects of social desirability, in that the laboratory task features social interactions with the experimenter. Specifically, although all data collected is being treated anonymously, the mere presence of the experimenter might increase the pressure of acting like a good, or at least not overly selfish person. This idea receives additional support from the self-reported donation intention. Specifically, after being debriefed about the fact that donations can only be submitted by the individuals themselves, most participants indicated to donate. Intriguingly, the probability of this intention was significantly lower in the online sample, which could be a reflection of lower social pressure. In addition, the online context is arguably less controlled and might yield less reliable performance measures, which also resonates with larger standard deviations in the online sample (visual inspection). These differences between the two contexts might also contribute to the discrepancies in the inter-individual difference results (see below). That said, especially the reduction of interference triggered by pro-environmental and personal outcomes was robust in both task context, confirming that social desirability is not the sole driving force for the observed modulations in pro-environmental trials. In this context it is important to note that, social influences can be observed at different levels. In a previous study using self-report measures, people indicated to engage more in PEB when being watched (Brick et al., 2017). The present study confirms this notion conceptually by means of different experimental settings (laboratory vs. online). However, another study employing determinants of PEB experimentally did not find significant influences of actual social observation on PEB (Lange, Brick, & Dewitte, 2020). Notably, the latter study manipulated social influences *within* the lab context (private vs. observed condition). In contrast to this, the present online task version entails no social interactions at all at any of the stages (task set-up, instructions, debriefing). To conclude, it seems likely that the discrepancy in RT data between laboratory and online context in the present study is partly related to social desirability (also reflected in donation intention), and partly due to heightened general attention to the task in the laboratory sample which may ameliorate differences between outcome types. The notion of increased attention is supported by overall higher response speed and fewer errors in the laboratory context. Whether performance facilitation is related to (unspecific) arousal or higher-level cognition (e.g., “I want to perform well because I am watched”) cannot be answered based on the present data.

Inter-individual differences. Above and beyond the performance modulations observed on average, the present study also revealed some evidence for inter-individual differences. First, in line with our hypothesis, we observed a relatively larger effect of pro-environmental outcomes as compared to personal ones (indexed by lower ER) in participants with pro-environmental attitude (indexed by REBS). This relationship did not survive correction for multiple comparisons in the full sample, but did so in the laboratory sample (which we did not predict in particular). The following considerations are hence exploratory and should be backed up by future studies. This finding generally in line with previous related studies that featured a lab measure of PEB (Lange et al., 2018), and confirms that this novel PEB task captures similar aspects as the self-report measures The fact that the correlation with REBS is based on the difference score between pro-environmental and personal reward trials might indicate pro-environmental outcomes have a higher relevance for individuals with a pro-environmental attitude. Second, we found a negative relationship between task performance and the NFC scale which was unique for own reward trials, but only in the laboratory sample (which we did not predict in particular). Specifically, participants with a lower affinity for cognitively challenging tasks displayed larger RT benefits for personal outcomes relative to pro-environmental and no reward trials. Note that the following considerations are exploratory as we did not observe the effect in the full sample. The pattern replicates previous work showing that people with an affinity to cognitively challenging tasks might be less guided by extrinsic reward signals (Sandra & Otto, 2018). Intriguingly, this seems to be unique to personal outcomes, while RT modulations triggered by pro-environmental outcomes are not dependent on NFC. While remaining speculative, this might again be a reflection of differences in motivational value of the two outcome types.

The observation these correlations were (mainly) featured in the laboratory sample could reflect differences in general data quality considering that the online context is less controlled and might promote careless and inattentive responding (Zorowitz, Niv, & Bennett, 2021). Evidence for this notion could be found in the reliability of the questionnaire data (Curran, 2016), but also the behavioral data itself (Hedge, Powell, & Sumner, 2018). When testing the split-half reliability of the trait scales (Table S7, left), we did not find differences between the online and the laboratory context. The majority of these split-half correlations were high ($p < .001$), except for reward sensitivity, which was however still significant in both samples (laboratory $r = .268$, $p = .038$; online $r = .372$, $p = .003$). There was also no systematic difference in score distributions (Table S6). Similarly, the split-half reliability analysis of the behavioral data (Table S7, right) attests high consistency for most of the behavioral measures in both task contexts ($p < .001$). Lower (or absent) correlations were only observed for ER in the own reward condition in both contexts (laboratory $r = .173$, $p = .186$; online $r = .279$, $p = .031$) and for ER in the pro-environmental reward condition in the laboratory sample ($r = .374$, $p = .003$). This likely reflects that ER drops more rapidly in these condition during the course of the experiment, and even more so in the laboratory context. While this may contribute to the differential correlation patterns between performance and questionnaire data, this does not seem to be primarily related to inattentive responding in the online sample. Rather, it might be another reflection of increased attention to the task in the laboratory sample due to the social context.

Relevance and critical assessment. Pressured by the climate crisis, different types of interventions have been implemented, both on a global societal level (such as divesting from fossil fuel) and on the individual level, including modifying cognitive dissonance and goal setting, as well as social influence techniques (Abrahamse & Steg, 2013; Osbaldiston & Schott, 2012). By focusing on cognitive effort and the inherent costs associated with it, the current study can contribute to understand (and potentially help to overcome) the knowledge-behavior gap, which is still one of the biggest challenges in PEB research (Brick, Bosshard, & Whitmarsh, 2021; Gifford, 2011; Kollmuss & Agyeman, 2002). Specifically, the present paradigm provides a controlled lab-based tool to test specific predictions about factors that may increase or decrease the willingness to invest cognitive effort for a pro-environmental cause. It goes beyond existing research in that it considers cognitive effort as the target behavior with an inherent cost rather than assessing the choice of an action based on its expected temporal or financial costs. As such, cognitive effort modulations capture a more general aspect of PEB in that environmentally-relevant behavioral change is often associated with cognitive effort at some point (information gathering, planning, implementation, and maintenance). This does not mean that the pro-environmental actions themselves are inherently effortful. After further experimental validation, we believe that this approach can also be used to test the impact of specific interventions (e.g., group manipulation; pre/post intervention; longitudinal design).

The present data shows that participants are generally willing to invest cognitive effort for pro-environmental outcomes, but that the effects are somewhat inferior as compared to personal ones. We note that this conclusion is specific for the tested population (local students), the outcome type (monetary incentives), and the task used to probe cognitive effort (Stroop task). In light of influential cognitive effort theories, resource allocation is considered a cost which has to be outweighed by the expected benefits (Shenhav et al., 2013). The reduced motivational value of pro-environmental outcomes in the present study might be explained by the absence of a direct relationship between a specific behavior and concrete consequences. Specifically, previous research has shown that cognitive effort investment strongly depends on action-outcome contingency, or efficacy (Frömer et al., 2021), which are naturally low for pro-environmental actions as the consequences are abstract and/or distant (Gifford, 2011). More generally, personal and pro-environmental outcomes differ vastly in terms of their utility (i.e., whether and how they can be used by the investor). Moreover, the mere fact that there is a discrepancy between the investor (participant) and the beneficiary (organization) in the pro-environmental condition may decrease the willingness to invest cognitive effort. With this in mind, it is intriguing that there is substantial overlap in how participants approach the task for the different incentives (the additional response speeding for personal reward being the only noticeable difference). This suggests that participants are mainly guided by the absolute incentive value and the type of goal, rather than additional factors like efficacy or utility. Note that these considerations are hypothetical at this point as the present study does not systematically test different reasons for the difference in motivational value, which is a valuable avenue for future research. Interestingly, similar relationships have been found in research on pro-social behavior, where participants have found to exert less effort (here, physical effort) when the action benefits others as compared to themselves (e.g., Imas, 2014; Lockwood et al., 2017). This raises the question whether broader social/altruistic motives might contribute to the observed pattern. This aspect cannot be addressed based on the present data.

Albeit being an incidental finding, the differences observed between online and laboratory sample are valuable for research on PEB. We tested participants from the same cohort of students with an identical task and identical instructions, the only clear difference being the (laboratory) environment itself. On the one hand, the differential behavioral pattern (additional facilitation for pro-environmental trials in the laboratory sample) might be explained by responding according to social desirable motives (as discussed above). On the other hand, one might suspect data quality issues due to inattentive responding in the online sample, which could explain discrepancies in the correlation analysis. This does not seem to be the case in the present study (as detailed above), which might partly be due to the nature of the Stroop task (engaging, fast paced) and/or a particularly motivated student cohort. These observations should be considered by researchers when designing experiments, e.g., by keeping experimenter influences to a minimum in the laboratory or by employing well-established tasks in an online setting.

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Competing interests

The authors have no competing interests to declare.

Data availability

The project is pre-registered at the Open Science Framework (OSF). De-identified raw data and supporting information can be found here: https://osf.io/ahs3u/.

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