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RESEARCH ARTICLE

More than a feeling: physiological measures of affect index the integration of effort costs and rewards during anticipatory effort evaluation

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Abstract

The notion that humans avoid effortful action is one of the oldest and most persistent in psychology. Influential theories of effort propose that effort valuations are made according to a cost-benefit trade-off: we tend to invest mental effort only when the benefits outweigh the costs. While these models provide a useful conceptual framework, the affective components of effort valuation remain poorly understood. Here, we examined whether primitive components of affective response—positive and negative valence, captured via facial electromyography (fEMG)—can be used to better understand valuations of cognitive effort. Using an effortful arithmetic task, we find that fEMG activity in the corrugator supercilii—thought to index negative valence—1) tracks the anticipation and exertion of cognitive effort and 2) is attenuated in the presence of high rewards. Together, these results suggest that activity in the corrugator reflects the integration of effort costs and rewards during effortful decision-making.

Keywords Cognitive effort · fEMG · Decision-making

In 1949, Zipf (2016) contended that he had discovered a unifying principle that governed "every individual's entire behaviour": the *principle of least effort*, which states that, in all situations, "a person will strive to minimize the probable average rate of his work-expenditure" (see also Hull, 1932; Ballé, 2002). While the least effort principle remains a ubiquitous and influential proposal in psychology, a key but unresolved question remains: *what* makes effort so aversive to humans? In other words, what phenomenological quality of cognitive effort exertion so effectively discourages people from taking cognitively demanding courses of action?

Contemporary theories of effort-based decision-making posit that an individual's decision to allocate cognitive effort is governed by a cost-benefit trade-off (Shenhav et al., 2017), such that individuals tend to allocate effort to a particular task if the benefits of effort exertion (e.g., reward incentives) outweigh its costs (Kool and Botvinick, 2018; Kurzban, 2016; Shenhav et al., 2013; Silvetti et al., 2018). An important tenet of this view is that the exertion of effort is intrinsically costly, such that it discourages pursuing effortful courses of action (Kool et al., 2010; Kurzban et al., 2013; Otto and Daw, 2019; Vogel et al., 2020), whereas rewards counteract this default tendency and mobilize effortful processing (Kool and Botvinick, 2018; Silver et al., 2021). While the source of this intrinsic effort cost is debated (Musslick and Cohen, 2021; Petitet et al., 2021; Holroyd & McClure, 2015), most theories converge in assuming that the subjective cost of effort increases monotonically with objective task demand level.

An important, but unexamined assumption of the cost-benefit account of effort valuation is that the exertion of cognitive effort is actually experienced as an aversive phenomenon (Kurzban, 2016; Saunders et al., 2017). Through the lens of cost-benefit effort evaluation, if effort is indeed aversive, we would expect that individuals' affective evaluations of effort exertion reflect the costs (i.e., task demand) and benefits (i.e., reward incentives) of the situation at hand.

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In other words, if the aversive quality of mental effort stems from the experienced output of motivational systems directing behavior towards appropriate actions (Kurzban et al., 2013), the "net utility" of an action—or at the least, its constituent elements, benefits and costs—should manifest in an individual's affective evaluation of a situation.

Affective states can be characterized by two distinct, but inter-related, primitive motivational signals—valence (unpleasantness versus pleasantness) and arousal (intensity)—which are thought to direct approach and avoidance tendencies towards stimuli (Russell, 1980). Accordingly, influential theories of emotion posit that these affective signals play an adaptive role in decision-making, responding to salient features of one's environment and directing us towards appropriate actions (Moors et al., 2013; Scherer, 2009). With respect to cognitive effort, affective evaluations could play a role in adaptively guiding cognitive processing away from undue strain by representing the "costs" of increased effort in terms of negative valence (Kurzban et al., 2013). Indeed, supporting the idea of a linkage between effort evaluation and affective response, previous work suggests that affective states can modulate effortful control processes (Dreisbach and Fischer, 2015; van Steenbergen, 2015) and that the mobilization of cognitive control processes is affectively tagged: actions that tax control and stimuli that signal high demand appear to be evaluated as more affectively negative (Vermeylen et al., 2019; Fritz and Dreisbach, 2013). Conversely, positively valenced stimuli promote more flexible decision-making strategies (Dreisbach and Goschke, 2004)—possibly by reducing the cost of such flexibility (Dreisbach, 2006). Negatively affective stimuli can trigger control costs (e.g., increased response times and reduced accuracy) akin to cognitive effort investment instead, even in the absence of objective demand manipulations (Dreisbach and Fischer, 2012).

While these past studies suggest a potential linkage between affect and cognitive effort evaluation in a general sense, two important questions remained unanswered: 1) Do individuals' affective evaluations of effortful tasks corroborate the idea that effort (both prospective and enacted) is experienced as aversive? 2) If so, do these affective evaluations incorporate information not only about the costs, but also the potential benefits tied to effortful action?

One challenge for understanding the interplay between mental effort evaluation and affect is capturing momentary affective responses under varying levels of prospective (or experienced) cognitive demand. Due in part to the fast (sub-second) time course of evaluative processing, affective responses often evince information that individuals do not have complete introspective access to or that may vacillate rapidly in the process self-report (Cunningham et al., 2008; Harmon-Jones et al., 2016). As such, the principal axes of affective response—valence and arousal—might be best understood by measuring rapid, pre-conscious physiological responses using facial electromyography (fEMG) and skin conductance response (SCR).

A spate of work has demonstrated that activity in the zygomaticus major muscle—a muscle that extends from the cheekbone to the corner of the mouth and is responsible for smiling—reflects positive affect and correlates with subjective (i.e., self-reported) ratings (Lang et al., 1993). Conversely, activity in the corrugator supercilli muscles—a small muscle group close to the eyes, located at the median end of the eyebrow (Fig. 1B)—reflects negatively valenced emotion and, in turn, is believed to reflect the experience of negative affect (Fridlund and Cacioppo, 1986; Lang et al., 1993; Larsen et al., 2003; van Boxtel, 2010). Critically, activity in these two muscles index positive and negative valence with high temporal resolution, affording measurement of transient and often subtle affective responses (Heller et al., 2011, 2014; Topolinski and Strack, 2015). Notably, during task performance, corrugator activity appears to differentiate between high and low concurrent demand (van Boxtel and Jessurun, 1993; Berger et al., 2020) and SCR—indexing physiological arousal, or the intensity of emotional response—has been shown to relate to anticipatory effort evaluation (Botvinick and Rosen, 2009). While these studies suggest potential associations between effort exertion and physiological measures of transient affect, the affective components of cost-benefit *evaluation* of effort itself, which would presumably reflect the putative costs, benefits—and their potential integration—remain to be investigated.

Accordingly, in two experiments, we examined whether the anticipation and exertion of cognitive effort at varying levels of cognitive demand (i.e., costs) and under varying reward incentives (i.e., benefits) are reflected in in physiological measures of affective response. To this end, we recorded fEMG activity and SCRs from participants while they performed an effortful arithmetic task (Vassena, Deraeve, et al., 2019a), in which we manipulated the level of cognitive demand (Experiment 1), and jointly manipulated demand and the reward incentive amount tied to correct responses (Experiment 2). Importantly, our task design temporally separates anticipation of upcoming effort—signaled via cues—from concurrent effort exertion (Fig. 1), allowing us to dissociate between participants' affective responses accompanying cost-benefit evaluation of the upcoming trial and effort exertion itself. In line with past work (van Boxtel and Jessurun, 1993; Berger et al., 2020; Larsen et al., 2003), we hypothesized that activity in the corrugator would correlate positively with demand level, whereas zygomaticus activity would negatively correlate with demand level, potentiated by reward incentive level. To foreshadow, we find that 1) corrugator fEMG activity—an index of negative affective response—tracks anticipated effort as well as concurrent effort exertion level, but more interestingly, also

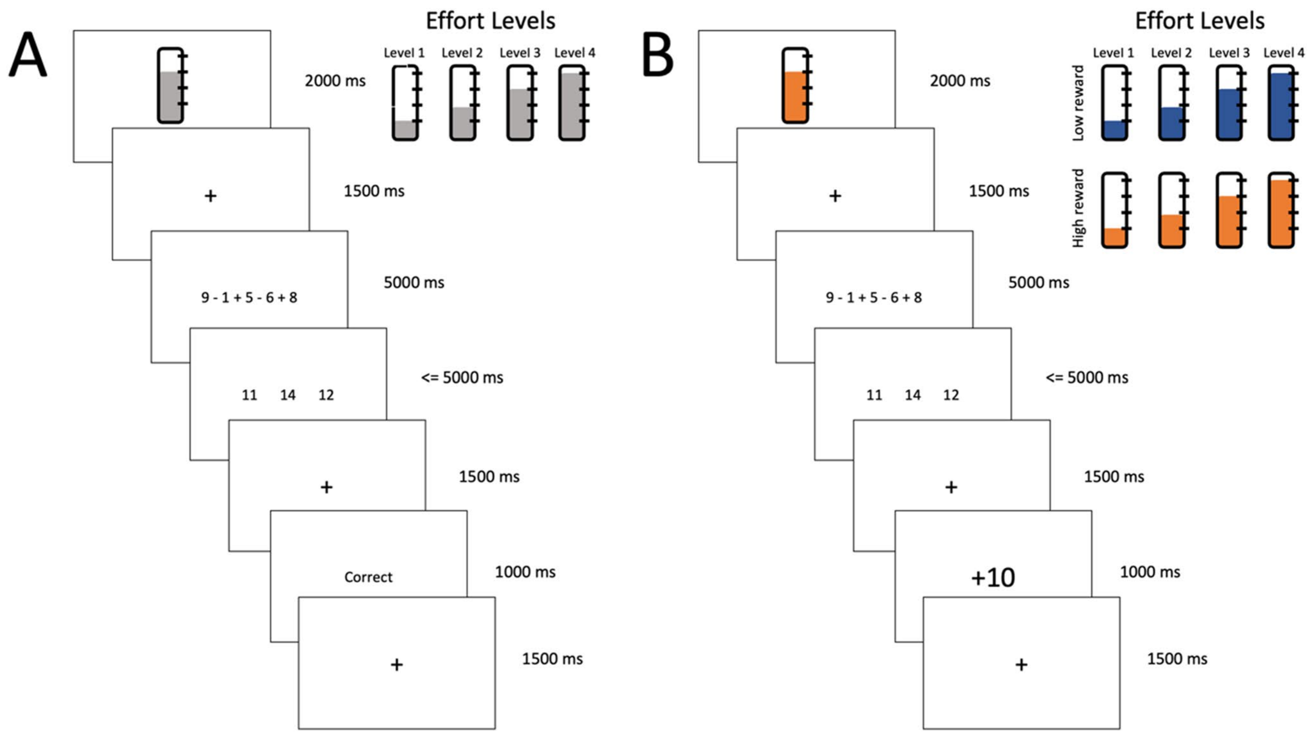

Fig. 1 Task diagram for Experiments (**A**) 1 and (**B**) 2. Panels with timings that contain ≤ were response terminated

reflects an integrated (or net) evaluation of the prospective costs (i.e., demand) and benefits (i.e., reward incentives) of the upcoming task during anticipation.

Experiment 1

Method

Participants

An a priori, power analysis revealed that 40 participants would yield 80% power (see Supplemental Materials). Accordingly, 44 healthy adult participants (40 females; average age = 20.50, SD = 1.88, range = 18-23) were recruited from McGill University's human participant pool. All participants gave informed consent before testing and were compensated with course credit. This procedure was approved by the McGill ethics committee (certificate number: 137-0816). Technical issues precluded the analysis of one participant's physiological data.

Procedure

The experiment was conducted in one two-hour session. Participants completed 200 trials of an effortful arithmetic task (Vassena, Deraeve, et al., 2019a; Vassena, Gerrits, et al., 2019b), which required participants to solve 5-digit mathematical problems (addition and subtraction) that ranged in difficulty across four effort levels: very easy (e.g., 4 + 9 + 1 − 1 − 1), easy (6 + 1 + 1 + 7 − 9), hard (6 + 8 + 7 + 1 − 9), very hard (3 + 9 − 5 + 8 – 7). Effort level depended on the amount of carrying and borrowing operations required (e.g., easy trials require carrying/borrowing once, whereas more difficult trials require carrying/borrowing and borrowing many times). Stimuli for the task were taken from previous work that has established a monotonic relationship between effort levels in these problems and cognitive effort exertion (Vassena, Deraeve, et al., 2019a; Vassena, Gerrits, et al., 2019b). Each problem was presented on the screen for 5,000 ms, after which three possible answers to the problem appeared (Fig. 1A). Participants had up to 5,000 ms to indicate their choice for the correct answer using the Q, W, or E keys. After making a choice, participants were given feedback based on their accuracy ("Correct" and "Incorrect").

Trials could either be cued or uncued. On cued trials, before seeing a problem, participants were presented with a cue—a "thermometer" filled to different heights—indicating how difficult the upcoming problem was going to be, with four possible levels (Fig. 1A). On uncued trials, no difficulty information was provided before the arithmetic problem. Participants first completed an uncued practice phase for 8 trials (for which data was not analyzed), followed by 48 trials of uncued problems, and finally 144 trials of cued problems.

Stimuli were presented against a white background. Math problems were presented as black text in Helvetica font with a height of 113.4 px (3 cm). Effort cues were 960 × 540 px (25.4 cm × 14.3 cm) consisting of a black stadium outline ("a thermometer") filled with a black stadium at four different heights (Fig. 1A).

SCR and fEMG recording and analysis

SCR and fEMG recordings were collected continuously throughout the entire experiment. SCR was measured via Ag-AgCl electrodes attached to the crease between the distal and middle phalanges of the first and second digits of the participant's non-dominant hand. fEMG activity was recorded over the left corrugator and zygomatic sites using cloth-base Ag-AgCl electrodes, following previous recommendations (van Boxtel, 2010). Both SCR and fEMG signals were measured using a MP160 unit (Biopac Systems, Inc., Goleta, CA) recording at a sample rate of 1,000 Hz. Following van Boxtel (2010), corrugator and zygomaticus signals were bandpass filtered between 20 Hz and 490 Hz, rectified, and low-pass filtered at 50 Hz before analysis. To measure changes in physiological activity in response to effort anticipation and exertion, the average difference of signal 1,500 ms before and after the stimulus onset—the effort cue for anticipation and the arithmetic problem for exertion—was computed per trial.

To analyze SCR, we employed a deconvolutional technique based on a physiological model of the general SCR curve that separates and quantifies the fast-varying (phasic) and slow-varying (tonic) components of the skin conductance signal (Benedek and Kaernbach, 2010; Otto et al., 2014). This technique was implemented using the Python module *pyphysio* (Bizzego et al., 2019). Effort-induced changes in SCR were computed as the average difference between phasic SCR 500 ms before and 1,500 ms after cue and problem onset.

Data analysis

Behavioural and processed physiological data were modeled using Bayesian hierarchical regression (a.k.a., mixed-effects regression) using the *brms* package in R (Bürkner, 2017) using uninformative priors. Specifically, we estimated a series of models predicting trial-level response times (RTs), accuracy, corrugator fEMG, zygomaticus fEMG, SCR on the basis of demand level (1 to 4) and cue condition (cued vs. uncued where appropriate), taking random intercepts over participants. Effort level was treated as a continuous predictor and was mean-centered and cueing condition (cued vs. uncued) was treated as a binary variable. Trial-level physiological signals were standardized within subjects. All reported coefficients (b) are median posterior values, credible intervals (CI, i.e., highest density intervals) are at the 95% level, and Bayesian *p*-values (P) represent one minus the proportion of the posterior that falls above or below zero (depending on the sign of the median posterior value: below zero if $b < 0$ and above if $b > 0$). In line with the traditional interpretation of frequentist *p*-values, Bayesian *p*-values can be interpreted probabilistically as "there is a (P×100) percent chance that the effect is zero or a reversal of the central tendency." All models were fit across 3 chains with 5,000 iterations each, discarding the first 2,500 samples of each chain for burn-in.

Results

Task performance

Overall accuracy in the task was high ($M = 0.79$, $SD = 0.40$; Chance level = 0.33, because three response options were provided). As expected, accuracy rates decreased and correct RTs increased with higher demand levels (Fig. 2A and B)—that is the more difficult the equation, the slower ($b = 0.25$, CI = [0.23, 0.27], $P = 0$) and less accurate participants responded ($b = -0.65$, CI = [−0.71, −0.59], $P = 0$). We also found that participants were faster ($b = -0.19$, CI = [−0.23, −0.13], $P = 0$) and more accurate ($b = 0.25$, CI = [0.11-0.38], $P = 0.0003$) on trials where demand levels were cued ahead of problem presentation. Finally, we observed a weak interaction between trial type and effort level, such that demand level-induced slowing ($b = -0.05$, CI = [−0.09, 0.00], $P = 0.0176$) and erroneous responding ($b = 0.13$, CI = [0.01, 0.26], $P = 0.0175$) were reduced on cued trials compared to uncued trials. Replicating the patterns of RTs and accuracy seen in past work using this arithmetic task (Vassena, Gerrits, et al., 2019b), these results suggest that our manipulation was successful at engendering increased demand across difficulty levels.

Physiological results

Corrugator fEMG In line with our hypothesis, we observed a linear increase in corrugator fEMG activity as a function of increasing demand level, both during the cue period (anticipation; $b = 0.04$, CI = [0.01, 0.06], $P = 0.0009$) and during the task period (exertion; $b = 0.04$, CI = [0.02, 0.06], $P = 0.0004$), indicating that that activity in the corrugator muscle was stronger when participants expected and solved harder problems compared with easier ones (Fig. 2C-D). During effort exertion, corrugator fEMG activity did not differ between trials with demand cues versus trials no demand preceding the task ($b = 0.00$, CI = [−0.05, 0.05], $P = 0.4921$), nor did we observe an interaction between cue presence and effort level ($b = -0.00$, CI = [−0.05, 0.04], $P = 0.4715$).

Zygomaticus fEMG Numerically, we observed a decrease in zygomaticus fEMG activity during presentation of the demand cue, but this effect was not statistically reliable (Fig. 2E; $b = -0.01$, CI = [−0.03, 0.01], $P = 0.1821$). We

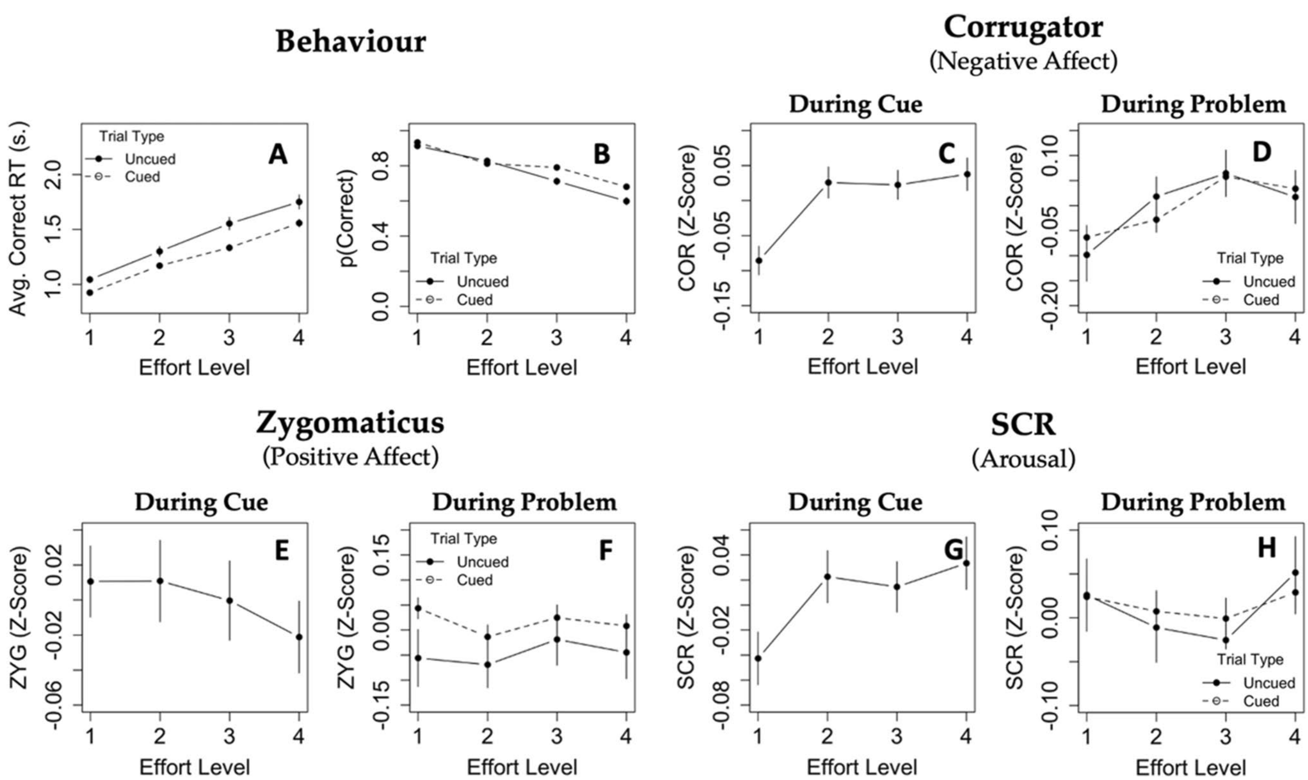

Fig. 2 Behavioural outcomes and physiological signals across effort levels and trial type in Experiment 1. The x-axis represents difficulty level of the equation to be solved (A, B, D, F, H) or the cue being presented (C, E, G). Solid lines represent uncued trials, and dashed lines represent cued trials. The y-axis represents the following: (**A**) the average response time for solving a problem correctly, (**B**) the average proportion of problems where the correct answer was identified, (**C, E, G**) the difference in physiological signal before and after the appearance of an effort cue, standardized within-subjects relative to all other signals during cueing, and (**D, F, H**) the difference in physiological signal before and after the appearance of the math problem to be solved, standardized within-subjects relative to all other signals during problem-solving

did not observe an effect of problem difficulty on zygomaticus activity during problem-solving (Fig. 2F, b = 0.00, CI = [−0.02, 0.02], $P = 0.4655$). However, we did find a weak but reliable modulation of task-concurrent zygomaticus fEMG activity by the presence of demand cues, such that activity higher during cued trials than uncued trials (b = 0.06, CI = [0.02, 0.11], $P = 0.0069$). We did not observe an interaction between effort level and trial type (b = −0.02, 95% CI = [−0.06, 0.03], $P = 0.2553$).

SCR We found that, during cue presentation, SCRs subtly increased as a function of effort level, such that anticipation of an upcoming effortful problem was associated with greater SCRs (Fig. 2G; b = 0.02, CI = [0.00-0.04], P = 0.0183). During problem-solving, we did not observe any systematic modulation of SCR as a function of demand level (b = 0.00, CI = [−0.02, 0.02], $P = 0.3819$), trial type (b = 0.00, CI = [−0.04, 0.05], P = 0.4215), or an interaction between the demand level and cue presence (b = −0.01, CI = [−0.05, 0.04], $P = 0.3945$; Fig. 2H).

These results provide support for our first hypothesis—namely, that the anticipation and exertion of cognitive effort exertion are tracked by physiological measures of affective response. However, these results speak only to a linkage between affective response and cognitive costs (i.e., prospective and anticipated cognitive demand). In Experiment 2, we examined whether these affective signals reflect anticipated and/or experienced effort costs, benefits, or a representation of integrated (net) utility—i.e., benefits minus costs—by measuring physiological activity as participants completed a (cued) arithmetic task under varying levels of demand and reward incentives.

Experiment 2

Method

Participants

According to an a priori power analysis, 50 participants was suitable to achieve 80% power (see Supplemental Materials). Sixty-six participants (77% female, average age = 22.98, SD = 3.95, range = 18-38) were recruited from McGill University's human participant pool and the community. All participants gave informed consent prior to testing and were compensated with course credit or \$10 CAN, plus a bonus of \$5 for their performance on the task. Technical issues precluded the analysis of eight participants' physiological data, leaving a final sample size of 58 participants.

Procedure

The design of Experiment 2 was identical to the previous experiment apart from the following changes. First, participants could now earn additional rewards for correctly responding. Specifically, on each trial, participants could win 1 or 10 points for correctly solving the math problem and were told that at the end of the experiments these points would be converted to an additional bonus payment (up to \$5 CAN). The amount at stake each trial was represented by the colour of the effort cue: blue cues meant that correctly solving the problem would earn them 1 point and orange cues meant that it would earn them 10 points (Fig. 1B). As in experiment 1, participants completed 192 trials: 24 trials of each combination of reward and effort level (e.g., low reward, effort level = 3). Second, the demand and incentive levels for all trials were cued, such that participants saw an effort cue (a "thermometer") before the arithmetic problem that they had to solve. Finally, after completing the task, participants rated how subjectively demanding they found each effort level, by rating all possible demand cues and responding (0-10) on two subscales of the NASA-TLX (Hart, 2006): the mental demand subscale ("How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex?") and the effort subscale ("How hard did you have to work (mentally and physically) to accomplish your level of performance?").

Results

Task performance

As in Experiment 1, overall accuracy in the task was high (p(Correct) = 0.87; Chance = 0.33) . Correct RTs increased (b = 0.16, CI = [0.14, 0.17], $P = 0$) and accuracy decreased (b = −0.57, CI = [−0.63, −051], $P = 0$) significantly as a function of effort level (Fig. 3A and B). We found little evidence for an effect of reward level (high vs. low) on RTs (b = 0.01, CI = [−0.02, 0.04], $P = 0.2791$) or accuracy rates (b = 0.08, CI = [−0.05, 0.21], $P = 0.1115$), or for any interaction between effort level and reward (RT: b = 0.01, CI = [−0.01, 0.04], $P = 0.1604$; accuracy: b = 0.02, CI = [−0.09, 0.14], $P = 0.3353$). This overall pattern of performance suggests that we successfully manipulated cognitive demand, whereas reward level did not appear alter task performance.

Physiological results

Corrugator fEMG Consistent with Experiment 1, we observed a linear increase in corrugator fEMG activity across effort levels both during presentation of the effort cue (Fig. 3C; b = 0.04, CI = [0.02, 0.06], $P = 0$) and during problem-solving (Fig. 3D b = 0.05, CI = [0.03, 0.07], $P = 0$). More interestingly, we found reward incentive level modulated corrugator fEMG activity, such that on trials with large potential rewards, corrugator fEMG activity was lower both during effort evaluation (i.e., during the effort cue; b = −0.04, CI = [−0.08, 0.00], $P = 0.0179$) and effort exertion (during problem of presentation; b = −0.05, CI = [−0.08, −0.01], $P = 0.0069$) compared to trials with small potential rewards. We found no evidence supporting an interaction between effort level and reward incentive on corrugator fEMG during either cue presentation (b = 0.01, CI = [−0.03, 0.04], $P = 0.3624$) or problem-solving (b = −0.00, CI = [−0.04, 0.03], $P = 0.4217$).

Zygomaticus fEMG During cue presentation, we found a negative trend for the effect of effort level on zygomaticus response (b = −0.01, CI = [−0.03, 0.01], $P = 0.1073$), such that increased effort level numerically, although not statistically reliably, reduced zygomaticus signals (Fig. 4E), but little evidence for the effect of reward magnitude (b = −0.02, CI = [−0.06, 0.02], $P = 0.1479$). We did not observed an interaction between effort level of reward level during cue presentation (b = 0.01, CI = [−0.04, 0.02], $P = 0.2857$). Furthermore, we observed little evidence that activity in the zygomaticus was modulated by effort level (b = 0.00, CI = [−0.02, 0.02], $P = 0.4501$) or reward magnitude (b = -0.01, CI = [−0.05, 0.03], $P = 0.2759$)—nor evidence for an interaction between the two (b = 0.02, CI = [−0.01, 0.06], $P = 0.0897$)—during problem-solving (Fig. 4F).

SCR In contrast to Experiment 1, we found little evidence that SCR was modulated by effort level during evaluation (i.e., cue presentation; b = 0.00, CI = [−0.02, 0.01], $P = 0.3404$) or problem-solving (b = −0.01, CI = [−0.01, 0.03], $P = 0.0841$), nor did we observe an effect of reward magnitude on SCR (cue: −0.02, CI = [−0.06, 0.01], $P = 0.1177$; problem: b = 0.00, CI = [−0.03, 0.04], $P = 0.3841$; Fig. 3G-H).

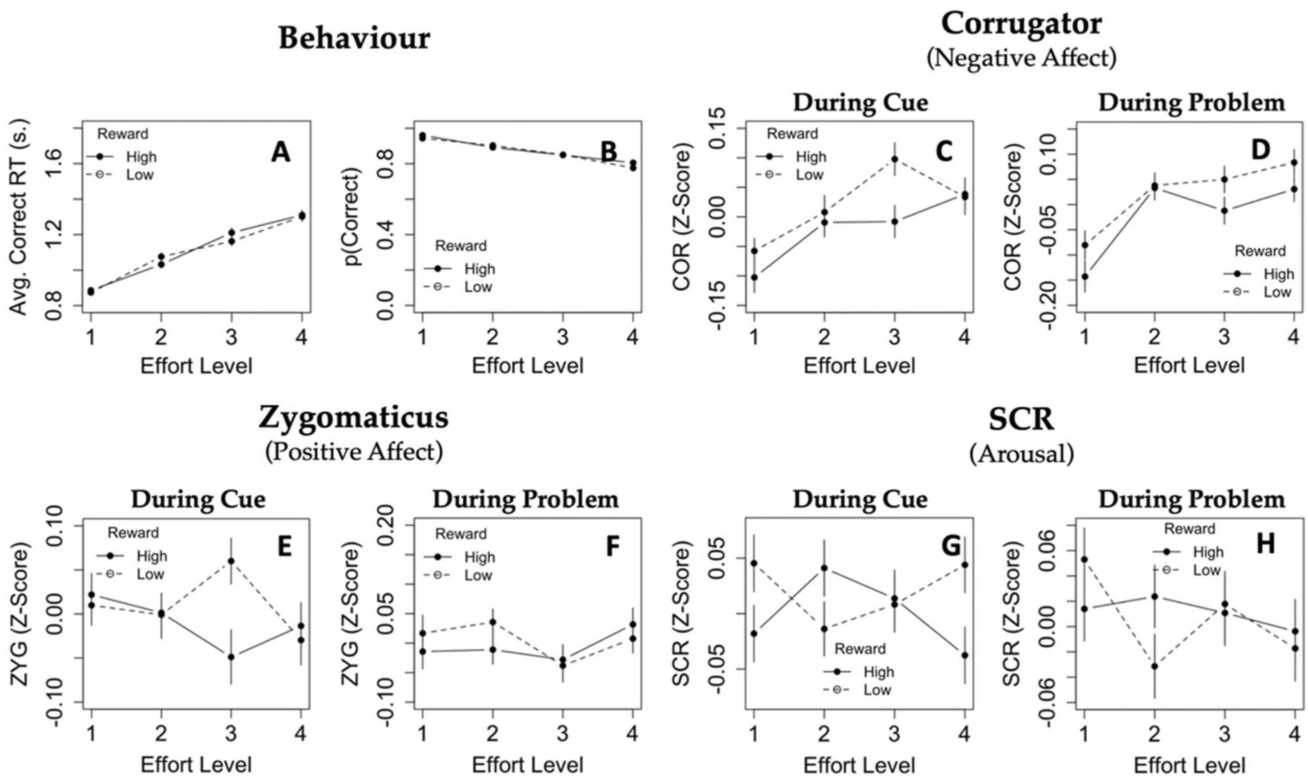

Fig. 3 Behavioural outcomes and physiological signals across effort levels and reward levels in Experiment 2. The x-axis represents difficulty level of the equation to be solved (**A, B, D, F, H**) or the cue being presented (**C, E, G**). Solid lines represent high reward trials, and dashed lines represent low reward trials. The y-axis represents the following: (**A**) the average response time for solving a problem correctly, (**B**) the average proportion of problems where the correct answer was identified, (**C, E, G**) the difference in physiological signal before and after the appearance of an effort cue, standardized within-subjects relative to all other signals during cueing, and (**D, F, H**) the difference in physiological signal before and after the appearance of the math problem to be solved, standardized within-subjects relative to all other signals during problem-solving

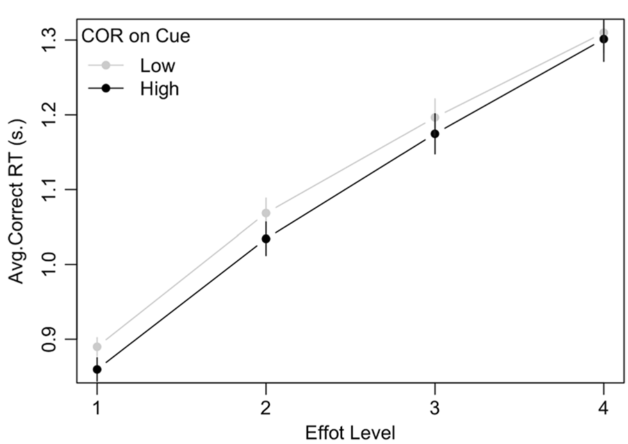

Fig. 4 Relationship between corrugator activation during the cue and performance on the ensuing task. The x-axis represents effort the x-axis represents difficulty level of the cue to be presented and the equation to be solved. The y-axis represents the average response time for solving a problem correctly. The colours represent the intensity of corrugator activity during the cue preceding the equation, illustrated by a median split (grey = lower than the median activation, black = higher than the median activation). Error bars represent standard error

Subjective demand ratings

Participants also provided subjective demand and effort ratings of the arithmetic problems by rating all possible cues they saw during the task (Fig. 1B). We found that higher-demand math problems were also rated as more demanding subjectively, in terms of both mental demand (b = 0.89, CI = [0.72, 1.07], $P = 0$) and experienced effort (b = 1.06, CI = [0.88, 1.23], $P = 0$), further demonstrating that our manipulation of subjective cognitive demand was successful (see Supplemental Materials; Figures S3A-B). We did not find a reliable effect of reward on mental demand (b = 0.14, CI = [−0.30, 0.57], $P = 0.2679$), but did find an interaction between reward and effort for mental demand ratings (b = 0.41, CI = [0.07, 0.75], $P = 0.0091$), such that, relative to low-demand problems, high-demand problems were perceived as more demanding when larger reward incentives were at stake. We also observed a robust positive effect of reward on effort ratings (b = 0.47, CI = [−0.07, 0.86], $P = 0.0133$), such that higher-reward cues were perceived as more effortful (Figures S3B).

Relationships between self-report measures and physiological reactivity

In an exploratory analysis, we also probed possible relationships between individual differences in subjective ratings of demand and effort—as indexed by TLX ratings in response to the demand/reward cues—and physiologically-measured negative affect evoked by these cues before each trial—as indexed by corrugator fEMG activity during cue presentation. In other words, did participants who reported more difficult trials as subjectively more effortful also exhibit increased corrugator fEMG activity in response to cues signalling this demand? To test this, we examined the relationship between each participant's TLX rating difference between the highest (4) and lowest effort levels (1), and the difference in (standardized) corrugator fEMG activity between the highest and lowest effort levels. We observed that corrugator fEMG activity correlated positively with both subjective demand ($r = 0.31$, CI = [0.08, 0.51], $P = 0.006$) and effort ratings ($r = 0.19$, CI = [−0.06, 0.41], $P = 0.067$), indicating that subjective demand and effort ratings mirrored corrugator fEMG activity during cue evaluation—although this effect was more pronounced in terms of mental demand ratings (Figures S3C-D). We also examined relationships between subjective demand and zygomaticus fEMG activity, as well as SCR, but we did not find any reliable inter-relationships between ratings and physiological responses (Figure S4).

Relationship between anticipatory physiological reactivity and task performance

Further, we conducted an exploratory analysis examining whether affective responses accompanying prospective effort evaluation—indexed by anticipatory corrugator fEMG activity evoked by effort/reward cues (Fig. 3C)—were associated with faster RTs on the ensuing arithmetic problems, which we take as a behavioral index of increased cognitive effort investment (Hübner and Schlösser, 2010; Manohar et al., 2015). To do so, we estimated a trial-by-trial regression predicting correct RTs on the basis of anticipatory (at cue) corrugator fEMG activity on that trial, controlling for objective effort and reward level, as well as other covariates likely to affect response times (trial number and previous error; Table S1). In doing so, we found a modest but statistically reliable negative predictive effect of corrugator activity on subsequent task RTs ($b = -0.01$, CI = [−0.02,0.00], $P = 0.0443$), such that stronger, negative-valenced physiological responses registering negative affect at cue presentation predicted faster RTs during arithmetic problem-solving (Fig. 4). In other words, this result suggests that heightened (negative) affective reactivity to prospective effort investment engendered greater effort investment—as indexed by faster responses—on the subsequent task.

General discussion

A large and growing body of work suggests that people find the expenditure of cognitive effort aversive and, as a consequence, avoid cognitively effortful activities (Kool and Botvinick, 2018). While past work has explained effort aversion in economic terms—do the benefits (i.e., rewards) of effort exertion outweigh the costs of effort exertion?—the affective nature of effort evaluation is less well understood (Inzlicht et al., 2015). A demonstration that these evaluations are indeed registered as negatively affective would help clarify the aversive nature of effort expenditure from a psychological perspective. In the present study, we find evidence that moment-to-moment variations in rapid affective anticipatory evaluations of effort—as captured by fEMG and SCR measurements—index an integrative signal of the relative costs (effort) and benefits (reward magnitude) of effortful allocation (Shenhav et al., 2013; Vassena et al., 2014). Specifically, we find that corrugator fEMG activity tracked increased task demands and integrated information about rewards, such that corrugator activity was 1) heightened when participants were asked to solve more complex arithmetic problems, 2) dampened when higher rewards were presented for correctly solving these problems, and 3) predictive of subsequent task performance.

Negative affective response tracks cognitive demand level

A key tenet of dominant theories of effort emphasizes the costly role effort plays in discouraging further engagement—i.e., effort is conceptualized here as a primitive and inherently aversive signal that discourages a cognitive agent from adopting a course of action (Kool and Botvinick, 2018; Kurzban et al., 2013). Analogously, arousal and valence can be viewed as primitive signals employed by the motivational system, which define, respectively, the intensity and pleasantness of the affective state evoked and in turn direct approach/avoidance behaviour towards stimuli (Moors et al., 2013; Scherer, 2009; Smith and Ellsworth, 1985). While past work suggests that corrugator and zygomaticus fEMG activity indexes these affective signals and is sensitive to the rated valence of stimuli such as pictures and sounds (Larsen et al., 2003), the physiological markers of affective evaluations of cognitive effort have received less attention (Berger et al., 2020).

Supporting this linkage, we found that corrugator fEMG activity tracked prospective and enacted effort levels and that SCR (indexing arousal) tracked anticipated effort exertion during an effortful cognitive task in a parametric fashion. This finding conforms well with the idea that cognitive effort is evaluated as aversive. That is, the cost of cognitive effort was reflected in physiological indexing negative affective response, Notably, however, we do not replicate the relationship between SCR and effort level in Experiment 2, hinting that negative valence may carry more information about evaluations of effort costs than physiological arousal.

Furthermore, in exploratory analyses, we found that increased corrugator activation during cue presentation led to increased effort exertion during task performance. Insofar as corrugator response indexes negative affect, this finding is consistent with popular theories of emotion that highlight the adaptive role of affect in decision-making, wherein affective signals work to adaptively guide an agent's actions—here, the recruitment and investment of cognitive resources—to salient changes in the environment—here, the degree of effort required and the prospective amount of reward at stake (Moors et al., 2013; Scherer, 2009).

An open question concerns whether activity in the corrugator can be taken as a selective signal for affective response or whether it might be additionally reflect recruitment and/or deployment of cognitive control. Past studies that examined the relationship between fEMG and *concurrent* cognitive effort exertion were unable to disambiguate whether variation in corrugator activity arise from changes in negative affect and/or in cognitive control exertion (Berger et al., 2020; van Boxtel and Jessurun, 1993; Silvestrini and Gendolla, 2009). We examined corrugator fEMG activity in the *prospective evaluation* of cognitive effort—i.e., during a cue phase where participants, presumably, are not actively exerting cognitive effort—finding that corrugator activity positively relates to the level of cognitive demand signaled by the cue and is further dampened by the prospect of larger reward. Echoing previous observations that negatively valenced stimuli evoke increased corrugator fEMG activity accompanying (Heller et al., 2011; Lang et al., 1993; Larsen et al., 2003), we found the most robust differentiation in corrugator activity during passive viewing of cues associated with varying demand and reward levels. We take these results as evidence that corrugator activity reflects, at minimum, the (negative) affective component of effort evaluation. An important avenue for future work would be to disentangle concurrent cognitive control deployment and affective response, for example, by examining the concordance between physiological, putatively "objective" measures of online effort, such as pupillometry and physiological measures of affective valence with fEMG, as proposed by van der Wel and van Steenbergen (2018).

Negative affective response is dampened by reward incentives

Similarly, models of cognitive effort investment predict that the default avoidance of effort can be counteracted by increasing incentives (Sandra and Otto, 2018; Sayalı and Badre, 2019; Kool and Botvinick, 2018). Indeed, we find a convergent result in the present data—corrugator fEMG activity also was attenuated in the face of larger reward incentive—suggesting that the affectively aversive character of effort is mitigated when effort expenditure is tied to larger rewards. In other words, rewards function to offset higher demands in the service of attaining valuable goals, both in computational frameworks and, as we have demonstrated, at a primitive psychophysiological level.

Importantly, corrugator fEMG activity tracked effort and reward levels not only during problem-solving, but also during cue presentation. This suggests that in addition to capturing the affective response associated with the engagement of cognitive resources (i.e., mental strain; in line with past work: Berger et al., 2020; van Boxtel and Jessurun, 1993) and the potential receipt of rewards, the anticipatory evaluation of rewarded effort expenditure also was indexed by physiological measures of affective response. Notably, we did not observe an interaction between prospective reward magnitude and effort intensity, suggesting that corrugator fEMG activity was modulated uniformly in the current task, indexing the integration of benefits (rewards) and costs (effort), consistently across effort levels. This is in line with past work, which suggested that that the (minimal) signature of cost-benefit integration in effort valuation may be subtractive in nature (Lopez-Gamundi et al., 2021; Vogel et al., 2020).

Notably, while corrugator activity indexed heightened reward incentives, task performance (response times and accuracy) did not. This is not entirely uncommon: while past work has found reward-induced modulations in task performance (Otto & Vassena, 2021), these effects are far from ubiquitous and many reward manipulations—particularly when rewards vary on a trial-by-trial basis, as in the present study—fail to produce reliable changes in behavioural indices of cognitive effort exertion (Otto and Daw, 2019; Sandra and Otto, 2018). Similarly, we found that participants' subjective reports about their effort outlay increased when faced with higher rewards, mirroring past work (Fairclough and Ewing, 2017). Notably, this pattern contrasts with our observed pattern of corrugator activity: while heightened reward incentives increased subjective reports of effort exertion, they also decreased corrugator activity. This suggests that on high-reward trials, participants outwardly reported that they needed to exert additional effort to maintain their performance, while at the same time exhibiting decreased negative affect, as indexed by corrugator activity. This finding is in line with recent proposals that subjective (self-report) and objective (task performance, Dreisbach and Jurczyk, 2022, or physiological, Kreis et al., 2020) measures of effort may differentially index unique facets of cognitive effort (Thomson and Oppenheimer, 2022). In this respect, it is interesting that physiological measures of negative affect—and, in particular, those measured *before* effort exertion—were negatively sensitive to changes in prospective reward, where coarser behavioural and subjective indices were not.

Conclusions

This pattern of results suggests that activity in the corrugator indexes an affectively salient integrative signal of net utility—the anticipated benefits of effort exert minus their presumed costs—that serves to guide human behaviour towards the least demanding, but most rewarding, course of action. In other words, the integration of demand and reward (i.e., the "net utility" resulting from cost-benefit analysis) may be "translated" into affective signals that, act beyond being epiphenomenal by-products of cost-benefit computations, appear to inform motivated performance (Inzlicht et al., 2015). Such a view is consistent with recent proposals for an "affective-signalling hypothesis," which proposes that the negative affective reaction to effortful control triggers behavioral adaptation (here, effort exertion; Dignath et al., 2020). In other words, the relationship between effort level, reward, and corrugator activation seen in the present study may in turn reflect the moment-to-moment felt output of a computed cost-benefit equation that people use to inform subsequent decisions about effort investments (Kurzban et al., 2013). To examine this possibility, future work should investigate how these physiological signals might predict future decisions to engage in (or withhold) cognitive effortful activity, which would elucidate the relationship between the well-documented propensity for people to avoid effort (Kool et al., 2010) to their affective evaluations of effort observed here.

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Author contributions S.D. conceived of the initial research question, designed and programmed all experiments, collected and analysed data, and co-authored the manuscript. E.V. designed the stimuli and conceived of the initial experimental design, as well as co-authored the manuscript. A.R.O. supervised the project, assisted in the conception and design of the experiments, secured funding, and co-authored the manuscript.

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Data availability Task code, processed data, and analysis scripts are available at https://github.com/seandamiandevine/EffEMG.

Declarations

Competing interests The authors declare no conflict of interest.

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