

Balancing the cognitive effort balance: effort being costly and valued

From linearity to optimality



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Abstract

Can exertion of cognitive effort be rewarding in itself? Where most research focuses on the aversive side of effort, there are also situations in which people explicitly enjoy cognitive effort exertion. Research on flow experiences points towards the intrinsic value of optimal challenging activities, such that intermediately challenging tasks receive higher liking and engagement scores compared to easy and difficult tasks. Intrinsic motivation accounts suggest that this value could arise from its potential for improvement. Moreover, pupillary dynamics have been associated with task engagement as well. The goal of this study was to investigate when cognitive effort exertion is intrinsically rewarding and hence preferred, and which cognitive processes are underlying this preference. In a design with individually defined difficulty levels and subjective and objective measures of engagement, we showed that intermediately challenging tasks received the highest subjective and objective engagement scores, as well as the greatest prediction error magnitude. These findings indicate that performance uncertainty might be the underlying mechanism of flow experiences. Moreover, greater pupil sizes during cue period of intermediate tasks together with smaller pupil size during easy and difficult tasks suggest that the brain at forehand differentiates between tasks that are worthwhile to engage in and tasks that are not. As the pupillary responses are following noradrenaline-based arousal activity, locus-coeruleus activity might mediate this relationship between optimal challenge preference and task uncertainty.

Keywords: Cognitive effort; Cognitive avoidance; Flow; Motivation; Cognitive control; Physiology

Introduction

Writing an academic paper requires for a lot of cognitive effort investments. Hence, students often perceive their thesis trajectory as frustrating and unpleasant. Nevertheless, this is precisely the job of millions of researchers. While researchers are well aware of these investments, they voluntarily engage in the task of writing papers, precisely because it is arduous and effortful. Although on a daily basis, cognitive effort often seems to be aversive, this example illustrates that investing cognitive effort is also rewarding in some way. This antithesis can be referred to as the effort paradox (Inzlicht et al., 2018), in which effort allocation can be both costly and valued. This paradox also applies to cognitive effort, roughly defined as intensity of mental activity, as the total amount of cognitive resources to select task-relevant target information and filtering out task-irrelevant distractors, needed to complete a certain action (Inzlicht et al., 2018; Tae et al., 2021). To date, it is not quite clear how effort can be experienced as both a cost and a value, and what underlies the individual preference for investing cognitive effort. Building on existing literature, the current study aims to shed light on this topic by taking the intrinsic value of cognitive effort into perspective.

Cognitive effort avoidance

The law of least mental effort, originating from the psychological field, proposes that when given a choice between equally rewarding options, individuals learn to avoid those options that require more effort (Hull, 1943). This principle of cognitive effort avoidance is supported by many lines of evidence, assuming that most people find cognitive effort exertion to be aversive and frustrating, and would therefore avoid it if possible (Aben et al. 2020; Kool et al. 2010; Kurzban, 2016). Prominent theories on effort avoidance have suggested that cognitive effort is penalized by an intrinsic cost as described in the ‘cost of effort’ hypothesis (Aben et al. 2020; Botvinick, 2007; Sayalı & Badre, 2019; Shenhav et al., 2013). For example, work from the behavioural field has provided a wide range of different tasks in which the preference for less effort is clearly visible (Kool et al., 2010; Westbrook et al., 2013). Studies adopting effort discounting paradigms showed that participants are willing to let go greater amounts of monetary reward in order to avoid more challenging tasks (Westbrook et al., 2013; Dixon & Christoff, 2012). Physiological studies showed that effort exertion coincides with increased sympathetic nervous system activation, which is associated to aversive signals (Dreisbach & Fischer, 2012; Hoshikawa & Yamamoto, 1997). On a neuronal level, brain regions associated with reward related signals (ventral striatum) show a parametrically decrease in activity with increased effort exertion (Botvinick et al., 2009; Dixon & Christoff, 2012;

Westbrook et al., 2013). Apart from the cost of effort, these findings have put forward the idea that effort exertion can even reduce the reward value of a tasks' outcome (Aben et al. 2020; Sayalı & Badre, 2019; Shenhav et al., 2013).

The nature of this intrinsic cost is still under debate. One prominent candidate is cognitive control, where the recruitment of cognitive control is what makes a task effortful (Sayalı & Badre, 2019; Shenhav et al., 2013; Székely & Michael, 2020). Cognitive control can be broadly defined as the set of mechanisms necessary for pursuing a goal, where distraction and competing responses must be overcome (Cools, 2016). Aspects of cognitive control allocation are the ability to switch between different tasks, maintenance and stabilization of goal representations (Cools, 2016), and conflict monitoring (Botvinick et al., 2001). Recent empirical work corroborates the finding that individuals seek to minimize cognitive control in using Demand Selection Tasks (DST). In such tasks, participants are introduced with two options yielding two tasks with different levels of required cognitive control, and they could choose freely between the two options in the absence of extrinsic reward. Studies using DST show that after learning that different options are associated with different demands, participants prefer to pick the option that requires less cognitive control (Kool et al., 2010; Schoupe et al., 2014; Sayalı & Badre, 2019; Westbrook et al., 2013). Moreover, people showed greater avoidance behaviour during tasks that require more task switching (Kool et al., 2010), maintaining a greater working memory load (Westbrook et al., 2013), or interference with response conflict (Schoupe et al., 2014). Also, a study using task-switching showed greater activity in the Frontoparietal Network (FPN), a network associated with switching, turned out to be accompanied by more avoidance (McGuire & Botvinick, 2010).

This is consistent with the Expected Value of Control model (EVC), which integrates the expected costs of a given task with the potential reward, to determine whether to engage in a control requiring task or to avoid it (Frömer et al., 2021, Shenhav et al., 2013). Specifically, the value of the immediate outcome is weighted against the intrinsic cost of executing the required amount of control, where the expected value of control is determined as a function of the likelihood of reaching an outcome minus the required control. Indeed, participants show greater engagement and are willing to exert more effort to obtain a greater reward, but when that reward requires more control, the costs may outweigh this reward leading to participants divesting their effort (Frömer et al., 2021). These ideas combined demonstrate that the exertion of cognitive effort is driven by a cost-benefit procedure for on the one hand the overall expected payoff of engaging in a certain action, and on the other hand the intrinsic costs of control associated to that action. Additionally, the necessary costs do not exceed its anticipated benefits.

In other words, a task is believed to be effortful to the degree that they require cognitive control (Frömer et al., 2021; Sayalı & Badre, 2019).

The value of effort

Recent theorizing assumes this may be just part of the story. The majority of studies analysing cognitive effort have focussed on the aversive side of effort, implying that the weighing is based on a calculation where one gets a certain outcome for minimal effort exertion, leading to the belief that effort is standardly registered as a cost. However, another line of research has argued that exerting cognitive effort is not always aversive; sometimes people voluntarily engage in effortful tasks in the absence of external rewards (Baranes, 2014; Csikszentmihalyi, 1991; Sayalı & Badre, 2019). For instance, challenging hobbies, master expertise or extreme sports, all require effort but are also rewarding and attractive in their own right. This suggests that sometimes engaging in an effortful task could be intrinsically rewarding, outweighing the cost, leading to the actual opposite preference. This is putting forward the idea that people can also attribute a positive value to effort exertion, rather than solely a cost. A critical question arises, when does effort exertion get a positive value?

Flow theory, another perspective

An influential line of research suggests that humans can be intrinsically motivated for optimal challenge, proposing that people focus on optimal challenging activities, characterized by a sense that the skill level is perfectly matched to the challenges at hand, and thereby avoid activities that are too easy or too difficult (Baranes et al., 2014; Csikszentmihalyi, 1991). For example, people spontaneously increased the difficulty of the video game they played to keep their accuracy around 50% throughout the experiment (Baranes et al., 2014). Engaging in optimal challenging activities might be intrinsically rewarding since it can induce a state of “flow” (Hektner & Csikszentmihalyi, 1996), contradicting previous literature of effort avoidance. Csikszentmihalyi described this flow state as being so deeply involved in an activity that nothing else seems to matter. According to the exact definition, the concept of flow refers to an activity that produces subjective experiences that are intrinsically rewarding apart from any extrinsic goods, even when it is difficult or dangerous (Hektner & Csikszentmihalyi, 1996; Csikszentmihalyi, 1991). Hence, being “in flow” leads to a state of concentration and commitment, reduced self-consciousness, feeling competent and in control, distortion of the sense of time or worry, and an intense feeling of happiness and enjoyment (Csikszentmihalyi & Nakamura, 2014). Such states are ensued in intermediate challenging activities, with

provision of clear goals and immediate feedback to how well one is performing. If the balance between one's ability and task demand is disturbed, such as when task demands are relatively lower compared to one's skills experiences of flow will turn into a state of boredom. When the task demands are relatively high compared to one's skills, feelings of stress, frustration, or anxiety can arise (Csikszentmihalyi, 1991). Consistent with this, participant's subjective liking and engagement ratings of the intermediately challenging effort condition ("flow") were greater than that of easy ("boredom") and difficult ("overload") (Ulrich et al., 2014). Moreover, flow experiences lead to recruitment of neural correlates as the striatal network, which are commonly associated with processing extrinsic rewards (Ulrich et al., 2014; Schouppe et al., 2014). Previous research has indicated that flow experiences are remarkably robust over a broad scale of activities ranging from physical and mental sports (Csikszentmihalyi & Nakamura, 2014) to making music and art (Bakker, 2005), regardless of its culture, class, gender or age.

The classical Yerkes-Dodson curve describes a relationship between engagement and arousal, in which an optimal level of arousal yields the greatest task engagement and subsequently boost performance (Csikszentmihalyi, 2000; Yerkes & Dodson, 1908). In line with this, these three different states (flow, boredom, and overload) are associated with different activation patterns of the two stress systems in our bodies: the sympathetic nervous system and the hypothalamic-pituitary-adrenal (HPA) axis (de Manzano et al., 2010; Keller et al., 2011; Peifer et al., 2014). Specifically, boredom is characterized by low physiological arousal, indicated by decreased sympathetic nervous system (low frequency heart rate variability) and HPA-axis (low absorption of cortisol). On the contrary, overload is associated with high physiological arousal. If the activity at hand is exceeding one's skills, it will cause stress, reflected by an increase in the sympathetic nervous system (high frequency heart rate variability) and HPA-axis (low absorption of cortisol) (Peifer et al., 2014). Both leading to impaired task performance. As flow is located between boredom and overload and is experienced during activities that are challenging but not threatening, flow-experiences are characterized by a moderate level of arousal, with moderate activity in the sympathetic nervous system and greater activity of the HPA-axis (high absorption of cortisol), yielding a high level of engagement (Csikszentmihalyi, 2000; de Manzano et al., 2010; Keller et al., 2011).

Learning progress motivation account

Now, as these intermediate levels of difficulty that yield an optimal level of challenge are preferred, a second question arises; what is the origin of the value of effort itself, i.e., how come people are more engaged and therefore more willing to exert cognitive effort when the

task level is intermediate? One prominent account that aims to explain mechanisms underlying intrinsic motivation is the Learning Progress Motivation Hypothesis (Oudeyer et al., 2016; Gottlieb & Oudeyer, 2018). This hypothesis proposes that the intrinsic motivational value of an action comes from its potential for improvement. In daily life, our brain is constantly trying to anticipate what will happen next. In doing so, an expectation is made of the possible outcome of an action. At any given time, we match this expectation with the actual outcome. When our expectation does not match with the actual output, there is a prediction error (PE), which scales with the mismatch (Schultz, 2016). Over time, people try to update their predictions (Gottlieb & Oudeyer, 2018). On one hand, activities that are too easy to predict, i.e., it's clear that one will perform the activity with almost perfect accuracy, yield a very low to zero PE magnitude. At the other hand, activities that are too difficult also yield low PE magnitude, since they are almost impossible to succeed. When activities match an intermediately capacity level, in which it's not clear whether one will perform successfully or not, there is a high PE magnitude. In other words, they experience a higher level of performance uncertainty. In classical reward learning theories, a positive PE, i.e., being better than expected, is believed to elicit intrinsic reward experiences (Schultz, 2016). Moreover, most activities with a higher level of performance uncertainty (high PE magnitude) yield room for uncertainty reduction (a change in PE), indicating a potential for improvement, which also elicits intrinsic reward experiences. Note that activities with random task instructions for example also yield high uncertainty levels but lack room for PE change. In summary, a higher level of performance uncertainty that coincides with a greater performance uncertainty reduction should trigger engagement, as it is hypothesized that actions in which predictions can be improved are intrinsically motivating. Therefore, intermediately challenging tasks should be preferred because they have a higher positive PE magnitude, and have room for changing the PE. Indeed, infants tend to avoid tasks including stimuli are too easy or too difficult, but preferably attend to stimuli of intermediate predictable level (Kidd et al., 2012). Additionally, studies on artificial intelligence demonstrated that simulated robots selectively attend to tasks where there was the greatest room for uncertainty reduction to foster improvement (Oudeyer et al., 2007; Gottlieb & Oudeyer, 2018).

Integrating flow and intrinsic motivation

Bridging flow literature and the learning progress motivation hypothesis, this learning component of empirically induced 'flow' states might be what underlies the value associated with cognitive effort exertion. During intermediately challenging tasks, which have higher PEs

and have greater room for improvement, exerting effort to allocate cognitive control could be valuable, which could result in the process of effort exertion being intrinsically rewarding. Tasks in which the performance is already at plateau or impossible to conduct, the extra effort might not matter (Frömer et al., 2021; Shenhav et al., 2013). In the current study, we used a novel paradigm with individually defined task conditions to see how people subjectively evaluate tasks varying in difficulty based on their own capacity. Furthermore, we investigated which computational mechanisms could explain these evaluations, by measuring how frequency of PE and PE change vary across task difficulty.

Locus coeruleus pupillary responses modulate relationship arousal and task engagement

Next to subjective reports of engagement, also objective measures can be taken into consideration. Now, according to a large body of work, task engagement is associated with locus coeruleus (LC) functioning (Aston-Jones et al., 1999). The LC is a small nucleus consisting of predominantly noradrenergic neurons located in the brainstem and provides the neocortex with the neuromodulator noradrenaline (NA) (Eckstein et al., 2017). As NA signalling is associated to arousal responses, a moderate level of arousal leads to intermediate levels of LC activity and hence optimal task performance (Aston-Jones & Cohen, 2005; Yerkes-Dodson curve) (Yerkes & Dodson, 1908). Specifically, according to the Adaptive Gain Theory (AGT), LC activity has been shown to exhibit two models of function: phasic and tonic (Usher et al., 1999). The phasic mode is marked by short bursts of action potentials (10-20Hz), which occurs in response to task-relevant events. Tonic activity is exemplified by stochastic discharge across a range of slower rates (0.1-5.0 Hz) (Devilbiss & Waterhouse, 2011; Aston-Jones et al., 1994; Aston-Jones & Cohen, 2005).

The close relationship between LC-NA activity and the pupillometry system has been established through numerous studies. For example, Evidence for a direct link comes from monkey research observing fluctuations in pupil size co-vary with event-driven LC spiking activity (Aston-Jones & Cohen, 2005; Varazzani et al. 2015). Moreover, several brain imaging studies measuring brain activity and pupil diameter found an indirect link between pupil size and LC activity (Murphy et al., 2014; Gilzenrat et al., 2010; Joshi et al., 2016; Joshi & Gold., 2020). Thus, combined evidence has argued that pupil size is a reliable, easily observable, index of the release of NA from the LC. Furthermore, phasic LC activity has been linked to task-evoked pupil responses (TEPR) with a small baseline pupil size and is associated with higher task performance (Aston-Jones et al., 1994; Hopstaken et al., 2015). Conversely, tonic LC activity has been associated with baseline pupil size in the absence of task evoked dilations,

and is associated with degraded task performance (Aston-Jones et al., 1999). Intriguingly, baseline pupil size was shown to be the highest and task-evoked dilations the lowest when participants decided to disengage from an effortful task and this pattern reversed when participants reengaged with the task (Gilzenrat et al., 2010). However, in this study external reward is taken as motivation, where participants' accuracy and the decision to engage was collinear, the possibility of internal rewards is overlooked. Critically, in the current study accuracy and task engagement were dissociated since there was no external reward directly associated to task performance. This allows participants to putatively report greater subjective task engagement for tasks on which they perform more poorly than for tasks on which they perform near perfect. In this way, our paradigm provides a novel tool not only for testing the learning potential underlying flow experiences, but also for investigating the link between pupil dilation and task engagement.

Additionally, although numerous studies have investigated pupil dynamics in the context of cognitive effort, there are doubts whether the pupil dynamics change as a function of task engagement as such (Castanheira et al., 2020; van der Wel & van Steenbergen, 2018) or merely reflects task demands (Beatty, 1982; Hershman & Henik, 2019; Irons et al., 2017; Moresi et al., 2008). For example, Moresi and colleagues (2008) reported larger pupil dilation for selection and preparation of difficult tasks in a finger-cuing paradigm. Also, Irons and colleagues (2017) observed that larger pupil dilation was driven by more difficult targets based on shape and colour. Although demand and effort typically co-vary when success is possible, extremely high task demands are expected to produce disengagement and withdrawal of effort (AGT). In the current study, we also addressed these dissociable predictions.

Aim of the current study

All in all, the goal of the current study is two-fold. As effort avoidance accounts suggest expected accuracy to be a predictor of task engagement, task engagement is predicted to decrease with task difficulty. However, according to the above-mentioned learning progress literature, people are more engaged in tasks that they are intermediately good at given their capacity, since these yield a learning potential. Based on intrinsic motivation accounts, task engagement should increase with greater prediction error and their minimization, i.e., performance uncertainty, yielding an inverted-U pattern across task difficulty. Therefore, as first objective, we tested the separation of these two accounts. We designed a novel experimental effort paradigm to see how people evaluate tasks varying in difficulty based on their own capacity. Specifically, four task conditions were determined on beforehand in which

each participant scored 100%, 75%, 50% and 25% correct, yielding an easy, two intermediate and one difficult condition. Subjective measures of engagement are acquired via flow statements (Ulrich et al., 2014). We hypothesized an inverted-U shape of flow statements as well PE magnitude across task conditions. Secondly, we investigated the if the phasic pupil mode would track subjective engagement in anticipation of effort investment, in the absence of direct external reward (Aston-Jones et al., 1994). Additionally, it is still unclear whether pupil size tracks effort exertion or task demand. Therefore, pupillary responses will also be measured within this novel paradigm. In line with the AGT we predicted a quadratic trend of phasic pupil responses over task difficulty following engagement scores, and not a linear trend, as predicted by task demand accounts. Moreover, we predicted that higher phasic pupil mode is accompanied by higher PE magnitude. In the end, by measuring both subjective and objective measures of task engagement at the same time, we were able to test whether the intrinsic value underlying effort exertion in optimal challenging activities arises from greater performance uncertainty, related to LC-NE-based arousal activity.

Methods

Participants

Forty English-speaking participants were recruited from the Radboud University participant pool (SONA Systems). All had normal or corrected-to-normal vision. None of them took eye medication that could influence pupil responses. They received a monetary reward (€10.00) for their participation and provided written informed consent prior to the experiment. Each participant was tested individually in a laboratory session lasting approximately 75 minutes. Participants were removed from the analyses if they had not completed the study ($N = 2$), or no reliable pupil dilation ($N = 2$). The final sample size of 36 (aged 19-64; $M = 26.2$; $SD = 9.6$; 20 women) allowed us to detect an effect size of Cohen's $d \geq 0.05$ with 80% power and alpha of 0.05 (Cohen's 1992).

Stimuli and Data Acquisition

During the computerized task portion of the experiment, participants were seated in a height-adjustable chair in front of a 23-inch monitor set to a resolution of 1920-1080 pixels, in a constant dimly lit room. Participants were instructed to keep their heads still and stabilized, rested in a chinrest positioned 50 centimetres away from the screen. All stimuli were delivered

and controlled via the software Matlab (version 2016b). Stimuli consisted of arithmetic summations of diverse difficulty levels, manipulated by summation length.

Procedure

The task

The participants started with a computerized task, which consisted of solving arithmetic summations varying in difficulty (e.g., $17 + 2$) There were two different phases: a capacity phase to determine the four task conditions, and a performance phase where those conditions are performed. Both will be explained in detail in the following sections. In both phases, participants had to solve summations by giving a free response within a time period of 18 seconds. They were instructed to answer as many trials correctly as possible, and to answer as soon as they knew the correct answer. The answer had to be entered digit by digit using numeric keys on the keyboard. Mistakes could be corrected using a “Backspace” button. Their input was immediately displayed on the screen. All summations were presented in a row, with accurate feedback (*correct, incorrect or too late*) provided immediately afterwards.

Capacity phase

The capacity phase served to determine the participants’ level of skill. Each difficulty level consisted of 4 summation trials. Starting at the easiest possible level, the difficulty level of the summations was continuously increased by one level. Specifically, a level-up adjustment occurred when the participant correctly answered at least one question of the same difficulty level. This procedure was continued until the participant scored 0% correct at all 4 summations of a certain difficulty level. When the capacity phase was finished, a sigmoid function was fitted to the resulting datapoints in order to estimate four task conditions based on participant’s own accuracy. The ‘Easy’ condition was kept the same across all individuals and yielded the following formula: $X + X$. All participants scored 100% correctly on this task condition. The subsequent task levels yielded lower accuracy: At ‘Intermediate1’ condition accuracy was 75%, at ‘Intermediate2’ condition accuracy was 50%, at ‘Difficult’ level accuracy was 25%. These individually determined task condition were used as the upcoming four effort levels in the following performance phase.

Performance phase

In the performance phase, the participant completed two blocks per task condition in a pseudo-randomized order (Fig 1). Specifically, each task condition was randomized in the first

half of the performance phase (“C-A-D-B”), and the same order was repeated for the second half (“C-A-D-B”). Each block consists of 8 trials, so that the entire performance phase comprised 64 trials in total. Prior to each block, participants underwent a standard 9-point calibration procedure of gazing shortly at 9 markers displayed on the screen sequentially, to achieve the best calibration accuracy. At the beginning of each trial, a letter cue (A, P, Q, Y) was presented to indicate the upcoming task condition. These cue-task condition pairings were counterbalanced across participants in such way that each letter had a similar likelihood of being paired with a task condition. This cue period lasted 3 seconds, to capture the entire response profile of the pupil. The cue was followed by a fixation cross of 1 second. Following the fixation cross, the participant solved a summation trial, the difficulty of which depended on the current task condition block. All cues, fixation crosses and summations were presented in red. Feedback consisted of a blue check mark for correct, an orangish cross for incorrect and an orange clock for too slow. All stimuli were presented against a green background. Stimuli and background colours were selected to keep the screen luminance ($0.3 \cdot R + 0.59 \cdot G + 0.11 \cdot B = \sim 110$) as well as the contrast of the stimuli against the background constant during the whole task, to rule out any influence of screen luminance on pupil responses. Lastly, a final fixation cross appeared on the screen. Depending on response time (RT) in the summation period, this last fixation cross duration was adjusted, so that the total trial duration was eighteen seconds. After each block, the participants provided a subjective flow rating, see below.

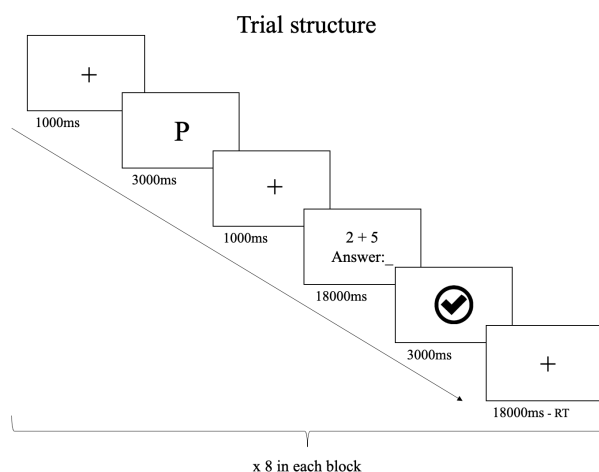


Fig 1. Description of one trial structure. Note that the final fixation cross duration was variable depending on RT only in the Performance Phase. During the Capacity phase, the final fixation duration was randomized with a mean of 2 seconds.

Subjective flow questionnaire

Subjective flow (flow index) was indexed by nine visual analogue ratings. The participant could range their response by moving the mouse on a horizontal line (10 cm in length), that had no anchors, except for the middle and endpoints. The answers were rated on a scale from 0 to 1. For 8 items, which measured the control component of flow, the endpoints were labelled *agree* and *disagree*. According to flow literature (Csikszentmihalyi, 1990; Ulrich et al., 2014), these items were used to monitor their involvement, enjoyment, perceived fit between skills and task demands, and feeling of control with respect to each difficulty level (Table 1). A 9th statement measured the second component of flow, which assessed participants' subjective sense of time, on the same horizontal line with endpoints labelled *very short* and *very long* (Ulrich et al, 2014; Keller and Bless. 2008).

Q1. I would love to solve math questions of that kind
Q2. I was strongly involved in the task
Q3. I was thrilled
Q4. The task was boring
Q5. I had the necessary skills to solve the calculations successfully
Q6. Task demands were well matched to my ability
Q7. During the task all thoughts on task-irrelevant issues that I am personally concerned with were extinguished
Q8. During the task my consciousness was completely focused on solving the math calculations
Q9. The time passed really quickly

Table 1. Flow questionnaire items.

Statistical analyses

All statistical analyses were conducted in Rstudio (Version 1.3.1093). The analyses included analysis of variance (ANOVA) and Bayesian modelling. For the ANOVA, we used the R package *ez*. Bayesian models were created in Stan computational framework and assessed with *brms* package (Bürkner, 2017). Alpha level of 0.05 was used for all analyses.

Behavioural data analysis

Response time and accuracy rate

Accuracy rate (percentage correct trials) and response time (seconds) assessed in the performance phase only were used in the analysis of the behavioural data. Mean accuracy rate as well as RTs for correct trials only were calculated for each task condition (easy, intermediate1, intermediate2 and difficult) for every participant. To test whether the paradigm worked as expected, a one-way repeated measures ANOVA was performed for accuracy rate as well as response time, using task condition (easy, intermediate1, intermediate2, difficult) as repeated measure. Additionally, to look at specific effects across task condition, pairwise t-test analyses were executed with a Bonferroni correction. The data was checked for sphericity. If this assumption was not met, a Greenhouse-Geisser correction was used (Field, 2009).

Flow measurement analysis

To address whether participants' flow ratings differ across task condition, we analysed the total flow score as well as four components: 'ability' (item 5 and 6), 'involvement' (item, 2, 7 and 8), 'liking' (item 1, 3 and 4) and 'time' (item 9). Individual ratings were averaged across each task condition, for total flow as well as for the four components. Repeated measures ANOVA was performed for total flow as well as the four components to test for significant differences between the task conditions. Significant differences were further investigated using Bonferroni corrected paired t-tests. In case of non-sphericity, a Greenhouse-Geisser correct was performed. All subjective reports were checked for outliers. Reports were considered outliers when they deviated ± 2.5 SD from the mean.

Model parameters analysis

Furthermore, to calculate previous prediction error (PE) scores, expected accuracy values (EV) were computed as the cumulative sum of the probability of a correct answer on each trial, and updated across the two sessions for each task condition separately. Subsequently, we estimated PEs by subtracting the EV from the corresponding accuracy value (Fig 2). Finally, PE values were averaged over trials across task condition for every participant. Moreover, we calculated previous PE difference score, which is a more direct proxy of learning. In order to investigate how previous PE, expected accuracy and PE difference change as a function of task condition, a repeated measures ANOVA was performed using task condition as repeated measure. Significant effects were followed by pairwise Bonferroni corrected t-tests. A

sphericity check was done. In case of violation, a Greenhouse-Geisser correction was applied (Field, 2009).

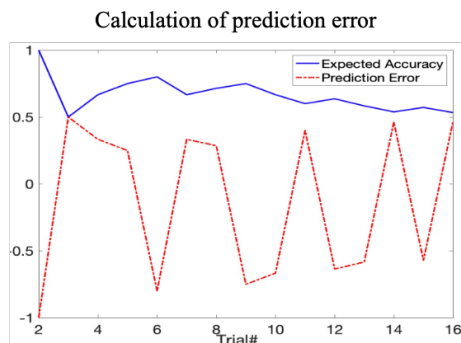


Fig 2. Calculation of prediction error from accuracy rates.

Pupillary data analysis

As in previous literature, pupil size, reported as pupil area, was registered during fixation, cue and feedback periods using an EyeLink 1000 eye tracker set to a sampling rate of 500Hz. The obtained raw pupillometry data were exported and pre-processed in Matlab before calculating a trial-by-trial task-evoked pupillary response (TEPR). First, missing data and eye blinks were detected, removed and smoothed by convolution with a 11 ms hanning-window. The smoothed pupil recordings were corrected using cubic spline interpolation. After interpolation, the residual pupil time series were bandpass filtered using a 0.02-4 Hz third-order Butterworth filter, to decrease noise and remove slow drifts (Knapen et al. 2016). We excluded 12.1% of the trials from further analysis which contained more than 40% NaNs ($M = 7.72$, $SD = 5.96$). Next, we checked for effects of gaze drift in x- and y-direction on task type with a linear mixed effects model. This gaze drift control analysis confirmed that the frequency of the saccades in both directions did not change as a function of task difficulty. Therefore, the effect of saccades from pupil responses were not removed. Subsequently, the time series were normalized within each block by z-scoring, in order to make comparisons between blocks and to correct for individual differences in pupil diameter (de Gee et al., 2014; Nassar et al., 2012, Urai et al., 2017). To control for variability in overall pupil size due to non-task related processes, a baseline correction was applied to the standardized pupil units on a trial-by-trial basis by subtracting the mean pupil diameter 200 ms before onset of the stimulus (Eckstein et al., 2019; Hershman & Henik, 2019). The final trial-by-trial TEPRs were calculated as the maximum pupil diameter observed in a period of 1.000 ms before and 3.000 ms after stimulus

onset (Gilzenrat et al., 2010). Trial-by-trial baseline pupil diameter was calculated as the average unfiltered pupil diameter during the 200 ms period before stimulus onset.

The pre-processed data were transported to Rstudio. Time course profiles during during baseline and cue presentation were investigated to see how pupil size changed during those periods. Subsequently, phasic pupil mode was extracted by subtracting average baseline pupil values from the cue pupil values. A repeated measures ANOVA was performed for baseline pupil size, cue pupil size, and phasic pupil mode respectively, using task condition as repeated measure. The data were analysed with pairwise Bonferroni corrected t-tests, in order to find specific potential differences between task conditions. Furthermore, we checked for sphericity. If this assumption was not met, a Greenhouse-Geisser correction was used (Field, 2009).

Pupillary – behaviour analysis

To test whether flow scores as well as the four components can be predicted by phasic pupil mode, on a trial-by-trial basis, we adopted a Bayesian regression model approach on the non-averaged data. The models included total flow index, involvement index, liking index, ability index, and time index as dependent variable respectively, with fixed effects as well as random slopes for task order, task condition and phasic pupil mode, where subject number entered as random effect (formula notation = (DV ~ TaskOrder + TaskCondition + PhasicPupilMode + (1 + TaskOrder + TaskCondition + PhasicPupilMode || SubjectNumber, data=d, REML=F)). Parameters were estimated using the sampler Hamiltonian Monte Carlo (MHC) with 5 chains of 2000 samples each. Significant predictors are determined by looking at the posterior distribution; a distribution not containing zero indicates a significant predictor.

To further probe the phasic pupil mode, we examined the influence of expected accuracy, previous trial PE and PE difference on phasic pupil mode on a trial-by-trial basis. We used a Bayesian model comparison analysis on the non-averaged data, where subject-level parameters are drawn from group-level distributions. Specifically, to find out which predictors explained the outcome measure Y_i phasic pupil mode best, where i referred to each subject. Our null model included the predictors trial number, task order and task condition. We added the predictors expected accuracy, previous PE and PE differences respectively to the null model (final model formula notation = (PhasicPupilMode ~ TrialNumber + TaskOrder + TaskCondition + ExpectedAccuracy + PreviousPE + PEdifference + (1 + TaskOrder + TaskCondition + PhasicPupilMode || SubjectNumber, data=d, REML=F)). The parameters were also estimated using MHC with 5 chains of 2000 samples each. Model comparison was

performed using Leave One-Out cross validation (LOO) scores, to evaluate the predictive fit of each model penalised according to the number of free parameters.

Results

Linear trend on accuracy and RT across task condition

We found that accuracy rate significantly decreased over the task condition ($F(3,105) = 106.639, p < .001$) (Fig 3A). When looking at the simple effects, significant differences were found in easy ($M = 0.964, SD = 0.010$), versus intermediate1 ($M = 0.693, SD = 0.027, p < 0.001$), easy versus intermediate2 ($M = 0.575, SD = 0.032, p < 0.001$), easy versus difficult ($M = 0.434, SD = 0.031, p < 0.001$), intermediate1 versus intermediate2 ($p = 0.002$), intermediate1 versus difficult ($p < 0.001$), and intermediate2 versus difficult ($p = 0.001$). The analysis of RT revealed a significant main effect of RT on task condition ($F(2.267,79.335) = 755.848, p < .001$) (Fig 3B). We found that RTs increased linearly with greater task difficulty, with significant lower RTs for easy ($M = 2.964, SD = 0.119, p < 0.001$) compared to intermediate1 ($M = 11.245, SD = 0.358, p < 0.001$), easy compared to intermediate2 ($M = 13.480, SD = 0.285, p < 0.000$), easy compared to difficult ($M = 15.195, SD = 0.217, p < 0.000$), intermediate1 compared to intermediate2 ($p < 0.001$), intermediate1 compared to difficult ($p < 0.001$), and intermediate2 compared to difficult ($p < 0.001$).

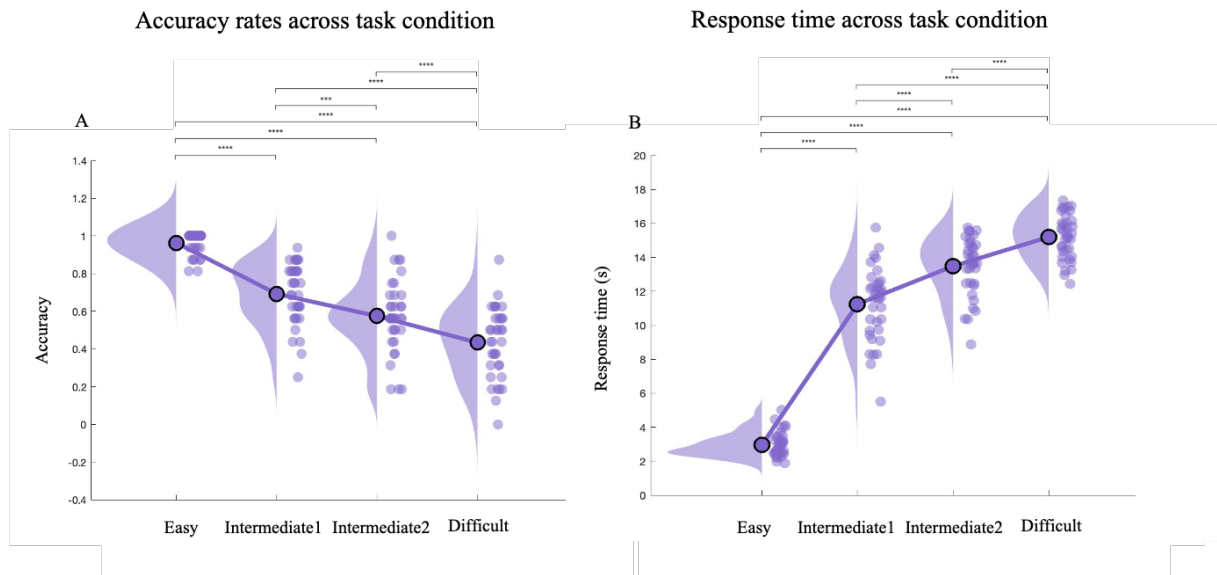


Fig 3. Raincloud plot for A) accuracy rate, B) response time (RT) across task condition. The dots display each participant's mean accuracy rate and correct RT.

Quadratic trends on total flow and liking, linear trends for involvement, ability and time

The flow index significantly differed across task condition ($F(1.686,140) = 19.186, p < .001$) (Fig 4A). While significant lower scores for easy were found ($M = 0.461, SD = 0.027$) compared to intermediate1 ($M = 0.654, SD = 0.028, p < .001$), but higher scores were found for easy compared to intermediate2 ($M = 0.636, SD = 0.024, p < .001$), and easy compared to difficult ($M = 0.613, SD = 0.024, p = .001$). No significant effects were found between intermediate1 and intermediate2 ($p = 1.000$), intermediate1 and difficult ($p = 0.412$), nor intermediate2 and difficult ($p = 1.000$). The results showed a significant effect of involvement on task condition ($F(1.479,51,765) = 32.617, p < .001$), where involvement scores significantly increased with greater task difficulty (Fig 4B). Pairwise t-tests revealed significant lower scores for easy ($M = 0.412, SD = 0.036$) versus intermediate1 ($M = 0.668, SD = 0.033, p < .001$), easy versus intermediate2 ($M = 0.710, SD = 0.031, p < .001$), easy versus difficult ($M = 0.720, SD = 0.035, p < .001$). No significant effects were found for intermediate1 versus intermediate2 ($p = 0.391$), intermediate1 versus difficult ($p = 0.120$), nor intermediate2 versus difficult ($p = 1.000$). We observed that liking scores significantly differed across task condition ($F(2.379,83.265) = 11.148, p < .001$), following a quadratic shape (Fig 4C). Specifically, liking scores were significantly lower for easy ($M = 0.341, SD = 0.031$) compared to intermediate1 ($M = 0.523, SD = 0.030, p < .001$), and easy compared to intermediate2 ($M = 0.472, SD = 0.018, p = .005$). Liking scores in the intermediate1 condition did not significantly differ between easy and difficult ($M = 0.441, SD = 0.047, p = 0.091$), between intermediate1 and intermediate2 ($p = 0.339$), intermediate1 and difficult ($p = 0.114$) nor between intermediate2 and difficult ($p = 0.928$). We found a linear trend for ability scores ($F(2.313,80.955) = 69.095, p < .001$) (Fig 4D). We observed significant higher scores for easy ($M = 0.763, SD = 0.030$) compared to difficult ($M = 0.577, SD = 0.039, p = 0.005$), intermediate1 compared to intermediate2 ($p = 0.040$), intermediate1 compared to difficult ($p = 0.002$), and intermediate2 compared to difficult ($p = 0.031$). No significant effects were found for easy versus intermediate1 ($p = 1.000$), nor easy versus intermediate2 ($p = 0.209$). Lastly, the results showed a significant linear trend ($F(1.428,49.98) = 32.492, p < .001$) (Fig 4E). Specifically, we found significant lower scores for easy ($M = 0.327, SD = 0.048$) compared to intermediate1 ($M = 0.668, SD = 0.040, p < .001$), easy compared to intermediate2 ($M = 0.696, SD = 0.043, p < .001$), and easy compared to difficult ($M = 0.713, SD = 0.038, p < .001$). Intermediate1 did not significantly differ from intermediate2 ($p = 0.872$), nor from difficult ($p = 0.643$). Intermediate2 did also not significantly differ from difficult ($p = 1.000$).

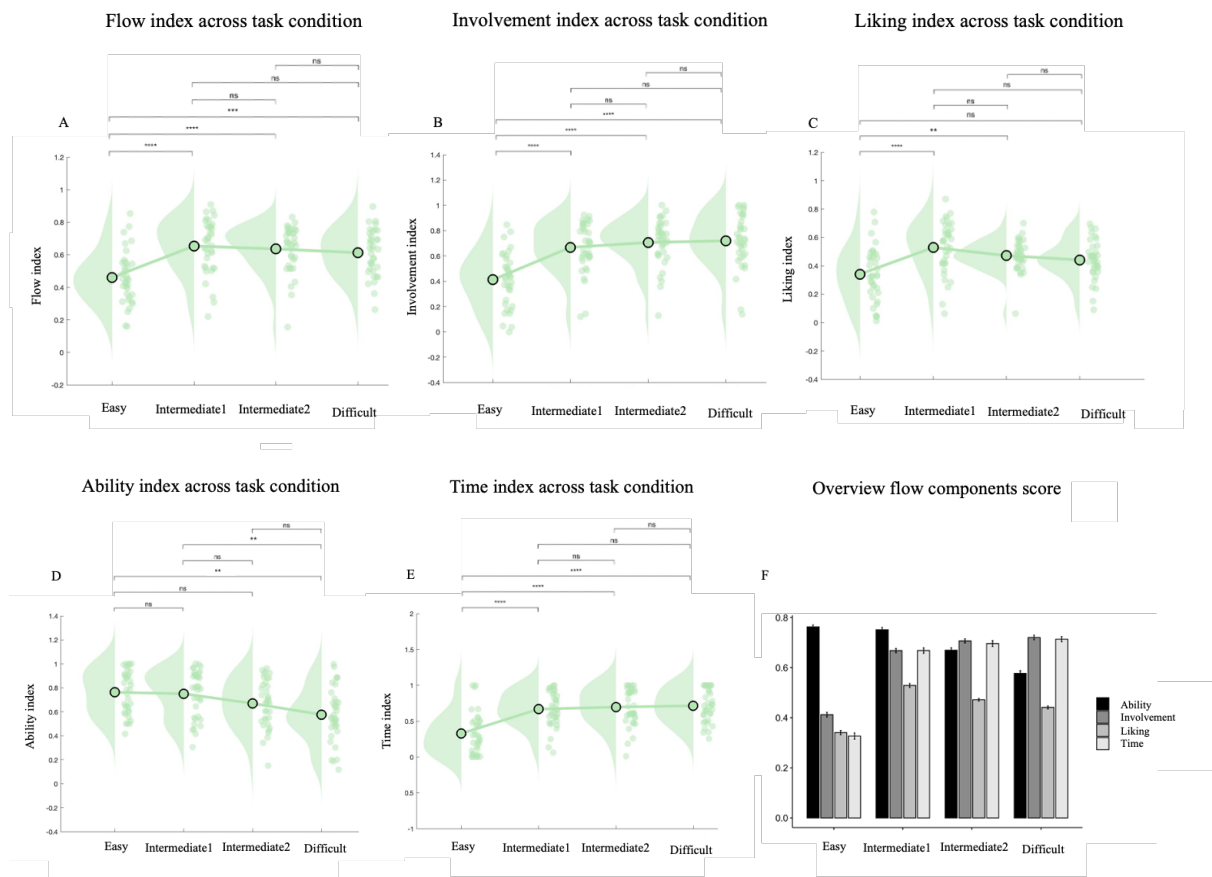


Fig 4. Raincloud plot for A) total flow index, B) involvement index, C) liking index, D) ability index, E), and time index across task condition. The dots display each participant's mean score. F) Bar chart showing the mean score of each component for each task condition, error bars indicate standard error.

Task condition affected model parameters

We showed a significant main effect of PE magnitude on task condition ($F(2.517, 88.095) = 4.862, p = 0.003$), following a quadratic trend (Fig 5A). When looking at the simple effects, we found significant smaller PEs for easy ($M = -0.007, SD = 0.007$) compared to intermediate1 ($M = 0.101, SD = 0.022, p < 0.001$), and easy compared to intermediate2 ($M = 0.078, SD = 0.024, p = 0.024$). No significant effects were found easy compared to difficult ($M = 0.056, SD = 0.025, p = 0.169$), intermediate1 compared to intermediate2 ($p = 1.000$), intermediate1 compared to difficult ($p = 0.915$), nor intermediate2 compared to difficult ($p = 1.000$). Regarding expected accuracy (Fig 5B), we observed a significant increasing linear effect of task condition ($F(3, 105) = 84.008, p < 0.001$) where easy ($M = 0.970, SD = 0.010$) yielded significantly higher rates than intermediate1 ($M = 0.610, SD = 0.035, p < 0.001$), intermediate2 ($M = 0.511, SD = 0.035, p < 0.001$), and difficult ($M = 0.385, SD = 0.034, p < 0.001$). Moreover, expected accuracy rates were also significantly higher in intermediate1 versus difficult ($p < 0.001$), and intermediate2 versus difficult ($p = 0.011$). No significant effect was observed for intermediate1 versus intermediate2 ($p = 0.180$). Lastly, we

found that PE differences significantly decreased over task condition ($F(3,105) = 27.938, p < 0.001$) (Fig 5C). Easy ($M = 0.073, SD = 0.022$) showed significantly lower PE difference than intermediate1 ($M = 0.311, SD = 0.026, p < 0.001$), intermediate2 ($M = 0.370, SD = 0.028, p < 0.001$), and difficult ($M = 0.401, SD = 0.031, p < 0.001$). No significant differences were found between intermediate1 and intermediate2 ($p = 0.790$), intermediate1 and difficult ($p = 0.123$), nor intermediate2 versus difficult ($p = 1.000$).

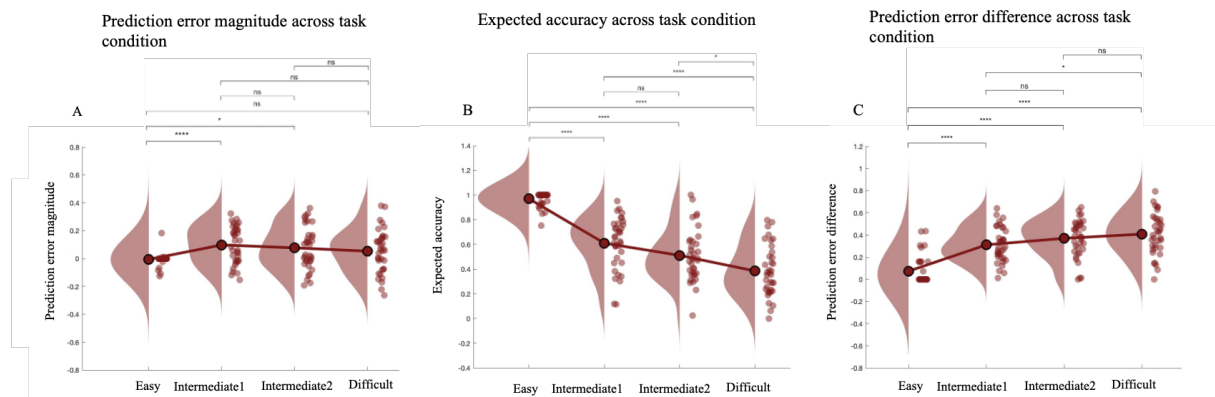


Fig 5. Raincloud plot for A) prediction error (PE), B) expected accuracy rate, and C) prediction error difference. The dots display each participant's mean PE, expected accuracy rate, and PE difference.

Phasic pupil mode follows quadratic shape

For baseline pupil size (Fig 6C), the results revealed a significant main effect of task condition ($F(3,105) = 65.319, p < .001$). Specifically, we demonstrated that easy significantly differed from intermediate1 ($p < .001$), intermediate2 ($p < .001$), and difficult ($p < .001$). No significant effects were found for intermediate1 versus intermediate2 ($p = 1.000$), intermediate1 versus difficult ($p = 1.000$), nor intermediate2 versus difficult ($p = 1.000$). Cue pupil size (Fig 6D) demonstrated a significant main effect ($F(3,105) = 11.043, p < .001$), in the sense that cue pupil sizes significantly differed between easy and difficult ($p = .011$), between intermediate1 and intermediate2 ($p = 0.019$), and between intermediate1 and difficult ($p < 0.001$). Cue pupil size did not show significant effects for easy versus intermediate1 ($p = 0.106$), easy versus intermediate2 ($p = 1.000$), nor intermediate2 versus difficult ($p = 0.052$). Lastly, we observed a significant main effect of phasic pupil mode ($F(3,105) = 17.234, p < .001$) (Fig 6E). We demonstrated that easy significantly differed from intermediate1 ($p < .001$), intermediate2 ($p < .001$), and difficult ($p = .024$). Moreover, we found significant differences between intermediate1 and difficult ($p = .005$). No significant effects were found for intermediate1 compared to intermediate2 ($p = 0.573$), nor intermediate2 compared to difficult ($p = 0.508$).

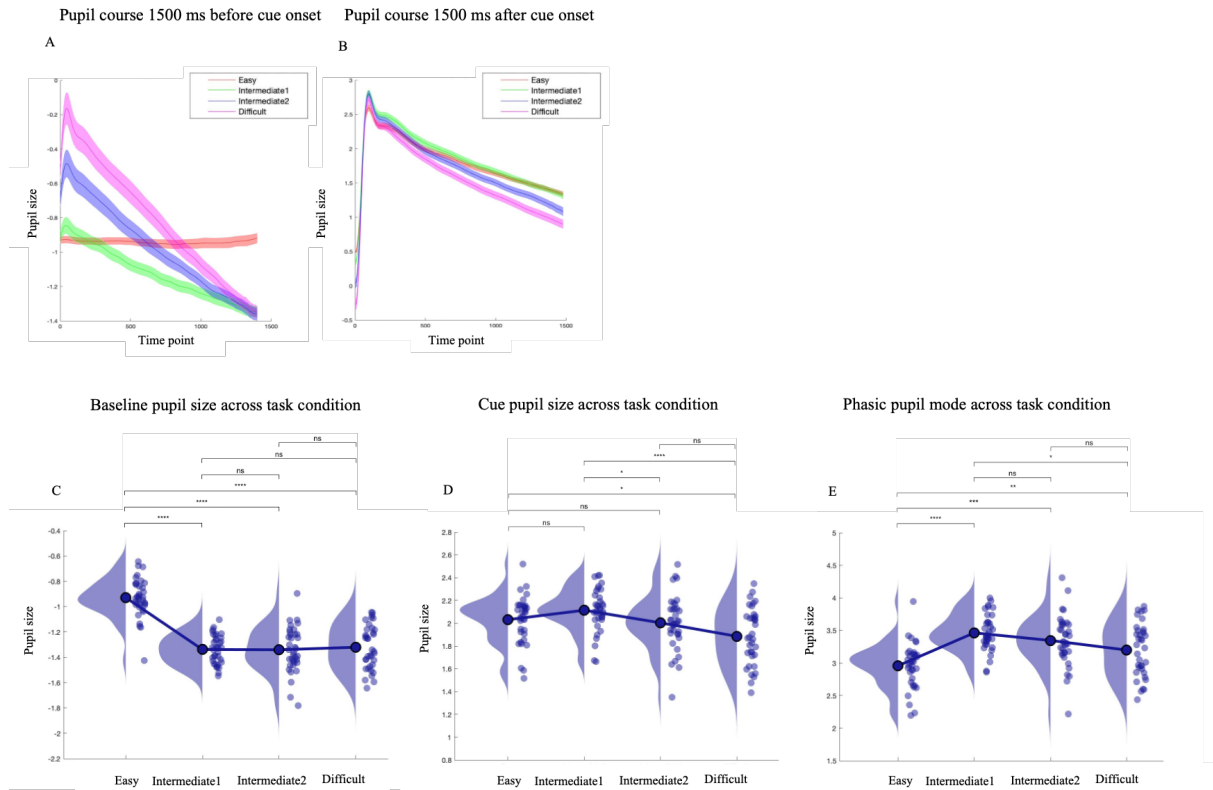


Fig 6. Pupil responses where A) plot the pupil time courses during 1500 ms before cue onset, B) plot the pupil time course during 1500 ms after cue onset. Raincloud plot for C) pupil responses during baseline period, D) pupil responses during cue period, and E) phasic pupil mode. The dots display each participant's mean pupil size (C-E).

Phasic pupil mode predicted liking experiences

At forehand, a variance inflation factor analysis was done for all the predictors, showing that the shared variance was low ($VIF_{TaskOrder} = 1.000$, $VIF_{TaskCondition} = 1.000$, $VIF_{PhasicMode} = 1.000$). For total flow index, we observed that task condition positively predicts a change in flow score ($B = 0.04$, $CI [0.04, 0.02]$). Task order ($B = 0.00$, $CI [-0.00, 0.01]$) and phasic pupil mode ($B = 0.01$, $CI [0.00, 0.01]$) were not likely to be a meaningful predictor of involvement index. Also, for involvement index, only task condition is a meaningful positive predictor ($B = 0.10$, $CI [0.07, 0.13]$). Task order ($B = -0.01$, $CI [-0.02, -0.00]$) and phasic pupil mode ($B = 0.01$, $CI [0.00, 0.01]$) are no meaningful predictor of total flow index. We can see that a higher phasic pupil mode ($B = 0.01$, $CI [0.01, 0.02]$) predicts a higher liking score, where task order ($B = 0.01$, $CI [-0.00, 0.01]$) and task condition ($B = 0.02$, $CI [-0.01, 0.05]$) are not likely to predict a change in liking score. We observed that task condition ($B = -0.06$, $CI [-0.09, -0.02]$) negatively and task order ($B = 0.02$, $CI [0.01, 0.03]$) positively predicts a change in ability score. Phasic pupil mode ($B = 0.01$, $CI [0.00, 0.02]$) turned out not to be a meaningful predictor. Finally, for time index, we see that again only task condition ($B = 0.12$, $CI [0.09, 0.16]$) is a meaningful predictor of time score. Task order ($B = -0.01$, $CI [-0.02, 0.01]$) and phasic pupil mode ($B = 0.01$, $CI [0.00, 0.02]$) are not likely to be a meaningful predictor. In summary, we

have observed that changes in liking index predicted changes in phasic pupil mode, but not total flow, involvement, ability and time.

Expected accuracy, previous trial PE, and PE difference predicted phasic pupil mode

We first checked the variance inflation factor analysis for all the predictors, which showed that the shared variance was low ($VIF_{TaskOrder} = 1.104$, $VIF_{TaskType} = 2.155$, $VIF_{TrialNumber} = 1.090$, $VIF_{PreviousPE} = 2.190$, $VIF_{ExpectedAccuracy} = 1.090$, $VIF_{PEdifference} = 1.063$).

When predicting phasic pupil mode, we observed that task condition ($B = 0.15$, $CI [0.07, 0.22]$), previous PE magnitude ($B = 1.04$, $CI [0.85, 1.23]$), expected accuracy ($B = 0.70$, $CI [0.40, 1.02]$), and PE difference ($B = 0.20$, $CI [0.09, 0.31]$) all positively predicts a change in phasic pupil mode. Trial number ($B = 0.03$, $CI [-0.00, 0.05]$) and task order ($B = 0.03$, $CI [-0.00, 0.05]$) turned out not to be a meaningful predictor.

Furthermore, we observed that the final model had the highest predicted accuracy, showing that phasic pupil mode was significantly predicted by expected accuracy, positive previous trial PE and PE difference (Table 2). The model including all parameters had the lowest LOOIC values, corresponding to better model performance. Additionally, we found that the second model, including positive previous PE, made the biggest difference in predicting the accuracy of the model (Fig 7).

Model	elpdLOO	p_LOO	LOOIC	elpdDiff	Parameters
Model3	-2538,771 ±30.025	62.234 ±2.638	5077.543 ±60.049	0.000 ±0.000	PE difference + Previous PE + Expected Accuracy + Trial No + Task Order + Task Condition
Model2	-2542.072 ±29.680	58.906 ±2.503	5084.145 ±59.360	-3.301 ±4.048	Previous PE + Expected Accuracy + Trial No + Task Order + Task condition
Model1	-2670.369 ±28.248	27.812 ±1.014	5340.737 ±56.496	-131.597 ±18.998	Expected Accuracy + Trial No + Task Order + Task condition
NullModel	-2676.988 ±28.315	28.970 ±1.114	5353.976 ±56.630	-138.217 ±19.497	Trial No + Task Order + Task condition

Table 2. Model comparison for phasic pupil mode. The elpdLOO's column shows the expected log predictive density estimate with its corresponding standard deviation. The p_LOO shows the effective number of parameters with its corresponding standard deviation. The elpdDiff columns shows the LOO differences across the two models together with the standard deviation of the elpdDiff.

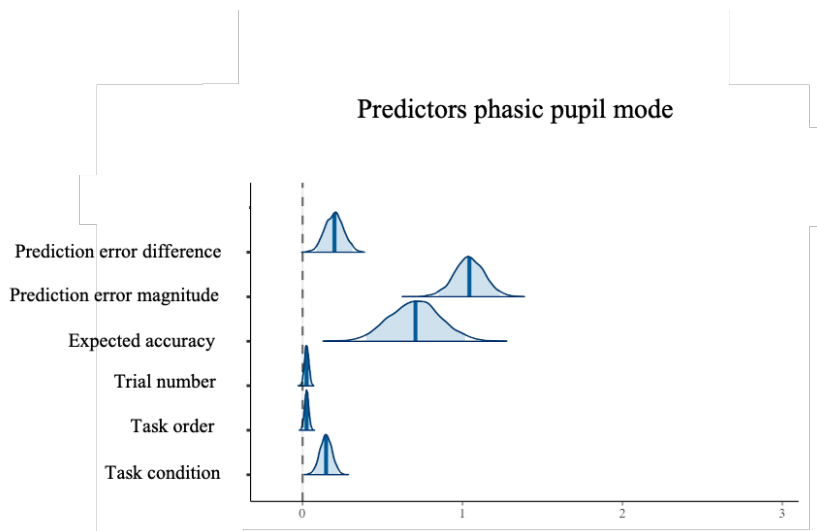


Fig 7. Densities of model parameter estimates. Credible interval of 95%.

Discussion

While a considerable body of research has pointed towards cognitive effort being aversive and costly, highlighting the critical role of expected external reward and the amount of control allocation when deciding to invest effort, the present study adds a further determinant of effort evaluation: performance prediction errors giving rise to intrinsic values for optimal challenging activities. To that end, both subjective measures as well as objective measures of task engagement were examined within a novel task paradigm, where task difficulty was manipulated based on participants' own capacity. Specifically, we tested whether participants experienced higher engagement and liking scores in intermediately challenging tasks and asked whether performance prediction errors could explain these preferences. Furthermore, we sought to demonstrate whether arousal-induced pupil sizes would track task engagement in the absence of reward, and whether this LC-based arousal changed as a function of performance uncertainty.

Previous literature on effort avoidance behaviour presumes that cognitive effort exertion is registered as costly (Botvinick, 2007). For example, in an fMRI study reward activation in the nucleus accumbens (NA) was decreased for rewards following a condition with a switch rate, yielding more effort exertion, compared to a condition without switching (Botvinick et al., 2009). Westbrook et al., (2013) confirmed and extended these findings in a discounting paradigm in which participants had to make a decision between performing a low-effort task (low *N*-back) for a small reward or a high-effort task (high *N*-back) for a larger reward. They measured the subjective value of cognitive effort by offering multiple decision trials to eventually reach a subjective equivalence, quantified as the cost of cognitive effort. Their

results indicated that people are willing to forgo substantial rewards to avoid cognitive effort (Dixon & Christoff, 2012; Westbrook et al., 2013). Moreover, other work showed that individuals are biased to avoid cognitive demand. Specifically, participants showed a tendency to choose actions that involved few task switches, indicating a minimization of cognitive control (Kool et al., 2010). This is consistent with the expected value of control theory (EVC) which predicts that the trial-to-trial variability in invested cognitive effort is determined by the cognitive control allocation (Shenhav et al., 2013). Specifically, the EVC proposes that the intrinsic cost of effort scales with the expected reward outcome minus the intensity of control needed to get that outcome. Hence, the allocation of control is driven by a cost-benefit analysis, weighing the benefits and the associated costs of executing a certain action (Shenhav et al., 2013). Consistently, this account predicts that effort avoidance behaviour increases with a greater associated cost, which can be a function of higher error rates, longer response times (opportunity cost of time), or higher stimulus response conflict. However, there may be other aspects at work that also influence the decision to engage in a task or not.

In the current project, we have shown that the highest liking and engagement scores were found for the intermediate tasks, followed by the difficult, and the easy condition, leading to an inverted-U shape of subjective engagement across task difficulty. As we found these higher liking and engagement scores for task conditions that did not yield the highest accuracy rates, these results are difficult to explain according to the cognitive effort avoidance literature. Critically, most studies consistent with effort avoidance accounts used commonly use objectively defined task conditions, ignoring participants' own capacity levels (Botvinick et al., 2009; Kool et al. 2010; McGuire & Botvinick, 2010; Westbrook et al., 2013). Although their task conditions differed in demand (high or low), often the hardest levels still yielded an accuracy level between 85% and 90%. As this level roughly corresponded with the current study's easy level, there was less to no performance uncertainty. Therefore, we argue that these studies felt short at covering a broad range of task performance and hence only showing the left side of our inverted u-shape (Botvinick, 2007; Kool et al. 2010; Westbrook et al., 2013).

Our findings provide compelling support for the flow literature that show activities with an intermediate level of complexity yielded greater subjective engagement scores, induced by a state of flow (Csikszentmihalyi, 1990; Ulrich, et al. 2014). For example, a study by Ulrich and colleagues (2014) compared subjective experiences and neural correlates of flow using three different conditions "boredom", "flow" and "overload" in which the difficulty level of arithmetic summations was manipulated. Critically, the demand level in the flow condition was continuously adjusted to match participants' individual level of capacity; an accuracy rate of

50%, in order to induce flow experiences. Specifically, a level-up change was applied by adding one digit to the mathematical expression after two correct responses in a row. This contrasted with the conditions boredom and overload in which accuracy rates were above 90% or less than 10% respectively, that are both incompatible with flow states. Thus, this flow condition was different from too easy or too difficult conditions via two ways: participants were not certain whether they would be correct or incorrect, i.e., greater performance uncertainty, and the difficulty level was dynamically adjusted over time. As the current study assigned four predetermined task conditions instead of a staircase algorithm, we experimentally controlled these conditions to examine performance uncertainty at its own, and task demands remained unchanged within each condition. Nevertheless, we found a similar pattern over task difficulty, confirming their findings.

Moreover, we have shown these intermediately challenging tasks also yielded the highest PE magnitude, mirroring the inverted-U shape of subjective engagement. Additionally, we observed that expected accuracy decreased with increased task difficulty, and PE change increased. Taken together, we suggest that performance uncertainty might be what underlies the subjective flow experiences for intermediately challenging tasks. This is consistent with intrinsic motivation accounts which point towards a learning opportunity acting as a guiding principle. For example, in a study using a computer game, participants were instructed to freely adjust the difficulty level (increased speed), in the absence of external reward. This study showed that participants spontaneously increased the difficulty level in order to keep their accuracy around 50%, thus gradually progress from easier to more difficult levels (Baraness et al., 2014). Other work demonstrated that artificial intelligence robots prefer to spend more time on intermediately challenging tasks yielding a high PE that could be reduced. When the PE reduction reached a plateau level, the robot started to spend more time on another intermediate task to repeat the same process (Gottfried & Oudeyer, 2018). Thus, activities with high performance uncertainty and maximal learning progress are preferred.

There are also other aspects linked to performance uncertainty that drive intrinsic rewards. For example, optimal incongruity, where people prefer activities that are not very familiar but also not completely new which produce both surprise and confirmation (Blain & Sharot, 2021). A high PE magnitude is also found in such activities. Other researchers proposed that people are motivated by curiosity and exploration (Kaplan & Oudeyer, 2007). Taking it to a broader scale, self-efficacy is also believed to play a role in the willingness to exert cognitive effort. Self-efficacy can be described as the likelihood of reaching a certain goal (Bandura, 1986) and refers to a personal judgement of how well people think their efforts are for certain

action are efficacious (Frömer et al., 2021). In an updated version of the EVC model, the effect of efficacy is integrated, where higher efficacy increases the amount of cognitive control allocation. Hence, the EVC theory predicts that next to outcome reward and difficulty level, efficacy also determines cognitive effort exertion (Frömer et al., 2021; Shenhav, Botvinick, & Cohen, 2013). According to the Self-Determination Theory, experiences of efficacy itself is intrinsically rewarding (Blain and Sharot, 2021). As by definition learning is influenced by efficacy where improvement increases the feelings of efficacy, both probably play a role in the intrinsic value of effort exertion. As such, investing cognitive effort for optimal challenging activities is worthwhile and rewarding, which could result in greater efficacy experiences (Hosseini & Fattahi, 2014). Subsequently, experiences of efficacy would be reduced for activities that are too easy or too difficult, because investing effort in too easy tasks might be not necessary and for difficult tasks this investment would not result in the expected outcome. A recent study manipulated efficacy experiences by the probability of outcome reward being contingent with participants' performance in a stroop task design (Frömer et al., 2021). They demonstrated that if participants perceived their efforts are efficacious, they are more likely to exert control, as indexed by higher contingent negative variation (CNV) amplitude, an event-related potential (ERP) known to track proactive control allocation, and higher P3b, ERP known to signal incentive evaluation, during initial cue period. However, they observed that TEPRs were larger when participants were expecting lower efficacy, compared to higher efficacy, contradicting their own findings. They interpreted this as pupillary dynamics tracking uncertainty, since they manipulated efficacy according to compatibility between reward and performance. How exactly efficacy influences task engagement in different situations needs further exploration.

Task engagement has been linked to locus coeruleus (LC) activity, which is to a large extent responsible for releasing noradrenaline (NE) in the brain. This LC-NE system is assumed to be involved in regulating arousal signals (Aston-Jones & Cohen, 2005). The anterior cingulate cortex (ACC) is one of the few cortical regions reported to have an afferent influence on the noradrenergic arousal signals, and hence believed to mediate the relationship between task engagement and LC activity. Muller and colleagues (2019) observed trial-by-trial relationship between pupil size and uncertainty of environmental states, where high pupil size was found in situations where participants were not sure whether they would get the outcome they expected for a certain option, and low pupil sizes were found in situations where the participants were quite sure of the outcome. Additionally, activity in the ACC predicted these changes in pupil size. Therefore, they suggested that changes in uncertainty might be tracked

by the LC-NE system, influenced by the ACC. Moreover, other studies also provided evidence for the link between ACC activity and uncertainty signals in a one-armed bandit task (Behrens et al., 2007), and a decision-making paradigm with accumulating evidence (Stern et al., 2010). Interestingly, as flow experiences are also characterized by an intermediate level of arousal, and an intermediate level of ACC activity (de Manzano et al., 2010; Keller et al., 2011), and direct stimulating of the vagus nerve was shown to reduce subjective reports of flow, potentially via its role in activating LC and modulating noradrenaline release (Colzato et al., 2018), we suggest a relationship between arousal-based LC-NE system and the value underlying intermediately challenging tasks, modulated by uncertainty signalling.

To test this relationship, we used pupil responses as a measure of LC-NE activity. According to the adaptive gain theory (AGT), two modes of LC-NE activity can be distinguished: the phasic mode and the tonic mode (Aston-Jones & Cohen, 2005). The phasic mode is characterized by momentary bursts of LC activity driven by task related processes, marked by a small baseline with task-evoked pupil responses (TEPR), and is associated with increased task engagement and performance. In the tonic mode, baseline activity and corresponding pupil baseline are lasting elevated without these momentary bursts, and is coupled to more distractibility and decreased task performance (Aston-Jones et al., 1999; Aston-Jones & Cohen, 2005). In that sense, the AGT proposes that these changes in LC-activity are modulated by task utility, where high utility favours exploitation (phasic mode), and low utility supports exploration (tonic mode) (Aston-Jones & Cohen, 2005). Previous work provided evidence that the pupillary responses tracked task utility (Gilzenrat et al., 2010). Specifically, participants were given the option to choose to escape trials and start over, in order to see how task utility influences pupillary responses. They demonstrated that these pupillary responses tracked trial-by-trial changes in task utility, by increased higher tonic mode when participants chose to disengage, escape, and increased phasic mode after the escape. However, as these results are interpreted as participants disengaging when the task was too difficult, participants were instructed to maximize their performance for external rewards resulting in participants disengaging because of their accuracy got too low and hence diminished the task utility.

In the current study, where task engagement and task performance were decoupled, we showed that the phasic pupil mode, low baseline and high task-evoked pupil responses (TEPR), was the highest in anticipation of intermediately challenging tasks and lower during easy and difficult tasks, following an inverted-U function across task condition. Additionally, when addressing whether liking and engagement scores were associated with the phasic pupil mode,

we demonstrated that liking scores predicted phasic pupil mode on a trial-by-trial basis. This could indicate that liking a task elicited higher phasic pupil responses. These findings suggest that at forehand our brain is less engaged when the upcoming task difficulty is very easy or very hard, and more engaged when it matches one's capacity. These results are hard to explain from a pure demand account where TEPRs show a monotonic relationship with task difficulty (Irons et al., 2017; Moresi et al., 2008, van der Wel & van Steenbergen, 2018). Castanheira, LoParco, and Ross Otto (2020) also aimed to demonstrate whether TEPRs changes as a function of effort investment. They investigated individual differences in cognitive capacity (executive functioning ability on a stroop task) and intrinsic motivation to exert effort (need for cognition scale), as well as modulating reward incentives while keeping the task demand constant. Using a DST, they found larger TEPRs for better task performance, in the absence of reward. As they observed a stronger relationship between TEPR and task performance for individuals with lower cognitive capacity, as well as increased TEPR in response to performance-contingent rewards, they concluded that pupillary responses could serve as a reliable index for cognitive effort investments rather than reflecting task demand (Castanheira et al., 2020).

Finally, with the current design we were able to take a closer look at what predicts phasic pupil responses on a trial-by-trial basis. We have found that expected accuracy, previous trial PE and PE difference all were significantly predictors of the phasic pupil mode. Interestingly, the most variance could be explained by previous PE. This demonstrates that error minimization and becoming better over time do result in greater phasic pupil responses, but that being better than expected has the biggest influence. In other words, a greater phasic pupil mode, i.e., higher task engagement, was found for positive PEs, when participants were unexpectedly correct on the previous trial. In line with these results, other work also found that pupil dilation increased as a function of performance PE in a flanker task where participants had to focus on a target and ignored congruent or incongruent distractors (Braem et al., 2015). So, keeping track of PEs might be crucial for deciding to engage or not (Sayalı & Badre, 2021). Thus, our results show that in anticipation of an intermediately challenging task, the brain gets more motivated to invest effort in a task when there is a possibility of improvement. This phenomenon might be related to arousal-based LC-NE activity, where the pupillary dynamics track performance uncertainty.

It is worth noting that while LC-induced arousal has been previously shown to modulate pupil size, the neurotransmitter dopamine (DA) has also been associated with pupil size modulation. The dopaminergic system is mostly located in the midbrain ventral tegmental area (VTA) and substantia nigra (SN), and is traditionally involved in reward processing and value-

based behaviour (Olds & Milner, 2020; Schultz et al., 1997; Schultz, 2007). Moreover, DA is involved in tracking reward uncertainty, in a way to facilitate learning. For example, DA is known to track reward prediction errors, the discrepancy between expected and outcome rewards, where higher pupil size is found for cues predicting reward (Gershman & Uchida, 2019; O’Doherty et al., 2003). This is believed to be the basis of reinforcement learning (Gershman & Uchida, 2019). While at odds with our original prediction, it is plausible that next to noradrenergic neurons, dopaminergic sources could also have influenced the current pupil responses, probably in an interacting way. Nevertheless, both NE as well as DA are responsible for the same process. But, since the source of pupil changes is unknown, it would be interesting to disentangle both effects by including measures of DA, in addition to noradrenaline. A reliable way to do this, would be by also measuring spontaneous eye blinks, which are believed to reflect striatal DA functioning (Karson, 1983; Tummeltshammer et al., 2019).

Some conditions of the current study contain some inherent constraints. First, due to the fact that participants read the question, might look away when thinking, turn to the keyboard to make a response, or other reasons for not fixating at the middle of the screen, pupil measures during the time period of reading and solving the question are not completely reliable. Therefore, we were limited to measuring during cue period, the moment of deciding to exert effort or not. Apart from that this anticipation period is interesting on its own, it would also be interesting to look at the period of actual effort exertion. As intrinsic motivation accounts suggest that the actual improvement, this could account for the relatively small effect of PE change in explaining the phasic pupil mode. One other relevant issue might be the practice effect. In the present study, people start in the capacity phase to determine four individually matched task conditions of 25%, 50%, 75% and 100% accuracy rate. However, when looking at the actual accuracy rates during those four conditions, we see that the difficult condition yielded a higher average accuracy rate than expected, implying that participants have already improved their skills by performing in this experiment. Thus, our difficult condition turned out to be very much in the range of the participants’ performance and hence not experienced as very difficult. This could therefore have contributed to the relatively high flow scores and high phasic pupil mode during the difficult condition compared to the other three task conditions. Future research could take this practice effect into account. Lastly, although we measure engagement in the absence of external reward, to trigger flow experiences external feedback on performance must be provided (Csikszentmihalyi, 1990). Hence, we were not able to test whether these findings would also hold in the absence of external feedback.

In summary, we showed that intermediately challenging tasks were coupled with greater task engagement and greater PE magnitude. Moreover, intrinsic motivation for cognitive effort exertion might be tracked by arousal-based LC-activity, as these tasks also showed the highest phasic pupil mode, predicted by higher liking scores. Therefore, we suggest that the underlying mechanism of liking intermediate tasks might be the room for improvement, a bit of the learning process itself and the expectations to be correct. In other words, the fact that people could potentially learn something makes them more aroused at forehand and makes them more willing to exert their efforts on, where people are less or disengaged in tasks that are too easy, or too difficult, where they probably can't improve themselves. To reiterate, though effort is costly and investing it could be avoided, the current study provides one missing link between these theories, suggesting that a performance uncertainty induced learning potential makes it worthwhile to invest cognitive effort, that might outweigh the associated costs. Thus, the main insight of this study is that effort is not per se aversive but can also be rewarding in itself. Yet, the specific mechanisms need to be further elaborated. We may suggest that the aspects of intrinsic reward could be added to the updated version of the EVC, where extrinsic and intrinsic rewards are integrated. Therefore, future studies should investigate which situational factors influence the balance between the costs and benefits, where the rewards are extrinsic as well as intrinsic. Some suggestions to improve the methodology can be provided. For example, to use a design incorporating fMRI measures to examine activity in the ACC and LC in a more direct way. Another interesting option would be stimulating other salience networks to affect ACC and LC and see if subjective and objective engagement increase. Additionally, future work could also investigate how individual characteristics can explain individual variation in one's motivation to engage in activities and effort exertion. For example, stress and anxiety might be interfering with the processes underlying engagement (Berggren et al., 2013; Judah et al., 2013; Patzelt et al., 2019). Next to this, people differ in their need for cognition (Cacioppo et al., 1984; Cohen et al., 1955), which has also been linked to effort avoidance (Kool, et al., 2010, Kührt, et al., 2021; Westbrook et al., 2013). In the end, research findings in the field of effort exertion may have implications for artificial intelligence developments, pedagogic programmes, and educational practices. Deeper understanding of these basic motivational processes may be crucial for optimising learning in a society where distractions are more present and temping than ever.

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