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9 Forced Choices Reveal a Trade-Off between Cognitive Effort and Physical Pain

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Abstract

Cognitive effort is described as aversive, and people will generally avoid it when possible. This aversion to effort is believed to arise from a cost–benefit analysis of the actions available (e.g., study hard for an upcoming test or socialize with friends). The comparison of cognitive effort against other primary aversive experiences, however, remains relatively unexplored. Here, we offered participants choices between performing a cognitively demanding task or experiencing thermal pain. We found that cognitive effort can be traded off for physical pain and that people generally avoid exerting high levels of cognitive effort. We also used computational modelling to examine the subjective value of effort and its effects on response behaviours. Applying this model to decision times revealed asymmetric effects of effort and pain, suggesting that cognitive effort may not share the same basic influences on avoidance behaviour as more primary aversive stimuli such as physical pain.

Keywords: cognitive effort, pain, decision-making, behavioural economics

How Aversive is Cognitive Effort? Forced Choices Reveal a Trade-Off between Cognitive Effort and Physical Pain

People generally describe cognitive effort as an aversive experience to be avoided whenever possible (Kurzban, 2016). However, exerting effort is often instrumental in obtaining rewards, in which case the costs of effort must be weighed against potential gains and expected benefits of other, less effortful alternatives (Kool & Botvinick, 2014). Avoidance of effort, then, is thought to reflect a cost–benefit analysis aimed at optimizing cognitive resource allocation (Kool & Botvinick, 2018; Kurzban, Duckworth, Kable, & Myers, 2013; Shenhav et al., 2017). However, at a phenomenological level effort feels intrinsically unpleasant beyond just an abstract ‘cost’. Indeed, effort is often metaphorically associated with pain, as in familiar vernacular expressions such as “it hurts to think” or “my head hurts from thinking too hard”. However, direct comparisons between effort and pain remain to be examined beyond the mere metaphor. The goal of the present study was therefore to compare the aversive value of cognitive effort against that of physical pain through explicit choices whereby individuals must choose between the two aversive goods.

Effort and pain appear to share important similarities in terms of their respective functions; feelings of effort seem to promote conservation and optimization of limited cognitive resources (Kool & Botvinick, 2018; Richter, Gendolla, & Wright, 2016), while pain is designed to trigger protective behaviours aimed at preventing injury (Eccleston & Crombez, 1999). In both cases, effort and pain appear to act as stop signals interfering with the pursuit of ongoing activities in order to preserve the energy and integrity of the organism (Shackman et al., 2011). Moreover, as with cognitive effort, responses to pain can be flexibly overridden in the service of greater rewards (Vlaev, Seymour, Dolan, & Chater, 2009). However, wilfully accepting pain

appears to require substantial self-regulatory effort, even in extreme situations where accepting a certain amount of pain could mean avoiding probable death (Ralston, 2004). Thus, an apparent conflict emerges between an instrumental system that can choose to accept pain in exchange for greater rewards, and a Pavlovian system commanding us to avoid injury at all costs (Dayan & Seymour, 2009). On this view, the drive to escape pain can override more deliberative behaviours so as to prevent us from overthinking our responses when injury is imminent (e.g., Lewis, Niznikiewicz, Delamater, & Delgado, 2013).

Interestingly, cognitive effort appears to share some of the aversive characteristics of pain: effort is generally felt as an unpleasant urge to disengage and avoid overly demanding actions. The origin of this unpleasantness and its effect on behaviour remains a topic of current discussion (Shenhav et al., 2017). Present leading theories define effort costs as the consequence of computational limits on cognitive systems, or as ‘opportunity’ costs that are later integrated in a cost–benefit analysis of the action (Kool & Botvinick, 2018; Kurzban et al., 2013; Shenhav et al., 2017). Many of these studies estimate the ‘subjective value’ (SV) of effort by examining how rewards can be discounted by effort costs (e.g., Chong et al., 2017; Westbrook, Kester, & Braver, 2013). Recent studies have also begun to highlight the mathematical (i.e., functional) form of cognitive effort costs and how the SV of effort changes non-linearly with increasing demands (Białaszek, Marcowski, & Ostaszewski, 2017; Chong et al., 2018, 2017; Kool & Botvinick, 2018). The estimation of SV allows incommensurable goods, such as cognitive effort and pain, to be revalued as units on the same scale (Levy & Glimcher, 2012), allowing for better comparison and understanding of their influence on choices. As the SV cannot be observed directly, computational modelling can be used to infer SV from choices people make between two or more goods.

In turn, the influence of cognitive effort can be further examined through decision latencies (or response times; RTs). Using SV as an analogue for effort costs, we can compare the speed at which choices are made to lend insight into the strategies used to decide between cognitive effort and pain. For example, if effort and pain share similar aversive characteristics, we should expect higher intensities to slow responses to choosing that good (e.g., high pain levels slow responses to choosing the pain option), indicating increased avoidance. At the same time, we should expect to see faster responses to choosing the alternative option (e.g., high effort levels speed responses to the pain option), indicating increased escape-like behaviour. Indeed, avoidance of pain involves a set of automatic processes that help us avoid further injury (Andersen, 2007), but these processes may be overridden by higher-order systems in the presence of competing goals (Claes, Crombez, & Vlaeyen, 2015; Van Damme, Van Ryckeghem, Wyffels, Van Hulle, & Crombez, 2012). We therefore sought to examine whether avoidance of cognitive effort shows a similar pattern when the competing alternative is aversive, rather than rewarding.

In this study, we aimed at comparing the aversive properties of cognitive effort and pain in order to address the important but previously unexamined questions of 1) whether individuals will explicitly trade off cognitive effort with physical pain, and 2) to what extent the subjective valuation of cognitive effort relates to pain and how this SV subsequently affects decision latencies. If the first question is true, we can then make the striking prediction that people will accept physical pain to avoid exerting cognitive effort. To examine these questions, participants performed a simple economic decision-making task (e.g., Westbrook, Kester, Braver, Myers, & Freer, 2013; Westbrook, Lamichhane, & Braver, 2019) where they had to choose between

performing a cognitively demanding task or receiving painful thermal stimuli in order to avoid exerting effort.

By offering various levels of pain and cognitive demand—which were experienced directly after each choice—we were able to assess the ‘pain value’ of cognitive effort. We used computational modelling to fit different mathematical functions to participants’ choices to rescale effort levels into units (SV) commensurable with pain. We then used the computed SV of effort alongside pain levels to assess their impact on choice response latencies. That is, we analysed choice response times to find potential similarities and differences between the influences of effort and pain on the speed with which decisions are taken.

Finally, as the decision to exert cognitive effort or experience pain is highly subjective, we were interested in inter-individual differences that govern how people value and choose to avoid effort or pain. While mental effort is generally described as aversive, a given level of effort is experienced as more costly for some than for others (Cacioppo & Petty, 1982; Inzlicht, Shenhav, & Olivola, 2018), suggesting that the intrinsic value of effort influences decisions on whether to avoid it (e.g., Sandra & Otto, 2018; Westbrook et al., 2013). Similarly, there are well documented trait differences in how individuals evaluate and respond to pain (Sullivan, Bishop, & Pivik, 1995). To this end, we also examined the influence of individual differences in aversion to effort expenditure (Cacioppo, Petty, & Feng Kao, 1984) and pain (Sullivan et al., 1995) upon choices. However, decisions between two may be dependent on the actual experience of exerting effort or feeling pain, rather than the value attributed to them. To this end, we also individually calibrated task difficulty and pain intensity to control for differences in cognitive ability and pain perception, allowing us to better address the attributed value to pain or effort and its role in decision-making.

Results

In a novel effort–pain decision-making paradigm (Figure 1), participants made a series of choices between a cognitively demanding task and a painful stimulus, each of which had five different levels that varied parametrically from low (i.e., low cognitive effort or low pain) to high (i.e., high cognitive effort or high pain). To elicit different levels of cognitive demand, we used the N -back working memory task, ranging from $N = 0$ to $N = 4$, wherein stimuli were sequentially presented, and participants asked to respond whether the stimulus presented N times previous was the same or different from the current stimulus. The N -back task imposes increasing demands upon executive functions like selective attention, monitoring, and updating (Smith & Jonides, 1999), and is perceived as effortful, with self-reported effort increasing systematically with increasing N (Westbrook et al., 2013). Critically, we calibrated the difficulty of the N -back task (the interval between successive stimulus presentations; see Buhle & Wager, 2010) to account for differences in cognitive ability across participants (see Methods). To elicit pain, thermal stimuli were applied to the participant’s left forearm whereby increasing noxious heat would elicit exponential increases in reported pain intensity (Atlas, Lindquist, Bolger, & Wager, 2014; Price, McHaffie, & Larson, 1989). In line with the N -back calibration, the painful temperatures used for each participant were also individually calibrated to account for subjective differences in pain perception (Jepma, Jones, & Wager, 2014), in order to roughly equate the five levels of effort and pain across participants.

Following an established task design (Soutschek, Kang, Ruff, Hare, & Tobler, 2018), we systematically paired each possible effort and pain levels to create 25 unique effort–pain pairs, each repeated twice. Depending on each choice, participants were either required to perform a trial of the offered N -back level or would receive the offered painful temperature. As a

manipulation check, we examined performance as a function of N -back level and pain ratings as a function of the calibrated temperatures, and found that performance declined with increasing N -back levels, $\beta_{N\text{-back level}} = -0.07$, 95% CI $[-0.07, -0.06]$, $t(149.75) = 13.27$, $p < .001$, and pain ratings increased with higher temperatures, $\beta_{\text{pain level}} = 12.76$, 95% CI $[11.50, 14.03]$, $t(111.61) = 19.56$, $p < .001$ (see Supplementary Tables 1 & 2). We note that a pilot experiment conducted prior to the present study using a nearly identical protocol ($n = 20$) revealed qualitatively similar results to those described below (see the Supplementary Text).

Figure 1. Example of a trial for the decision-making task. Participants made a choice between a level of the N -back task and a level of pain. If participants chose the effortful option, they performed the N -back task at the given level. If the painful option was chosen, participants received the corresponding painful stimulus and avoided performing the N -back task.

Choice Behaviour

Examining choice behaviour, we found that when the level of cognitive demand was high, people preferred to accept a physically painful stimulus rather than exert cognitive effort (see Figure 2). Statistically, a multilevel logistic regression predicting pain choices as a function of pain and N -back levels confirmed the trade-off between cognitive effort and pain, such that as the level of required cognitive effort increased, people were more likely to accept the painful stimulus in exchange for avoiding the effortful task, $\beta_{N\text{-back level}} = 1.60$, 95% CI [1.19, 2.04], $z = 7.34$, $p < .001$.

Figure 2. Averaged heatmap of choice behaviour across participants as a function of pain stimulus level (horizontal axis) and N -back level (vertical axis) on offer (see Supplementary Table 3 for model estimates). Lighter colours indicate a higher probability of accepting the painful stimulus.

Conversely, as the level of pain offered increased, people were more likely to accept the effortful cognitive task, $\beta_{\text{Pain level}} = -1.24$, 95% CI [-1.49, -1.02], $z = 10.40$, $p < .001$. We also observed a significant negative interaction between the level of cognitive effort and the level of pain offered, $\beta_{\text{Pain level} \times N\text{-back level}} = -0.12$, 95% CI [-0.25, 0.003], $z = 2.03$, $p = .042$, suggesting

that the scales governing effort and pain levels offered may not have been perfectly matched . This effect—which should be interpreted with caution due to the null value falling just inside the 95% confidence interval—suggests that at higher concurrent levels of pain and cognitive effort, there was a slight preference for choosing to exert cognitive effort over experiencing pain. This was supported by a separate intercept-only regression model examining the average probability of choosing the pain stimulus (not accounting for the level of pain or level of effort offered), finding that the painful option was chosen approximately 28% of the time, $\beta_{\text{intercept}} = -0.92$, 95% CI $[-1.25, -0.60]$, $z = 5.54$, $p < .001$. This overall difference in acceptance rates, however, does not necessarily imply a fundamental difference between cognitive effort and pain, but rather, that the levels we offered were not necessarily optimized for obtaining 50/50% acceptance/rejection rates. Critically, average *N*-back performance was above chance at all levels of effort, demonstrating that participants were indeed engaged and correctly performing the task, $F(1, 149.75) = 175.98$, $p < .001$ (see Supplementary Table 1).

Individual Differences in Aversion to Effort and Pain Sensitivity

While the above findings indicate that people, on the whole, are willing to accept physical pain in order to avoid cognitive effort, an individual's propensity to accept pain—or effort—might also depend on how salient or aversive the two outcomes are to the individual decision-maker. For example, to some individuals the challenge of expending cognitive effort can be viewed as intrinsically rewarding (need for cognition [NFC]; Cacioppo et al., 1984; see also Inzlicht, Shenhav, & Olivola, 2018; Sandra & Otto, 2018). Furthermore, people also differ on the level at which pain is perceived as threatening (pain catastrophizing [PCS]; M. J. L. Sullivan et al., 1995).

First, we found that participants with higher NFC levels were more likely to avoid pain and choose the cognitively effortful option when both goods were at higher intensities (see Figure 3a), reflecting their higher willingness toward exerting cognitive effort (Cacioppo & Petty, 1982). Specifically, we found a significant moderating effect of NFC on the interaction between the level of pain and level of cognitive effort on offer, $\beta_{\text{NFC} \times \text{Pain level} \times \text{N-back level}} = -0.12$, 95% CI $[-0.25, -0.01]$, $z = 2.12$, $p = .034$, suggesting that as the levels of pain and cognitive effort increased, participants higher in NFC chose the cognitively effortful option more often compared to lower-NFC participants. Put another way, participants with higher NFC levels became less sensitive to cognitive effort as pain levels increased than participants with lower NFC levels. NFC did not significantly interact with any other effects in the model, $ps > .25$ (see Supplementary Table 6). Examining the moderating effect of NFC on *N*-back performance revealed no significant predictive effect, $\beta_{\text{NFC} \times \text{N-back level}} = 0.00$, 95% CI $[-0.01, 0.02]$, $t = 0.92$, $p = .36$.

Next, we found that pain catastrophizing also decreased acceptance of the painful option at higher intensities of effort (Figure 3b). More specifically, we found a significant moderating effect of PCS on the influence of the *N*-back level on choice behaviour, $\beta_{\text{PCS} \times \text{N-back level}} = -0.48$, 95% CI $[-0.87, -0.10]$, $z = 2.42$, $p = .015$, suggesting that participants with higher PCS are more willing to pay higher effort costs to avoid pain. Surprisingly, we did not find a significant moderating effect of PCS on any other predictors of choice behaviour, $ps > .31$ (see Supplementary Table 7). While for both NFC and PCS, higher scores indicated a preference for cognitive effort, the two measures were not significantly correlated, $r(36) = -.26$, $p = .12$, and suggesting that the two individual differences separately influenced choice behaviour (see

Discussion). Model estimates and inter-correlations between individual differences collected are reported in Supplementary Tables 4 and 5.

Figure 3. Predicted likelihoods of accepting the pain option at each *N*-back and pain level moderated by need for cognition and pain catastrophizing. **(a)** Those higher in need for cognition were more likely to choose the effortful option, especially when pain and effort offers were both in the higher, more aversive range (e.g., 4-back vs. 80/100 pain). **(b)** Similarly, those higher in pain catastrophizing preferred to avoid the pain option (and thus choose the cognitive effort option) at increasing *N*-back levels. NFC = need for cognition, PCS = pain catastrophizing.

Computational Modelling of Subjective Value

To better understand the relationship between cognitive effort and pain, we fit a series of computational models to identify the mathematical form that best explained how cognitive effort was subjectively valued in comparison to pain. Previous studies have used similar approaches to examine how exerting cognitive and physical effort discount potential monetary rewards (Białaszek et al., 2017; Chong et al., 2018, 2017; Hartmann, Hager, Tobler, & Kaiser, 2013), as well as the relationship between reward discounting by physical effort versus delay discounting

(e.g., Klein-Flügge, Kennerley, Saraiva, Penny, & Bestmann, 2015; Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010). Here, rather than discounting rewards, we were interested in how increases in the aversive value of cognitive effort traded off with another well-known aversive experience: physical pain.

Following previous work on cognitive effort costs (Chong et al., 2018, 2017), we compared a series of models (see Table 1) fit to cognitive effort levels that assumed different functional forms of subjective value—linear, exponential, parabolic, and hyperbolic—in order to transform cognitive effort into units more directly comparable to pain levels. As noted earlier, we calibrated the temperatures used for each participant based on their reported sensitivity to the painful stimuli. By assessing how each model accounted for each participant’s trial-by-trial choices, we were able to capture how people value the aversive nature of cognitive effort. These four value functions were input to a logistic function predicting choices and fit using maximum likelihood estimation separately for each model (see Methods).

We found that participants’ choices were best described by a parabolic weighting of effort levels (Figure 4a):

$$SV = k * E^2$$

where SV is the subjective value of cognitive effort for a given level of effort E (0-back, 1-back, 2-back, 3-back, or 4-back), and k is a scaling parameter which signals the steepness of the function (higher values of k represent a larger sensitivity to the aversiveness of the effort level on offer). The newly computed SV s were then taken as input to a logistic choice function:

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

where $Pr(pain)$ represents the probability of choosing the pain option for a given SV against the pain level P on offer (10/100, 28/100, 45/100, 63/100, or 80/100; Figure 4b). The β parameter

reflects the sensitivity of the logistic function to value differences, and the c parameter captures bias towards one option over the other (i.e., an overall preference for choosing pain over effort). Separate k (median = 0.18), β (median = 1.50), and c (median = 0.38) parameters were estimated for each participant.

Table 1

Goodness-of-fit Estimates from Computational Models on Cognitive Effort Levels

	Linear	Exponential	Parabolic	Hyperbolic
AIC	1223.32	1245.43	1143.59	1293.65

Note. Separate models were fit for each mathematical function on participants' data; AIC = Akaike Information Criterion (Akaike, 1974).

Figure 4. (a) Higher offered effort levels led to a parabolic increase in the SV of effort. This value was compared against the pain level on offer before being fit to participants' choices. (b) Averaged heatmap of choices predicted from the parabolic model fit to effort levels. Lighter colours indicate a higher probability of choosing the pain option.

Choice Response Times (RTs)

Using the model-estimated SVs for cognitive effort, we examined choice response times to choosing between pain and cognitive effort in order to see how the aversiveness of each good on offer influenced the speed with which a choice was made. To do so, we estimated a multilevel linear regression to predict choice RTs, allowing us to separately examine the effects of the

chosen and unchosen good upon choice latencies for both pain and effort choices (see Methods). Effort levels were transformed into SV units by applying the parabolic function above using the median population-level k parameter for all participants.

Overall, participants took longer to choose the pain option as compared to the effort option (linear contrast, $p = .005$; RT effect estimates are shown in Figure 5a), supporting the notion that response behaviours can be inhibited by aversive stimuli (Geurts, Huys, den Ouden, & Cools, 2013; Huys et al., 2011), and suggesting that the prospect of pain may exhibit a stronger inhibitory influence on choices than cognitive effort. There was also an overall significant effect of trial number, wherein RTs became faster over time, $\beta_{\text{Trial}} = -0.01$, 95% CI $[-0.01, -0.01]$, $t(32.68) = 7.16$, $p < .001$.

For both choice types, the aversiveness of the ultimately chosen option—i.e., SV_{effort} when choosing the effort option ($\beta_{SV_{\text{effort}} \times \text{Effort}} = 0.14$, 95% CI $[0.10, 0.19]$, $t(28.67) = 6.77$, $p < .001$) or pain level when choosing the pain option ($\beta_{\text{Pain level} \times \text{Pain}} = 0.14$, 95% CI $[0.09, 0.18]$, $t(24.32) = 6.28$, $p < .001$)—slowed RTs as the intensity of the offer increased. We observed no significant difference between the magnitude of these two effects (linear contrast, $p = .78$), indicating that while participants were overall slower to choose pain, increases in aversiveness for both cognitive effort and pain similarly slowed RTs when choosing the corresponding good (see Figure 5b).

However, in examining the effect of the aversiveness level of the unchosen good upon RTs, we observed an asymmetry in RT speeding (or facilitation) between effort and pain choices: when choosing the pain option, the SV of effort did not have a significant effect on RTs, $\beta_{SV_{\text{effort}} \times \text{Pain}} = 0.01$, 95% CI $[-0.03, 0.05]$, $t(26.30) = 0.60$, $p = .55$; conversely, when choosing the effort option, the pain level on offer significantly sped RTs to choose the option, $\beta_{\text{Pain level} \times \text{Effort}} =$

302 -0.06 , 95% CI $[-0.08, -0.04]$, $t(27.97) = 5.34$, $p < .001$. A linear contrast revealed a significant
303 difference between the magnitudes of these two effects, $p = .004$, suggesting that pain had
304 stronger speeding effects on choosing the alternative option (i.e., away from pain) than did
305 cognitive effort. Taken together, our RT analysis reveals that for both pain and effort, the
306 aversiveness level of the chosen good slows choices (Kim, Shimojo, & O'Doherty, 2006).
307 However, an important asymmetry emerged: SV of effort did not influence RTs when choosing
308 pain, but the pain level on offer sped RTs away from pain and toward the effort option.

Figure 5. (a) Estimated beta weights (presented in log-units) for the choice RT model. Positive values indicate an increase in predicted RTs (i.e., slowing down) and negative values indicate a decrease. RTs significantly increased at higher levels of the chosen good (i.e., at higher levels of SV_{effort} when choosing the effort option and higher levels of pain when choosing the pain option. Error bars represent the 95% CI based on the SEs from the model; *** $p < .001$ (see Supplementary Table 8 for full information on coefficient estimates). **(b)** Averaged heatmaps of the predicted RTs for choosing the pain option (left) and choosing the cognitive effort option (right).

Discussion

How aversive is cognitive effort? Here using a forced-choice decision-making task between cognitive effort and pain we showed that cognitive effort can sometimes be aversive enough to drive people to accept physical pain as a means of escape. As prospective cognitive demands increased, people were more likely to avoid exerting effort and instead choose to receive a painful thermal stimulus. Computational modelling revealed that the aversive value ascribed to cognitive effort increased parabolically as effort levels increased. To this point, participants made effort-avoidant choices even when faced with the maximum ethically permissible pain level: on average participants accepted the painful stimulation calibrated to 80/100 (100 = “extremely intense” pain) approximately 28% of the time in order to avoid performing the cognitively difficult 4-back task (see Figure 2). At the same time, as the level of pain offered increased, people were more inclined to avoid pain and instead choose to exert effort, demonstrating that, at some level, there is a trade-off between cognitive effort and primary aversive stimuli such as pain.

Moreover, we found that the decision between cognitive effort and pain was significantly influenced by trait differences in Need for Cognition (NFC) and Pain Catastrophizing (PCS). Higher NFC and higher PCS both predicted a preference for choosing cognitive effort over pain; however, the two measures were not correlated (see Supplementary Table 5) and thus appear to exert independent influences on choice behaviour. Specifically, as higher-NFC individuals perceive cognitive effort as less unpleasant, and therefore will often place a higher intrinsic value on effort exertion (Cacioppo & Petty, 1982; Cacioppo et al., 1984), they appear to prefer effort over pain even when cognitive demands are highest (e.g., 4-back) or painful temperatures are lowest (e.g., 10/100, 0 = “No pain at all”). At the same time, higher-PCS individuals tend to

exaggerate, ruminate, and feel helpless about pain (Sullivan et al., 1995), and thus avoid the painful option and choose effort even as the level of cognitive demand increases. Surprisingly, we found no relationship between PCS and the influence of pain levels on choice behaviour. That is, higher-PCS individuals did not adjust their decision behaviour at higher intensities of pain relative to lower-PCS individuals, but instead preferred to choose the alternative effortful option to avoid pain, even when that option itself may have been highly aversive.

Although we observed a trade-off between cognitive effort and pain, which suggests common aversive characteristics between the two, the present findings do not allow us to conclude that the aversive value of cognitive effort is necessarily equivalent to that of physical pain. In fact, previous work has examined choices between appetitive and aversive outcomes (Plassmann, O'Doherty, & Rangel, 2010), as well as appetitive goods of different categories, finding that the goods can be compared using a 'common currency' (Chib, Rangel, Shimojo, & O'Doherty, 2009; Levy & Glimcher, 2012). It follows that aversive goods of different categories may also be traded off once mapped to a common scale. To address this, we used computational modelling to infer the SV of cognitive effort and rescale effort to units more directly comparable to pain. We found that the aversive SV of cognitive effort increased parabolically when pain levels were assumed to be linear, showing that increases in the SV of effort were smaller at lower intensities of effort relative to higher intensities of effort. This finding contrasts with a recent study showing hyperbolic discounting of rewards by cognitive effort (Chong et al., 2017; cf. Chong et al., 2018) and suggests that discounting by cognitive effort may be dependent on the category of the alternative good. This conclusion, however, remains to be further investigated by future studies examining discounting of different categories of goods by cognitive effort.

Informed by the modelling approach described above, we found that choices were slower for more aversive levels of the chosen good—i.e., higher SV_{effort} levels predicted slower effort choices, and higher pain levels predicted slower choices to pain. Cognitive effort and pain therefore appear to share similar inhibitory effects on actions. However, we observed that pain uniquely facilitated (i.e. sped) choice RTs to the opposing effort option, whereas offered cognitive effort did not influence decision times for choices made to the alternative painful option.

This observed asymmetry may suggest that below a certain level of intensity, the motivational system can drive avoidance behaviour similarly to prevent overexerting cognitive systems or experiencing pain (Inzlicht et al., 2018; Talmi, Dayan, Kiebel, Frith, & Dolan, 2009; Vlaev et al., 2009). However, at higher intensities of pain, the body's survival mechanisms appear to take control and drive decisions away from pain, even when the alternative may itself be aversive. Pain, therefore, appears to recruit more primitive systems that govern responses when the prospect of pain is high. Conversely, decisions to exert cognitive effort rely on higher-order motivational systems (Kurzban et al., 2013; Shenhav et al., 2017) which do not engender the same level of urgency to avoid as more primary reinforcers, such as pain.

What, then, is the adaptive function of effort avoidance? Cognitive effort's intrinsic cost appears to prevent us from wasting processing resources and to disengage from inefficient actions, enabling those resources to be applied towards a different task or goal (Inzlicht et al., 2018; Kool & Botvinick, 2018; Kurzban et al., 2013; Otto & Daw, 2019). However, the urgency of the drive to avoid cognitive effort does not appear to share the same fundamental urgency as the drive to avoid further pain (Navratilova & Porreca, 2014); failure to avoid effort may be unpleasant, but failing to avoid pain can be life threatening (e.g., Nagasako, Oaklander, &

Dworkin, 2003). In effect, the purpose of treating cognitive effort as costly is to disengage us from those actions that are not sufficiently rewarding. By contrast, the ultimate function of pain is to preserve life and, as such, is the last line of defence against injury and further pain.

The findings reported above also lend insight into the role of cognitive effort in the experience of pain. The temperatures administered in the present study were above the activation threshold for nociceptors found within the skin (Plaghki & Mouraux, 2003; Treede, Meyer, Raja, & Campbell, 1995) and show that the higher temperatures elicited a strong, painful sensation (max. temperature used: 49 °C). Many studies have looked at the effects of cognition on acute and chronic pain (for reviews, see Buhle & Wager, 2010; Bushnell, Čeko, & Low, 2013), but few, if any, have examined how the aversiveness of cognitive effort may affect the pain experience and its potential role in making decisions about pain (Bar-On Kalfon, Gal, Shorer, & Ablin, 2016).

In summary, these findings demonstrate that cognitive effort can be as aversive as physical pain—and, perhaps surprisingly, that people will sometimes use pain as a means to avoid exerting effort. While these results highlight similarities in the aversive qualities of cognitive effort and pain, we also observed important differences. Contrary to cognitive effort, pain appears to elicit an avoidance response that interferes with instrumental decisions to prevent self-injury. This reflects the specialized role of pain in survival—address the source of (potential) injury or the consequences may be dire. Cognitive effort, although aversive, does not appear to have the same level of urgency: while thinking hard may ‘hurt’, it is unlikely to cause actual harm. A potential avenue for future research would be to leverage functional neuroimaging to understand how these two goods—cognitive effort costs and pain signals—could be encoded either by common or distinct regions, and how these regions direct avoidance behaviours, to

further elucidate effort's similarities and differences with pain or other aversive physical experiences.

Methods

Thirty-nine healthy volunteers (29 females, mean age = 21.44 years, SD = 2.64 years) were recruited for the study through the McGill University community. Exclusion criteria for the study were previous or current diagnosis of a psychiatric or neurological disorder, chronic pain syndrome or neuropathy, history of alcohol or other substance abuse, and regular (> 2 weekly) use of analgesics, anticonvulsants, narcotics, antidepressants, and/or anxiolytics. Participants were compensated for their time with either psychology course credits or at the rate of \$15 CAD/hr. Informed written consent was obtained from all participants and the study was approved by the McGill University Research Ethics Board.

Procedure

The study consisted of a single 2-hour session. After giving written informed consent, participants were given several computerized tasks to examine their choice behaviour between a painful thermal stimulus and a cognitively effortful task (the *N*-back task; see below). The E-Prime 3.0 software (Psychology Software Tools, 2016) was used to present the computerized tasks throughout the experiment. We first determined participants' sensitivity to the painful stimuli as well as their ability to perform the cognitive task. Following this, participants completed a series of questionnaires and measures of individual differences. Finally, participants were offered a series of choices between different levels of a painful stimulus and a difficult cognitive task.

Pain calibration

To determine a participant's sensitivity to the thermal stimuli, we applied several temperatures to the inner surface of the left forearm. For this, thermal heat was applied to 4 different sites on the surface of the arm using a 9-cm² thermal contact probe (TSA-II Neurosensory Analyzer, Medoc Ltd. Advanced Medical Systems, Israel). Five temperatures ranging equally between 45 °C and 49 °C were applied once to each of the four sites (20 total stimulations) from 32 °C baseline to the target temperature (9.5 s rise time, 8 s plateau, 2.5 s fall time). Following each stimulation participants indicated the sensation as either painful or non-painful and rated the sensation using a visual analogue scale (VAS). For temperatures rated as non-painful, participants rated the intensity of the sensation from 0 ("No warmth at all") to 100 ("Very hot, without pain"). If participants indicated the sensation as painful, they rated the intensity of the stimulus from 0 ("Not intense at all") to 100 ("Extremely intense"). These ratings were input into a regression model to calculate the temperatures used later in the experiment (see Supplementary Table 2 for average calibrated temperatures).

***N*-back Calibration**

After determining sensitivity to the thermal stimuli, and to adjust for differences in cognitive ability, participants completed a second calibration task performing the *N*-back working memory task. In this, letters were presented sequentially, and participants asked to indicate whether the currently presented letter was the same or different from the letter that was presented *N* letter characters previous. The 2-back version of the *N*-back was used to calibrate the inter-stimulus interval (ISI; the time between presented letters; min: 19 ms, max: 2583 ms). Before each letter, a fixation cross was presented for 250 ms. Participants performed 15 trials of the 2-back task with the ISI (i.e., difficulty) being adjusted after each trial to find a performance level between .75 and .85 based on the sensitivity measure *A* (Zhang & Mueller, 2005).

Measures of Individual Differences

Following the calibration tasks participants completed several questionnaires as well as a measure of working memory capacity. The questionnaires administered included the Need for Cognition Scale (Cacioppo et al., 1984), the Pain Catastrophizing Scale (Sullivan et al., 1995), the Fear of Pain Questionnaire (McNeil & Rainwater, 1998), the Behavioral Inhibition System and Behavioral Activation System scales (Carver & White, 1994), and the Big-Five Inventory (John, Donahue, & Kentle, 1991). Following completion of the questionnaires, participants completed a computerized version of the Operation Span task (Unsworth, Heitz, Schrock, & Engle, 2005). See Supplementary Table 5 for correlations between the different measures.

Decision-Making Task

For the main experimental task, participants made a series of choices between 5 different levels of the N -back task ($N = 0$ to $N = 4$, where $N = 0$ required participants to respond to ‘X’ with one button and all other letters with a different button) and 5 different painful stimuli (temperatures corresponding to 10, 28, 45, 63, and 80 out of 100 on a pain scale). On each trial participants were presented with two options: one of the five options for the pain stimulus and one of the five options of the N -back. After making their decision, participants either performed the given level of the N -back or received the corresponding painful temperature. The duration of both the N -back and the painful temperature was approximately 20 seconds. The speed of the N -back (the presentation speed of the letters) was fixed across all five levels to the speed obtained from the calibration procedure at the beginning of the experiment (calibrated using the 2-back). Each level of the N -back was systematically paired with each level of pain and participants made a total of 50 choices between effort and pain (i.e., each effort–pain pairing was presented twice).

Accuracy feedback was provided after completing the *N*-back, but no punishments were given for poor performance (e.g., performing at or below chance level; see Supplementary Table 1 for *N*-back performance findings). After receiving the painful temperature, participants rated the intensity of the stimulus on a Visual Analogue Scale (VAS) from 0 = “No pain at all” to 100 = “Extremely intense” so as to verify their perception of the painful stimulus (see Supplementary Table 2 for pain ratings findings).

Data Analysis

We constructed a series of multilevel models using the “lme4” package (Bates, Mächler, Bolker, & Walker, 2015) for the R language. To determine the random effects structure for each model, the maximal model was first fit (i.e., all random effects included) and then random effects systematically removed when the model failed to converge (e.g., Matuschek, Kliegl, Vasishth, Baayen, & Bates, 2017; see Supplementary Materials for model formulae). Choice RTs were log-transformed to remove skew, and trials with RTs greater than 3 standard deviations away from the participant’s mean were removed from analysis (< 1.2% of total trials). Data from one participant were removed from analysis due to failure to follow task instructions. Wald tests were used to evaluate the significance of the predictors in the logistic models on choice behaviour. Data from 7 participants were excluded from analysis in the model on RTs due to a computer error in the starting position of the cursor on the screen. The Kenward–Roger (1997) approximation was used to test the significance of the predictors in the linear model on RTs, utilizing the “doBy” package (Højsgaard & Halekoh, 2018) to linearly contrast the beta estimates where relevant. All significance tests were two-tailed and are supplemented with 95% bootstrapped confidence intervals (10,000 resamples) where possible. A null/intercept-only model on the response data revealed an intraclass correlation coefficient of .21.

Computational Modelling

Participants' choices in the decision-making task described above were fitted with linear, exponential, parabolic, and hyperbolic functions to determine which functional form best represented the data. Data from one participant were not included in the computational modelling as the participant chose the effort option on every trial. Each function was separately fit to effort levels (i.e., N -back level) on offer during the task. The remaining data were input into a logistic function with maximum likelihood estimation utilizing the *scipy.optimize.fmin* function in the SciPy package (Virtanen et al., 2020) for Python. The mathematical functions fit to effort and pain levels were as follows:

$$\text{Linear: } SV = k * E$$

$$\text{Exponential: } SV = e^{k * E}$$

$$\text{Parabolic: } SV = k * E^2$$

$$\text{Hyperbolic: } SV = \frac{1}{1 - k * E}$$

where SV represents the subjective value of cognitive effort, E represents the effort, or N -back, level on offer (coded 1, 2, 3, 4, or 5), k is the scaling parameter signalling the steepness of the function. The resulting SV s were then input to a logistic function:

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

where $Pr(pain)$ represents the probability of choosing the pain option, P represents the pain level on offer (coded 1, 2, 3, 4, or 5), β is the parameter capturing the steepness of the logistic function, and c being a parameter to capture overall bias towards one of the two options. For each choice domain, separate k , β , and c parameters were used when fitting the model. Final model fits were compared using AIC.

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Competing interests

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