Acute pain impairs sustained attention

Matthew K. Robison¹, Derek M. Ellis², Margarida M. Pitaes², Paul Karoly², & Gene A. Brewer²

¹ University of Texas at Arlington

² Arizona State University

Author note

Matthew K. Robison, Department of Psychology, University of Texas at Arlington; Derek M. Ellis, Department of Psychology, Arizona State University; Margarida M. Pitaes, Department of Psychology, Arizona State University; Paul Karoly, Department of Psychology, Arizona State University; Gene A. Brewer, Department of Psychology, Arizona State University.

Correspondence concerning this article should be addressed to Matthew K. Robison, 313 Life Science Building, 501 Nedderman Drive, Box 19528, Arlington, TX 76019. E-mail:

matthew.robison@uta.edu

Abstract

Pain affects the lives of many individuals by creating physical, psychological, and economic burdens. A critical psychological factor negatively affected by pain is one's ability to sustain attention. In order to better understand the effect of pain on sustained attention we conducted three experiments utilizing the psychomotor vigilance task, thought probes, and pupillometry. In Experiment 1, participants in acute pain exhibited overall poorer task performance. However, this effect was localized to the relative frequency and duration of the participants' slowest responses with their faster responses being equivalent to a no-pain control group. In Experiment 2, we replicated the procedure and included periodic thought probes to overtly measure subjective experiences during the task. Participants in pain reported fewer "on-task" thoughts and more thoughts directed toward the source of their pain. In Experiment 3, we replicated the procedure while simultaneously tracking pupillary dynamics using an eye-tracker. Participants in pain had smaller task-evoked pupillary responses, which is thought to be an indicator of task engagement. However, the behavioral effects of pain from Experiments 1 and 2 were not replicated in Experiment 3. Taken together, pain led to poorer performance in the form of an increase in the relative frequency and extremeness of slow responses, increases in off-task thoughts, and reductions in a physiological indicator of task engagement. These data speak to theories of how pain competes with task goals for attention and negatively impacts behavior. The broader implications of this work are the identification of a low-level mechanism by which pain can interfere with normal cognitive functioning.

Keywords: pain; sustained attention; pupillometry

Public Significance Statement

Given the fact that many people deal with either acute or chronic pain on a daily basis, it is important to understand the impact of pain on cognitive functioning. In the present study, we examined the effect of acute pain on sustained attention, and the findings indicated that pain can occasionally interrupt ongoing cognitive operations, manifesting in impaired cognitive performance. These attentional deviations could be extremely important in professions that require sustaining attention to important, continual streams of information like aviation (e.g., transportation security, air traffic control, piloting), health care professions (surgery, nursing), and safety monitoring (e.g., lifeguards, naval watchkeeping).

Acute pain impairs sustained attention

The psychological and societal costs of acute and chronic pain are staggering. The Center for Disease control estimates that approximately 20.4% of adults in the United States suffer from chronic pain (i.e., pain that persists after the healing phase) and lists it among one of the most common reasons adults seek medical care (Dahlhamer et al., 2018). Chronic pain is linked to the use and overuse of pain medication (e.g., opioids), psychological issues (e.g., depression), and a lower quality of life (Gureje, Von Korff, Simon, & Gater, 1998). For example, Gaskin and Richard (2012) reported that the annual cost to the national economy associated with chronic pain is estimated to be \$560 to \$635 billion, more than heart disease, cancer, and diabetes combined. Research has attempted to bridge the biological, psychological, and social aspects of pain processing in the central nervous system to better treat physical and psychological generators of pain and reduce the likelihood that acute painful experiences develop into chronic pain disorders (for a notable example see the fear-avoidance model of Crombez, Eccleston, Van Damme, Vlaeyen, & Karoly, 2012). In the current study we examined how acute painful experiences generate interruptive effects on goal pursuit in a sustained attention task.

We chose to examine sustained attention in the present study because it models a broadly applicable situation wherein people must maintain their attention to a task that may not be inherently engaging. For example, when driving a car, a lapse of attention may cause an individual to react slowly to an important change in their environment like a pedestrian entering the road or another vehicle moving into their lane. Thus, the findings should be directly applicable to any situation in which quick and appropriate responses to changes in the environment is necessary. But even outside the scope of fast reacting, there are other situations in which our attention can have a tendency to move in and out of the task (e.g., meetings, classroom

lectures). Beyond these rather mundane situations, there are some occupational settings in which sustaining attention is supremely important. For example, any individual monitoring an ongoing stream of information to detect critical events (e.g., transportation security, lifeguarding, naval watchkeeping) must maintain tightly focused attention to avoid missing an important signal. Further, professions that require continual decision-making (e.g., air-traffic control, nursing) place high demands on a person's attention system. What we hope to demonstrate is that when someone is in pain, they have a hard time maintaining their attention, and this can have a myriad of important consequences (e.g., vehicular accidents, security failures, poor decision-making in health- and safety-critical contexts).

In their influential model of the interruptive function of pain on attention, Eccleston and Crombez (1999) argued that pain creates salient experiences that compete for attention during goal-directed behavior. Based on the early work of Walker (1971) and the supervisory attentional system of Norman and Shallice (1986), the model highlights the fact that pain avoidance represents a strong, evolutionarily hardwired superordinate goal. Thus, when a person selects a goal for action, pain will exert a strong pulling force for the person to attend to the pain as a means of managing it. Thus, the previous goal will become subordinate to the goal of managing pain, directing attention and action away from what would have otherwise been the active goal (e.g., listen to a conversation, exercise, read a book). This is the essence of the "interruptive" role than pain plays. It interrupts ongoing cognition by disrupting attention and hindering the execution of other goals.

Support for the Eccleston and Crombez model comes from behavioral studies examining neuropsychological batteries of tests that measure attention, executive functioning, and working memory. For example, Hart, Martelli, and Zasler (2000) reviewed the literature on chronic pain

impairments in neuropsychological functioning. The take-home message from this work was that neuropsychological impairments manifest in measures assessing attentional capacity, processing speed, and psychomotor speed. Along these lines, Moore, Keogh, and Eccleston (2012) used an acute pain manipulation in the context of a primary-task paradigm to examine the precise nature of pain's interruptive effects on behavior in a set of tasks including continuous performance, flanker, endogenous precueing, *n*-back, inhibition, attentional switching, and divided attention. Pain did not generally impair performance across all tasks but rather only a subset including *n*-back, attentional switching, and divided attention tasks. This led the authors to conclude that the deleterious effects of pain manifest in complex tasks as opposed to simpler tasks. Notably, the manner in which pain intrudes into focal awareness and disrupts task performance is a topic of ongoing debate, where some studies report influences of pain on lower-level cognitive task performance and other studies find influences on higher-level cognitive task performance. In the current study we will provide a possible explanation for these ambiguities in the field based on recent research on individual differences in attention control.

Previously cognitive psychologists have leveraged simple and choice reaction time tasks to provide low-level mechanistic explanations for why individuals differ in higher-order cognitive abilities such as working memory capacity and general-fluid intelligence. From such tasks, researchers can extract valuable information by examining the full distribution of response times (Ball & Brewer, 2018; Balota & Yap, 2011; Brewer, Lau, Wingert, Ball, & Blais, 2017; Costa, Dogan, Schulz, & Reetz, 2019; Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007; Unsworth, Redick, Lakey, & Young, 2010). From such studies, researchers have learned that high- and low-ability individuals primarily differ in the degree to which they experience attentional lapses – transient events where goal maintenance is lost and attention becomes derailed by irrelevant external or internal sources of distraction. Here we extend this method to

examine the impact of pain on cognitive functioning. In the context of this research, painful experiences serve as a distraction to achieving task-relevant goals (Eccleston & Crombez, 1999). Eccleston and Crombez's (1999) model calls pain an "interruptive" influence. However one point of ambiguity remains. Is the effect of pain *persistent* (i.e., a near-constant interruption), or *transient* (occasionally interruptive)? This may be a crucial source of ambiguity in the literature. Distributional modeling of response time data may allow us to resolve empirical discrepancies and advance theory. We hypothesized, based on the description of pain by Eccleston and Crombez (1999) as an interruptive influence on attention, that the effect would be transient. In other words, it would not exert a negative influence on attention at *all* times, but rather it would periodically gain access to the focus of attention, causing slow reaction times on a small subset of trials, but to a rather large extent on such trials.

The present study

In the present study, the psychomotor vigilance task (PVT) served as a measure of sustained attention. The PVT is a simple reaction time task¹ wherein participants are asked to sustain attention in preparation to respond to the unpredictable onset of a visual stimulus (Dinges & Powell, 1985). When that event occurs, the participant simply presses a button as quickly as they can, their response time is recorded, and the next trial starts. The task can last anywhere from 5 minutes to well over an hour. Using this task, the researcher can examine average response time, slowing of response time across the task (i.e., the vigilance decrement), and

¹ We use the term *simple* reaction time task here to differentiate the PVT from *choice* reaction time tasks where people must react to the onset of a stimulus and make a response-decision about the identity of that stimulus. In simple reaction time tasks, the participant makes the same response to the onset of a single stimulus. *Simple* here does not necessarily mean *easy* or *low-demand*.

intraindividual variability in response time. Additionally, the data from the PVT allow for distributional analyses to extract theoretically-meaningful performance parameters. For example, Unsworth et al. (2010) had a large group of participants complete this task along with a battery of working memory and executive functioning tasks. Participants' slowest response times provided the best predictive power in accounting for variance in executive control, working memory, and fluid reasoning abilities. A similar analysis will be undertaken in the current study to examine whether pain influences speed of information processing, the vigilance decrement, and/or intraindividual variability in psychomotor vigilance.

The hallmark of sustained attention tasks is a worsening of performance with time (i.e., the vigilance decrement). In the PVT, this manifests as a slowing of RTs across trials. Our first analysis used linear mixed effect modeling to test for three effects: an effect of trial, an effect of condition (pain), and an interaction between condition and trial. We entered trial and condition as fixed effects and participant as a random effect. Both intercepts and slopes were allowed to vary randomly across participants. We expected to observe an effect of trial such that RTs would increase across trials. We also expected an effect of condition such that participants in the pain condition would exhibit slower RTs. Finally, although we did not have a specific hypothesis *a priori* regarding vigilance decrements, it is possible that acute pain also causes a sharper vigilance decrement (i.e., a more pronounced slowing of RTs). If this is the case, a trial x condition interaction should emerge.

Figure 1. Reaction time distributions with hypothetical differences between pain and control condition in μ , σ , and τ .

The next step in our analysis was to fit ex-Gaussian distributions to the RTs to further examine the effect of pain. Parameters of ex-gaussian distributions can give a more fine-grained description for why aggregate estimates (e.g., mean RTs) differ across conditions or individuals. The ex-gaussian distribution has aspects of a gaussian distribution (μ and σ) and an exponential distribution (τ). In simple RT tasks, the μ parameter of the distribution can be interpreted as how fast an individual generally responds. The σ parameter can be interpreted as the amount of intraindividual variability in RT - how consistently the individual responds. The τ parameter reflects how positively skewed the distribution is. Typically, long RTs in simple reaction time tasks are interpreted as attentional lapses – occasional trials where a participant's attention falls away from the task, causing them to react very slowly to the onset of the stimulus. Thus each of these parameters will be informative when comparing the pain condition to the control condition. First, does acute pain cause a general slowing of responding? If so, we should observe an effect of pain on μ . Second, does pain lead to more inconsistency in responding? If so, we should observe an effect of pain on σ . Finally, does acute pain cause more (and more severe) attentional lapses? If so, we should observe an effect of pain on τ . Figure 1 visually displays how effects on μ , σ , and τ would affect the shape of the RT distributions.

The current study aimed to provide deeper insight into the interruptive effect of acute pain on cognitive performance. Prior research has provided strong evidence that pain influences neurocognitive functions but ambiguity remains about the mechanism(s) by which these deficits occur (Hultsch, MacDonald, Hunter, Levy-Bencheton, & Strauss, 2000; Meeus et al., 2015). A potential weakness in much of the prior research examining the influence of pain on attention, executive control, and working memory is the reliance upon mean RTs. Analyzing mean RTs

obscures intra-individual variability which is associated with executive control failures (Ball & Brewer, 2018; Balota & Yap, 2011; Brewer et al., 2017; Costa et al., 2019; Schmiedek et al., 2007; Unsworth et al., 2010). In Experiment 1 participants experienced acute pain administered by a pressure algometer and were asked to complete a sustained attention task. Detailed analyses of their reaction times (RTs) included the vigilance decrement, RT variability, and Ex-Gaussian modeling of the RT distributions. In Experiment 2, we replicated Experiment 1 and included thought probes periodically throughout the task to assess task-related, task-unrelated, and pain-related subjective attentional states. In Experiment 3, we replicated Experiment 1 and simultaneously measured pupillary dynamics. We provide a detailed analysis of the pupillary dynamics while participants are in pain including pre-trial pupil diameter (i.e., arousal) and task-evoked pupillary responses (i.e., task-engagement).

Experiment 1

In Experiment 1 a sample of participants completed a 10-minute sustained attention task in either acute pain or under a control condition. The primary dependent variable was RT, and we used several analytic techniques to drill down to specific mechanisms by which pain affects sustained attention. In addition to the sustained attention task, participants completed a 10-item version of the Positive and Negative Affect scales (PANAS; Watson, Clark, & Tellegen, 1988) both before the task and at the end of the task. We collected these data to test whether any potential effect of pain could be explained by shifts in affect due to the painful stimulus.

Method

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

Participants and procedure

We set out to sample 50 participants in each of the two conditions, and the day on which we achieved this desired sample size served as our stopping rule for data collection.² A total of 108 participants from the human subjects pool at Arizona State University completed the study in exchange for partial course credit. Participants first completed an informed consent form that specifically noted that they could be placed in physical discomfort. After signing the informed consent form, the experimenter prepared the participant for completing the task. First, participants completed a 10-item Positive and Negative Affectivity scale (PANAS; Watson et al., 1988) - five items measuring positive affect and five items measuring negative affect - how well each of the 10 adjectives described how they were *currently* feeling. Participants rated on a scale from 1 (very slightly or not at all) to 5 (very much). Then, participants rated their current level of physical pain on a scale from 1 (no pain at all) to 9 (worst pain I can imagine). They then completed a series of 10 practice trials with the task.

After the practice trials, participants were asked two questions regarding their expectations for the task. First, they were asked, “Based on your practice trials in the counting task, please rate the percentage of trials that you will be able to successfully complete (by successfully we mean the percentage of trials you will be able to complete in less than 00.300 - i.e., in less than 300 milliseconds/0.3 seconds).” Then, they were asked, “Based on your practice trials, please rate the percentage of participants that will perform this task slower than you. For example, if 100 people do this same counting task you are about to do, how many people you think will perform slower

² While we did not base our sample size on an *a priori* power analysis, a power analysis determined that with the final achieved sample, we had 80% power to detect a medium-sized effect ($d = .46$).

than you on average?” These data were collected as part of a different project and are not analyzed here. Then, based on their condition, the experimenter instructed the participant on how to use the pressure algometer.

The pressure algometer consisted of a plastic wedge with a cylindrical pressure point about 1 inch wide. Participants placed their non-dominant pinky finger in the algometer, making sure the pressure point rested between their first and second phalanx. Their dominant hand remained free for the task. Then, if a participant had been assigned to the pain condition, the experimenter gradually added weight to the algometer until the participant stated they were at a pain level of 7 on the 9-point scale. Thus each participant was allowed to tell the experimenter when they felt they were in a moderate, but not extreme, amount of pain. The participant then recorded this pain rating in the computer, the experimenter noted the weight on the algometer in grams, and the task immediately proceeded to the experimental trials. If the participant had been assigned to the control condition, the participant simply placed their non-dominant pinky in the algometer and no weight was added to the device. Thus, both groups completed the task with their non-dominant hand in the algometer the entire time. Otherwise the experimental procedure was identical across conditions. Participants then completed the PVT. In Experiment 1, the task lasted exactly 10 minutes. In Experiments 2 and 3, the task lasted exactly 115 trials.

At the end of the task, participants completed a second PANAS scale and the Somatosensory Amplification Scale (SSAS; Barsky, Wyshak, & Klerman, 1990). The SSAS has 10 items measuring sensitivity to physical stimuli in the environment (e.g., “even something minor, like an insect bite or a splinter, really bothers me”). Participants rated themselves on a scale from 1 (not at all like me) to 5 (very much like me) on how well each statement described them. Although Eccleston and Crombez (1999) specifically mention pain tolerance/somatic

sensitivity as a potential moderator of the effect of pain on attention, these data were not particularly informative in the present design, as our manipulations were between- as opposed to within-subjects. Thus, these data were not analyzed here.

In Experiments 1 and 2, participants completed the study in groups of up to 8 participants in a large experimental room. Participants were seated at individual computer stations with partitions separating them from neighboring participants. All participants within a session participated in the same condition (pain or control) to avoid participants becoming aware of the between-subject manipulation. Sessions alternated between pain and control conditions. In Experiment 3, participants completed the study individually on an eye-tracking computer. Participants were assigned to the pain and control conditions via sequential subject ID numbers. The experimental protocol was approved by the Institutional Review Board at Arizona State University.

Task

Participants completed the PVT (Dinges & Powell, 1985) as a measure of sustained attention. On each trial, a set of blue, underlined zeros appeared at the center of the screen (00.000). After an unpredictable time interval, the numbers started counting forward like a stopwatch. The participant's task was to press the spacebar as soon as they noticed the counter start in order to stop the stopwatch. After they pressed the spacebar, the numbers turned red and their reaction time for that trial remained on-screen for 1 second (e.g., 00.345). Participants were instructed to try to respond as quickly as possible on each trial. In Experiment 1, the waiting

times were randomly sampled from 1 to 5.5 seconds in 500-ms intervals. In Experiments 2 and 3, the waiting times were randomly sampled from 2 to 10 seconds in 500-ms intervals.³

Data analysis

We used R (R Core Team, 2017) for all our analyses. For data aggregation and manipulation, we used the *dplyr* package (Wickham, François, Henry, & Müller, 2018), the *lmerTest* package (Kuznetsova, Brockhoff, & Christensen, 2017) for specifying linear mixed-effects models, the *retimes* (Massidda, 2013) package to estimate Ex-Gaussian parameter estimates, the *lsr* (Navarro, 2015) and *EMAtools* (Kleiman, 2017) packages to estimate effect sizes, the *lavaan* (Rosseel, 2012) package for mediation analyses and the *papaja* package (Aust & Barth, 2018) to generate the manuscript in R markdown. The data and analysis code are publicly available on the Open Science Framework at <https://osf.io/cx7ej/>.

We screened the data for outlying data points and participants with two procedures. First, we trimmed any RTs shorter than 200 ms, which typically indicate anticipatory responses, and any RT longer than 3000 ms, which can inappropriately skew distributions. Any participant who had more than 10 such RTs was eliminated from the analysis. Then, we averaged each participant's RTs. If any participant's mean RT fell outside 3 standard deviations of their condition mean, they were also excluded from the analysis.

³ This was an unintentional discrepancy between experiments. The original study upon which the PVT is based used a variable wait time from 1 to 10 s (Dinges & Powell, 1985). Recent experiments using this task have employed a variable wait period of 2 to 10 s (Massar, Lim, Sasmita, & Chee, 2016; Unsworth & Robison, 2016). Invariability in wait times makes the stimulus onset predictable, thus decreasing reaction times and negating the vigilance decrement (Unsworth, Robison, & Miller, 2018).

Results & Discussion

The outlier screening procedure removed 1.19% of RTs across all participants, and no participants had 10 or more screened RTs. Only 1 participant had a mean RT outside 3 *SDs* of their condition's mean. This left a sample of 55 participants in the control condition and 52 participants in the pain condition.

As a first step RTs were examined as a function of trial and condition with a linear mixed effect model. Both the intercept and effect of trial were allowed to vary randomly across participants. The model revealed a significant effect of trial such that RTs slowed across time ($b = 0.38$, $SE = 0.05$, $p < .001$, Cohen's $d = 1.40$) and a significant effect of condition, such that participants in the pain condition were slower overall ($b = 11.98$, $SE = 2.96$, $p < .001$, $d = 0.54$). However there was no significant trial x condition interaction ($b = 0.08$, $SE = 0.05$, $p = 0.07$, $d = 0.31$). Hence, participants in the pain condition did not show significantly steeper vigilance decrements. Figure 2 shows fitted lines for each condition. Next we fit an ex-Gaussian distribution to each participant's RTs and examined these parameters across conditions. Figure 2c shows the fitted distributions for each condition. Participants in the pain condition had significantly greater σ and τ estimates, on average.⁴ There was not a significant difference in μ across conditions (see 1).

⁴ We excluded any participants whose parameter estimates fell outside +/- 3 *SDs* of their condition's mean from these analyses. This procedure excluded 1 participant in the pain condition and 1 participant in the control condition.

Table 1
Ex-Gaussian parameter estimates by condition in Experiment 1

Parameter	Control	Pain	<i>t</i> (df)	<i>p</i>	Cohen's <i>d</i>
μ	258.40 (37.70)	242.03 (59.54)	-1.69 (103)	0.09	-0.33
σ	36.46 (29.71)	60.13 (60.41)	-2.57 (103)	0.01	0.50
τ	74.02 (40.90)	113.46 (88.53)	-2.96 (103)	< .01	0.58

Note. Standard deviations are in parentheses.

Figure 2. Fitted lines for reaction times (RTs) by trial and condition, and b) fitted density curves for distributions of RTs for each condition in Experiment 1.

Figure 3. a) Positive and b) Negative affect ratings by time (pre-task vs. post-task measurements) and condition (pain vs. control) in Experiment 1. Error bars represent +/- one standard error of the mean. Positive affect ratings decreased from pre-task to post-task measurements in both conditions. n.s. = not significant at $p < .05$, *** $p < .001$.

Finally, we examined the pre- and post-task positive and negative affect ratings from the PANAS. These data are plotted in Figure 3. We submitted responses to two separate linear mixed effect models with fixed effects of time (pre-/post-task measurement), condition (control/pain), and their interaction, and a random effect of participant. The effect of time was allowed to vary across participants. For positive affect, the model revealed a significant effect of time, such that positive affect ratings dropped from the pre-task to post-task measurements ($b = -0.14$, $SE = 0.04$, $p < .001$, $d = -0.72$). The main effect of condition ($b = 0.09$, $SE = 0.07$, $p = 0.19$, $d = 0.26$) and the time x condition interaction ($b = 0.05$, $SE = 0.04$, $p = 0.22$, $d = 0.25$) were not significant. For negative affect, there was not a significant main effect of time ($b = 0.04$, $SE = 0.03$, $p = 0.22$, $d =$

0.25), but there was a significant main effect of condition, ($b = 0.15$, $SE = 0.06$, $p = 0.009$, $d = 0.53$), qualified by a time x condition interaction ($b = 0.12$, $SE = 0.03$, $p < .001$, $d = 0.83$). As is visible in Figure 3, the conditions did not differ in negative affect on the pre-task ratings. But after the task, participants who had been in the pain condition reported much higher negative affect than participants who had been in the control condition. Importantly, the conditions did not significantly differ in pre-task positive affect ratings ($p = 0.56$) or negative affect ratings ($p = 0.64$). Participants in the two conditions also did not differ on the SSAS ($t(99) = -1.77$, $p = 0.08$).

As a test of whether the change in mean RT, σ , and τ could be attributed to changes in negative affect among participants in the pain condition, we examined whether negative affect mediated the effect of pain on RT and τ . We did so via the *lavaan* package in R (Rosseel, 2012). There was no mediation of the effect of pain on RT via negative affect (indirect effect = -0.04, $SE = 0.04$, $p = 0.34$). We repeated this analysis on σ and τ , and the results were quite similar. The model on σ no significant mediation of the effect of pain on σ via negative affect (indirect effect = 0.04, $SE = 0.05$, $p = 0.47$). The model on τ revealed a significant direct effect of pain on tau ($b = 0.26$, $p = 0.011$). Finally, there was no mediation of the effect of pain on τ via negative affect (indirect effect = 0.02, $SE = 0.05$, $p = 0.68$).

As hypothesized, participants placed in acute pain demonstrated significantly worse task performance than participants in the control condition. However this effect manifested in a rather specific way. Although both groups showed significant vigilance decrements, participants in the pain condition did not show steeper vigilance decrements. So pain did not lead to a differentially worse slowing of RTs across time. The ex-Gaussian distributional analyses also provided some rather specific results. Participants in the pain condition showed significantly larger σ and τ parameters, but they did not have significantly higher μ parameters. Thus, we can conclude that

participants in acute pain demonstrated more intraindividual variability in attentional focus (σ) and more frequent and severe attentional lapses (τ). Thus, consistent with predictions made by Eccleston and Crombez (1999), pain had a *transient* rather than a *persistent* effect on attention. That is, pain occasionally interrupted ongoing cognitive processing and usurped an external task goal causing more frequent and more extremely slow responding. Finally, these effects were not simply due to changes in negative affect. These findings offer rather specific reasons for how acute pain disrupts cognitive performance.

The findings of Experiment 1 motivated us to complete two follow-up experiments. We interpreted the effects on the σ and τ parameters of the ex-Gaussian analyses to mean that participants in pain were switching their attention more readily between the task and the source of their pain. If that is the case, acute pain should produce both subjective and physiological indicators of task disengagement. To measure subjective task disengagement – and attention to pain – we implemented thought probe methodology in Experiment 2. To measure engagement physiologically, we used pupillometry in Experiment 3. Previously, researchers have used pupillometry as a physiological measure of attentional allocation. Importantly, it can be used to index global arousal levels as well as attentional outlay during cognitive processing (see Beatty & Lucero-Wagoner, 2000, for review). The follow-up experiments thus had two goals: 1) replicate the experimental effects observed in Experiment 1 with well-powered designs, and 2) add multimodal corroborating evidence for the conclusion that acute pain causes a withdrawal of attention away from a primary task and toward the source of pain.

Experiment 2

In Experiment 2 we aimed to replicate this pattern of results and assess whether these transient fluctuations of poor task performance are accompanied by self-reports of attention to their source of pain. To achieve this aim a thought probe procedure was used as commonly found in the mind wandering literature (Weinstein, 2018). This method allows for the measurement of subjective experiences of participants as they complete the task, giving further insight into the psychological experience of acute pain. Based on the model of Eccleston and Crombez (1999), we had the relatively straightforward hypothesis that participants in the pain condition would report thinking about their finger (i.e., their pain) more often than participants in the control condition, and that they would report being focused on the task less often. These data would provide corroborating evidence that attention is consciously diverted to sources of pain, causing poorer cognitive processing.

Method

Participants and procedure

Based on the results of Experiment 1, we used the condition effect size from the linear mixed effect model in a power analysis. With this effect size, a sample of at least 76 participants in each condition would detect an effect of this size with 80% power. We used the day we reached this sample size as our stopping rule for data collection. A total of 182 participants from the human subjects pool at Arizona State University completed the study in exchange for partial course credit (99 men, 83 women, $M_{age} = 18.92$, $SD_{age} = 1.17$). All participants completed an informed consent form before participating.

Task

The PVT was quite similar to that used in Experiment 1 with a few exceptions. First, the wait times ranged from 2 to 10 seconds in half-second intervals. Second, rather than the task lasting for exactly 10 minutes, the task lasted exactly 115 trials which took about 16 minutes (on average, participants in Experiment 1 completed 108 trials.) Third, the task in Experiment 2 included thought probes. We needed a longer time to achieve a similar number of trials because we added a 2-second fixation screen (+++++) before each trial to Experiments 2 and 3. Otherwise, the experimental procedures were the same.

Thought probes

After 20 randomly-sampled trials (4 in each block of 23 trials), participants were presented with a thought probe. The probe screen asked, “What were you thinking about in the few seconds prior to this screen appearing? Press the key that best describes your thoughts.” The screen provided 5 options: 1) I was totally focused on the current task, 2) I was thinking about my performance on the task, 3) I was thinking about my finger in the device, 4) I was thinking about things unrelated to the task, and 5) My mind was blank. We coded response 1 as on-task, response 2 as task-related interference, response 3 as thoughts about their finger, response 4 as mind-wandering, and response 5 as mind-blanking. Participants made their response by using the number keys on the keyboard. After they made their response, the task immediately resumed.

Results & Discussion

The RT screening procedure removed 5 participants for having more than 10 RTs outside 200 - 3000 ms. The outlier screening procedure removed an additional 4 participants for having mean RTs outside 3 *SDs* of their condition’s mean. This left 85 participants in the pain condition

and 88 participants in the control condition. For the remaining participants, 0.21% of RTs were removed for falling outside 200 and 3000 ms.

Just as in Experiment 1, we fit a linear mixed effect model with fixed effects of trial and condition and a random effect of participant. The model revealed a significant effect of trial such that RTs slowed across time ($b = 0.70$, $SE = 0.05$, $p < .001$, $d = 2.00$). Participants in the pain condition were again slower overall, but this effect was not significant ($b = 6.47$, $SE = 3.58$, $p = 0.07$, $d = 0.21$). Finally, there was no significant trial x condition interaction ($b = -0.07$, $SE = 0.05$, $p = 0.14$, $d = -0.21$). Thus, the effect of pain on average RT was smaller in Experiment 2 compared to Experiment 1. Figure 4 shows fitted lines for each condition as a function of trial. Next we fit an ex-Gaussian distribution to each participant's RTs and examined these parameters across conditions. Paired-samples t -tests on each parameter revealed significant effects of pain on σ and τ , but not μ (see Table 2). These results also replicated Experiment 1.

Table 2:

Ex-Gaussian parameter estimates by condition in Experiment 2

Parameter	Control	Pain	$t(df)$	p	Cohen's d
μ	255.98 (49.91)	242.00 (74.45)	-1.43 (167)	0.15	-0.22
σ	61.51 (44.11)	81.97 (66.85)	-2.35 (167)	0.02	0.36
τ	122.33 (71.32)	150.53 (96.12)	-2.17 (167)	0.03	0.33

Note. Standard deviations are in parentheses.

Figure 4. a) Fitted lines for reaction times (RTs) by trial and condition, and b) fitted density curves for distributions of RTs for each condition in Experiment 2.

Figure 5. Thought-probe responses in Experiment 2. TRI = task-related interference. Error bars represent +/- one standard error. n.s. = not significant at $p < .05$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Figure 6. a) Positive and b) Negative affect ratings by time (pre-task vs. post-task measurements) and condition (pain vs. control) in Experiment 1. Error bars represent +/- one standard error of the mean. Positive affect ratings decreased from pre-task to post-task measurements in both conditions. n.s. = not significant at $p < .05$, $*p < .05$, $***p < .001$.

Next, we examined responses to the thought probes. Participants in the pain condition reported fewer on-task thoughts ($t(171) = 2.09$, $p = 0.039$, $d = 0.32$) and more thoughts about their finger; ($t(171) = -6.80$, $p < .001$, $d = 1.03$). However they also reported less mind-wandering ($t(171) = 3.11$, $p = 0.002$, $d = 0.47$). There were no significant differences between conditions in mind-blanking ($p = 0.07$) or task-related interference ($p = 0.27$). These data are plotted in Figure 5. While perhaps unsurprising, these data confirm the idea that participants in the pain condition experienced their attention being drawn away from the task and toward the source of their pain.

Finally, we examined responses to the PANAS scale. These data are plotted in Figure 6. Similar to Experiment 1, we examined responses with linear mixed models on positive and negative affect separately. For positive affect, the model revealed a significant effect of time,

such that positive affect ratings dropped from the pre-task to post-task measurements ($b = 0.78$, $SE = 0.10$, $p < .001$, $d = 1.24$). The main effect of condition ($b = 0.12$, $SE = 0.14$, $p = 0.4$, $d = 0.13$) and the time x condition interaction ($b = -0.16$, $SE = 0.14$, $p = 0.26$, $d = -0.17$) were not significant. For negative affect, there was not a significant main effect of time ($b = -0.01$, $SE = 0.02$, $p = 0.64$, $d = 0.12$), but there was a significant main effect of condition, ($b = 0.08$, $SE = 0.04$, $p = 0.031$, $d = 0.32$), such that participants in the pain condition reported higher negative affect. The time x condition interaction was not significant ($b = 0.02$, $SE = 0.02$, $p = 0.51$, $d = -0.10$). Importantly, the conditions did not significantly differ in pre-task positive affect ($p = 0.75$) or negative affect ratings ($p = 0.13$). Participants in the two conditions also did not differ on the SSAS ($t(180) = -0.22$, $p = 0.83$).

We ran the same mediation models from Experiment 1 to examine whether changes in RT, σ , and τ in the pain condition were mediated by negative affect. In Experiment 1, these effects were *not* mediated by negative affect, but we wanted to replicate that finding here. The direct effect of pain on post-task negative affect ratings was not significant ($b = 0.16$, $SE = 0.44$, $p = 0.72$), and neither was the direct effect of pain on RT ($b = 0.08$, $SE = 0.08$, $p = 0.28$) nor was the direct effect of negative affect on RT ($b = 0.03$, $SE = 0.10$, $p = 0.78$). Thus there was no mediation of the effect of pain on RT via negative affect (indirect effect = 0.004, $SE = 0.02$, $p = 0.82$). We repeated this analysis on σ and τ . The model on σ revealed a significant direct effect of pain on σ ($b = 0.18$, $SE = 0.07$, $p = 0.015$). However, post-task negative affect ratings did not have a significant direct effect on sigma ($b = -0.02$, $SE = 0.08$, $p = 0.840$), and thus there was no mediation of the effect of pain on sigma via negative affect (indirect effect = -0.002, $SE = 0.01$, $p = 0.849$). The model on τ revealed a significant direct effect of pain on tau ($b = 0.16$, $SE = 0.08$, $p = 0.031$). However, post-task negative affect ratings did not have a significant direct

effect on τ ($b = 0.02$, $SE = 0.08$, $p = 0.805$), and thus there was no mediation of the effect of pain on τ via negative affect (indirect effect = 0.003, $SE = 0.02$, $p = 0.856$).

Experiment 3

In Experiment 3, we attempted to replicate the pattern of behavioral data with two additional dependent variables: pretrial pupil diameter and task-evoked pupillary responses. It is possible that acute pain is a hyperarousing stimulus, one that pushes people into a state of distractibility that harms cognitive performance (Aston-Jones & Cohen, 2005; Yerkes & Dodson, 1908). If this is the case, we should observe significantly greater pretrial pupil diameter in the pain condition. Finally, we measured task-evoked pupillary responses as a measure of task-engagement. These responses scale with cognitive load, suggesting they are sensitive to the amount of effort people are exerting (Beatty & Lucero-Wagoner, 2000). Further, task-evoked pupillary responses are typically higher when participants self-report higher task-engagement and show better task performance (Hopstaken et al., 2015a, 2015b; Hopstaken, Linden, Bakker, Kompier, & Leung, 2016; Robison & Unsworth, 2019; Unsworth & Robison, 2016, 2017). Thus if pain negatively impacts task-engagement or effort, participants in the pain condition should show smaller task-evoked pupillary responses.

Method

Participants and procedure

Experiments 2 and 3 were run simultaneously. We used the same power analysis for Experiment 3 based on the results of Experiment 1. Therefore the target sample size for Experiment 3 was 76 participants in each condition. Data collection was stopped at the end of an

academic term, just shy of our target sample. A total of 149 participants from the human subjects pool at Arizona State University completed the study in exchange for partial course credit (82 men, 67 women, $M_{age} = 19.50$, $SD_{age} = 3.18$). All participants completed an informed consent form before participating. The experimental protocol was approved by the Institutional Review Board of Arizona State University.

Task

The PVT used in Experiment 3 was nearly identical to that used in Experiment 2, except it did not include thought probes. We made one other change to the task - the addition of a 2-second fixation screen between each trial. This screen served two purposes: 1) it allowed evoked changes in pupil diameter to return to baseline, and 2) it served as our measurement of pretrial pupil diameter (see Unsworth & Robison, 2016 for similar method). Finally, participants completed the experiment individually on an eye-tracker so we could collect pupillary data.

Pupillometry

Throughout the task, participants sat with their head position fixed in a chinrest positioned 60 cm from the monitor. A Tobii T-1750 eye-tracker continuously recorded pupil diameter binocularly at 60 Hz. We used the average of the right and left eye pupil diameter as our dependent variable. We excluded missing data points due to off-screen fixations and blinks. Linearly interpolating missing data points did not systematically change the pattern of results, so we report the uninterpolated data. For the pretrial pupil diameter, we averaged pupil diameter over the 2-second fixation screen. For the task-evoked pupil diameter, we averaged the data into a series of 50-ms bins from the time period between 200 ms before stimulus-onset and 1200 ms after stimulus onset. We baseline corrected task-evoked pupil diameter on a trial-by-trial basis by

subtracting each value from the average of the 200-ms period before stimulus onset. Thus, on each trial we measured a change in pupil diameter with reference to the 200-ms window immediately preceding stimulus onset. Then, we averaged these values across trials for each participant and then across participants within each condition. To statistically compare the task-evoked responses between conditions, we used the average pupil dilation over the period where the task-evoked response is maximal (400 - 800 ms post stimulus-onset).

Results & Discussion

Table 3:

Ex-Gaussian parameter estimates by condition in Experiment 3

Parameter	Control	Pain	t (df)	p	Cohen's d
μ	264.36 (67.38)	254.49 (75.30)	-0.83 (141)	0.41	-0.14
σ	62.62 (55.06)	74.25 (63.61)	-1.17 (141)	0.24	0.20
τ	122.41 (86.50)	136.48 (92.35)	-0.94 (141)	0.35	0.16

Note. Standard deviations are in parentheses.

Figure 7. a) Reaction times (RTs) by trial and condition (lines represent best-fitting line for each condition), b) RT distributions by condition in Experiment 3.

Figure 8. a) Positive affect and b) Negative affect ratings by time (pre-task vs. post-task) and condition (pain vs. control) in Experiment 3. Error bars represent +/- one standard error of the mean. Both conditions reported significant decreases in positive affect from pre- to post-task measurements. Only the pain condition reported a significant increase in negative affect from pre- to post-task measures. n.s. = not significant at $p < .05$, $**p < .01$, $***p < .001$.

Figure 9. Pretrial pupil diameter by trial and condition in Experiment 3. Both conditions showed a significant decrease in pretrial pupil diameter across trials, but this effect did not differ across conditions, and the conditions did not differ overall. Lines represent the best-fitting line for each condition. Shaded error bars represent the standard error of the estimate.

Figure 10. Task-evoked pupillary responses by condition in Experiment 3. Participants in the pain conditions showed significantly shallower task-evoked pupillary responses. Shaded areas represent $\pm$ one standard error.

Only 1 participant was removed for having 10 or more RTs outside 200 - 3000 ms. The outlier screening procedure removed an additional 4 participants for having a mean RT outside 3 *SDs* of their condition's mean. This procedure left a final sample of 71 participants in the pain condition and 73 participants in the control condition. For the remaining participants, 0.18% of RTs were removed for falling outside 200 and 3000 ms.

Just as in Experiments 1 and 2, we analyzed task performance with linear mixed effect modeling and ex-Gaussian distributional analyses. There was an effect of trial on RT ($b = 0.79$, $SE = 0.08$, $p < .001$, $d = 1.60$), replicating Experiments 1 and 2. But unlike Experiments 1, participants in the pain condition did not exhibit significantly slower RTs than the control condition ($b = 2.59$, $SE = 6.35$, $p = 0.68$, $d = 0.11$). Similar to Experiments 1 and 2, there was no significant trial x condition interaction ($b = 0.01$, $SE = 0.08$, $p = 0.93$, $d = 0.02$). These data are

plotted in Figure 7. The ex-Gaussian analysis also did not reveal a significant effects of pain on μ , and unlike Experiments 2 and 3, there were not significant effects on σ , or τ (see Table 3). All the effects were in the same directions as in Experiments 1 and 2, but were smaller in magnitude (see Figure 11).

The next set of analyses examined responses to the pre- and post-task PANAS. These data are plotted in Figure 8. Responses to the positive and negative scales were separately analyzed using linear mixed effect modeling. The model on positive affect revealed a significant main effect of time, such that positive affect decreased from pre- to post-task measures ($b = 0.68$, $SE = 0.11$, $p < .001$, $d = 1.05$). The main effect of condition ($b = 0.25$, $SE = 0.15$, $p = 0.1$, $d = 0.28$) and the time x condition interaction ($b = -0.10$, $SE = 0.16$, $p = 0.5$, $d = -0.11$) were not significant. The model on negative affect revealed a significant main effect of time, but this was qualified by a time x condition interaction ($b = 0.08$, $SE = 0.03$, $p = 0.004$, $d = -0.48$). As is visible in Figure 8, participants in the two conditions did not differ in the pre-task measurement of negative affect. But participants who had been in the pain condition reported a significant increase in negative affect, whereas participants in the control condition did not. Importantly, the conditions did not significantly differ in pre-task positive affect ($p = 0.24$) or negative affect ratings ($p = 0.71$). Participants in the two conditions also did not differ on the SSAS ($t(147) = 1.03$, $p = 0.30$).

Our final set of analyses examined pretrial and task-evoked pupil diameters. Pretrial pupil diameter presumably measures arousal. Pretrial pupil diameter into a linear mixed effect model with effects of trial, condition (pain), and a trial x condition interaction. The model revealed a significant effect of trial ($b = -0.001$, $SE = 0.0003$, $p < .001$, $d = -0.72$). However, participants in the pain condition did not show significantly greater arousal than participants in the control condition ($b = 0.04$, $SE = 0.04$, $p = 0.33$, $d = 0.12$), and there was no trial x condition interaction

($b = 0.000$, $SE = 0.000$, $p = 0.24$, $d = 0.20$). Therefore, we did not observe evidence that the pain condition placed those participants in a hyperaroused state, as we had hypothesized. These data are plotted in Figure 9.

Figure 10 shows the average task-evoked pupillary response for each condition. As is evident in the figure, participants in the control condition showed a significantly larger task-evoked response, as hypothesized. To statistically verify this, we averaged the change in pupil diameter over the window from 400 to 800 ms post stimulus-onset and compared these values across conditions. Indeed, this comparison revealed a significant difference in pupil dilation between the control condition and the pain condition ($t(142) = 2.33$, $p = 0.021$). So despite not showing any significant differences in RTs, participants in the pain condition did show a significantly smaller physiological response to the onset of the stimuli. Usually, task-evoked pupillary responses are used to measure attentional effort. Here, the participants in the pain condition did appear to show reduced effort to the task physiologically.

Figure 11. Effects on a) average RTs, b) μ , c) σ , and d) τ across Experiments 1, 2, and 3. The overall estimates are from combining data across all three experiments. Error bars represent 95% confidence intervals around each point estimate (circles).

Summary

The effects of pain varied across experiments. To summarize the magnitude of the effects on average RT, μ , σ , and τ , we plotted the effects and their associated standard errors in Figure 11. Specifically, we used the main effect of pain (in milliseconds) from the full model (main effects of trial, condition, and trial x condition interaction) for each experiment. Then, we merged

all data into a single dataset and estimated the effect for all experiments combined. The point estimate is shown as a circle, and the error bars represent 95% confidence intervals around those estimates. For the remaining plots (Figures 11b, c, and d), we used the standardized effect size (Cohen's d) from a t -test comparing the parameter estimates across the two conditions for each experiment. Then, we merged the data from all experiments and performed a single t -test on the parameter estimates for all participants combined. Again, the circles in the plots represent the point estimate of the effect size and the lines represent 95% confidence intervals around those estimates.

General Discussion

Across three experiments the effect of pain on sustained attention was investigated by examining mean RTs, changes in RT across the task, and RT distributions from a simple RT/sustained attention task. Additionally, thought probes (Experiment 2) and pupillometry (Experiment 3) provided further insight into underlying cognitive processes impacted by pain. In Experiments 1 and 2, the effect of pain changed the shape of the RT distributions in a systematic and interesting way. Specifically, acute pain produced significant increases in estimates of both σ and τ . Thus being in pain caused participants to show more variability in RTs and more positive skewing of the RT distributions - presumably reflective of more and more severe attentional lapses. This is consistent with the idea of pain being an “interruptive” influence. It occasionally enters awareness and draws attention away from ongoing goals, causing detriments to goal-oriented cognitive operations. Importantly, these interruptions are transient in nature. That is, if pain was a constant source of attentional disruption, we would have seen a different effect on the distribution of RTs - an increase in μ . That was not the case. In fact, the combined dataset suggested a negative effect of pain in μ . Although this effect was not statistically significant in

any individual experiment, in the aggregated data it was indeed significantly different from 0. An interpretation of this effect would be that on many trials, participants in pain are actually hyperattentive to the task as a means of coping with the pain. Directing attention toward the task and away from their pain could be a way of reducing the perception of pain. This is something that Eccleston and Crombez (1999) specifically note in their theory - that there can be bidirectionality of the effects pain with regard to attention. Attending to pain can reduce cognitive processing for an external task, but attending to a task can reduce the degree to which pain is perceived. But, given that this effect was only significant in the combined dataset and quite modest in size ($d = -0.28$), it should be interpreted with a degree of caution.

In Experiment 2, participants' responses to thought probes suggested that the locus of this behavioral deficit in RTs was an increase in exteroceptive thoughts (i.e., thinking about their finger in the device) and a decrease in task-related thoughts. Lastly in Experiment 3, participants in the pain condition had smaller task-evoked pupillary responses. Historically, task-evoked pupillary responses have been interpreted as indices of effort or task-engagement (see Beatty & Lucero-Wagoner, 2000). The fact that task-evoked responses were smaller in the pain condition in Experiment 3 indicated were less task-engaged when in pain. However, it is worth noting that the behavioral effects that were observed in both Experiments 1 and 2 (larger σ and τ estimates) were not observed in Experiment 3. Why we observed an effect on the task-evoked pupillary responses and not an effect on behavior was a bit unclear. Perhaps the stark differences in the two situations (e.g., participants in Experiment 3 were sitting with their heads in a chinrest) was enough to reduce the effect of pain on behavior. All the observed effects were in the same hypothesized direction as Experiments 1 and 2, but were weaker. So perhaps the effect on the task-evoked response should be interpreted with caution. But taken together, the data indicated that acute pain served as a distraction, transiently gained access to consciousness, usurped

attention, and negatively impacted participants' ability to sustain attention and maintain task engagement.

Eccleston and Crombez (1999) developed a model of how pain interrupts goal-oriented behavior by competing for attention. Our results are broadly consistent with this model insofar that pain negatively impacted performance in the PVT similar to prior studies (Hultsch et al., 2000; Meeus et al., 2015). The negative impact of pain on the psychomotor vigilance task was accompanied by an increase in participants reporting of exteroceptive thoughts which is also consistent with the hypothesis that pain competes for attention during goal-pursuit. However, there are several theoretical contributions of the present work that go beyond confirming predictions from the model. Specifically, we have shown that pain competes for attention transiently rather than persistently throughout the task. Thus in addition to providing general support for Eccleston and Crombez (1999)'s model, we provide a rather specific explanation for how pain interrupts ongoing task completion. We also show that task-evoked pupillary changes were reduced when participants were in pain which suggests that pain not only competes for attention but also reduces task engagement.

The current study may also provide some important details that address existing ambiguity in the field. Specifically, some studies report that pain negatively impacts lower-order cognitive tasks, whereas other studies fail to find an effect. As can be seen in the ex-Gaussian analyses, it is possible that pain negatively impacts performance by creating more variability and longer RTs. Thus, at best it is ambiguous when prior studies have reported mean RTs in these types of tasks. The current study underscores the fact that simply estimating average RT induces a degree of data reduction that can limit the interpretation of one's findings and may even yield insignificant results when there was a true difference present (i.e., a reduction in statistical power).

Implications

The findings of the present study have implications for a variety of situations. The data demonstrated that acute pain can impact one's ability to maintain attention to a given task. Here, we operationalized attention with speeded responses to the onset of a visual stimulus. Take for example a situation where speeded responding is indeed important: driving a car. Despite the fact that it is a relatively routine activity, driving requires attention to a dynamic environment. Any lapse of attention could cause the driver to miss a critical event (e.g., a pedestrian entering the roadway, another vehicle entering the driver's lane), causing slower responding and perhaps preventing the driver from avoiding a collision. In fact, when examining RTs on trials where participants reported being on-task versus when they reported thinking about their finger in the device, RTs were on average 74 ms slower when thinking about their finger. This might seem like a trivial difference. However, if a driver is traveling at 40 MPH, that 74-ms delay in responding translates into an additional 4 feet of stopping distance. That 4 feet may be the difference between successfully stopping before a collision and not. The present data suggest pain could put people at greater risk for such lapses. But we believe the results are applicable even beyond speeded decisions. For example, engaging in learning in a classroom environment requires sustained attention. Deviations of attention, perhaps caused by pain, could lead to impaired learning and worse academic achievement. As a final example, our data suggest that people whose jobs rely on sustained attention to detect rare yet important events (e.g., transportation security officers, lifeguards) would be impacted by pain. Such jobs might be repetitive in nature, yet these people must remain vigilant for the rare but important events (e.g., a dangerous item in luggage, a drowning swimmer). If the person is in pain, our data suggest it will be harder for this person to consistently attend to the job, potentially missing critical signals.

Limitations

The current study examined acute pain and not chronic pain. While this certainly limits our ability to generalize our findings to a clinical population, we contend that the current results point to new approaches to characterize neurocognitive ability in persons with pain. Specifically, we advocate for examining full RT distributions to better understand the specific manner by which chronic pain is influencing neurocognitive ability. It is plausible that chronic pain conditions may interrupt cognition in a more sustained manner than acute pain. Importantly, in the current study participants were in a moderate amount of pain which may have led to our findings of changes in the slow responses and not changes across all trials. In our more recent experiments, the pain induction method has been adjusted in an attempt to achieve more consistent pain thresholds. Specifically, instead of the participant adding weight to the algometer to increase their pain level, the participant starts with a moderate amount of weight and can add weight, reduce weight, or leave it unchanged to achieve a desired pain threshold. This procedure has led to a more consistent baseline level of weight between participants and quantifiably similar pain thresholds (i.e., total amount of weight being applied to finger).

Future Directions

Future research should examine how various levels of pain influences the shape of participants RT distributions to measure how the severity of the pain input scales with the engagement with the task. Likely, the more severe pain experiences will lead to more exteroceptive thoughts and a higher frequency of slow responses in the task. Another future direction is to examine whether any interventions (cognitive or pharmacological) can help participants shield themselves from the attentional capture of pain and whether this shielding helps them achieve levels sustained attention comparable to those not in pain. A final direction

that warrants discussion here is the use of neuroimaging to better track these momentary fluctuations between states of exteroceptive thoughts and states of task-engagement and understand which neural circuit manages the balance between these two states.

Conclusion

The interruptive function of pain on goal-pursuit is possibly a core component of pain's deleterious effect on cognition. In the current study we have shown that pain induces a very specific performance profile in the context of a sustained attention task. This profile is characterized by an increase in the number and latency of long RTs, which we interpret as evidence for transient attentional capture by pain. Attentional capture from pain encroaches on awareness and is accompanied by reductions in psychophysiological indicators of task engagement. Individuals who experience pain likely experience multiple failures of goal-pursuit in important personal and professional contexts. These failures can lead to negative feedback, poor outcomes, and increased opportunities for psychopathology.

References

- Aston-Jones, G., & Cohen, J. D. (2005). An integrative theory of locus coeruleus-norepinephrine function: Adaptive gain and optimal performance. *Annual Reviews of Neuroscience*, 28, 403–450. <https://doi.org/10.1146/annurev.neuro.28.061604.135709>
- Aust, F., & Barth, M. (2018). *papaja: Create APA manuscripts with R Markdown*. Retrieved from <https://github.com/crsh/papaja>
- Ball, B. H., & Brewer, G. A. (2018). Proactive control processes in event-based prospective memory: Evidence from intraindividual variability and ex-gaussian analyses. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 44, 793.
- Balota, D. A., & Yap, M. J. (2011). Moving beyond the mean in studies of mental chronometry: The power of response time distributional analyses. *Current Directions in Psychological Science*, 20, 160–166.
- Barsky, A. J., Wyshak, G., & Klerman, G. L. (1990). The somatosensory amplification scale and its relationship to hypochondriasis. *Journal of Psychiatric Research*, 24, 323–334.
- Beatty, J., & Lucero-Wagoner, B. (2000). The pupillary system. In J. T. Cacioppo, L. G. Tassinary, & G. Bernston G (Eds.), *Handbook of psychophysiology*, 2nd ed. (pp. 142–162). Cambridge University Press.
- Brewer, G. A., Lau, K. K., Wingert, K. M., Ball, B. H., & Blais, C. (2017). Examining depletion theories under conditions of within-task transfer. *Journal of Experimental Psychology: General*, 146(7), 988.

- Costa, A. S., Dogan, I., Schulz, J. B., & Reetz, K. (2019). Going beyond the mean: Intraindividual variability of cognitive performance in prodromal and early neurodegenerative disorders. *The Clinical Neuropsychologist*, 33, 369–389.
- Crombez, G., Eccleston, C., Van Damme, S., Vlaeyen, J. W., & Karoly, P. (2012). Fear-avoidance model of chronic pain: The next generation. *The Clinical Journal of Pain*, 28, 475–483.
- Dahlhamer, J., Lucas, J., Zelaya, C., Nahin, R., Mackey, S., DeBar, L., ... Helmick, C. (2018). Prevalence of chronic pain and high-impact chronic pain among adults—united states, 2016. *Morbidity and Mortality Weekly Report*, 67, 1001.
- Dinges, D. F., & Powell, J. W. (1985). Microcomputer analyses of performance on a portable, simple visual rt task during sustained operations. *Behavior Research Methods, Instruments, & Computers*, 17, 652–655.
- Eccleston, C., & Crombez, G. (1999). Pain demands attention: A cognitive–affective model of the interruptive function of pain. *Psychological Bulletin*, 125, 356.
- Gaskin, D. J., & Richard, P. (2012). The economic costs of pain in the united states. *The Journal of Pain*, 13, 715–724.
- Gureje, O., Von Korff, M., Simon, G. E., & Gater, R. (1998). Persistent pain and well-being: A world health organization study in primary care. *Jama*, 280, 147–151.
- Hart, R. P., Martelli, M. F., & Zasler, N. D. (2000). Chronic pain and neuropsychological functioning. *Neuropsychology Review*, 10, 131–149.

Hopstaken, J. F., Linden, D. van der, Bakker, A. B., & Kompier, M. A. (2015a). The window of my eyes: Task disengagement and mental fatigue covary with pupil dynamics. *Biological Psychology, 110*, 100–106.

Hopstaken, J. F., Linden, D. van der, Bakker, A. B., Kompier, M. A., & Leung, Y. K. (2016). Shifts in attention during mental fatigue: Evidence from subjective, behavioral, physiological, and eye-tracking data. *Journal of Experimental Psychology: Human Perception and Performance, 42*, 878–889.

Hopstaken, J. F., Van Der Linden, D., Bakker, A. B., & Kompier, M. A. (2015b). A multifaceted investigation of the link between mental fatigue and task disengagement. *Psychophysiology, 52*, 305–315.

Hultsch, D. F., MacDonald, S. W., Hunter, M. A., Levy-Bencheton, J., & Strauss, E. (2000). Intraindividual variability in cognitive performance in older adults: Comparison of adults with mild dementia, adults with arthritis, and healthy adults. *Neuropsychology, 14*, 588.

Kleiman, E. (2017). *EMAtools: Data management tools for real-time monitoring/ecological momentary assessment data*. Retrieved from <https://CRAN.R-project.org/package=EMAtools>

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software, 82*, 1–26.
<https://doi.org/10.18637/jss.v082.i13>

- Massar, S. A., Lim, J., Sasmita, K., & Chee, M. W. (2016). Rewards boost sustained attention through higher effort: A value-based decision making approach. *Biological Psychology*, *120*, 21–27. <https://doi.org/10.1016/j.biopsycho.2016.07.019>
- Massidda, D. (2013). *Retimes: Reaction time analysis*. Retrieved from <https://CRAN.R-project.org/package=retimes>
- Meeus, M., Van Oosterwijck, J., Ickmans, K., Baert, I., Coppieters, I., Roussel, N., ... Nijs, J. (2015). Interrelationships between pain processing, cortisol and cognitive performance in chronic whiplash-associated disorders. *Clinical Rheumatology*, *34*, 545–553.
- Moore, D. J., Keogh, E., & Eccleston, C. (2012). The interruptive effect of pain on attention. *The Quarterly Journal of Experimental Psychology*, *65*, 565–586.
- Navarro, D. (2015). *Learning statistics with r: A tutorial for psychology students and other beginners. (Version 0.5)*. Adelaide, Australia: University of Adelaide. Retrieved from <http://ua.edu.au/ccs/teaching/lsr>
- Norman, D. A., & Shallice, T. (1986). Attention to action. In *Consciousness and self-regulation* (pp. 1–18). Springer.
- R Core Team. (2017). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>
- Robison, M. K., & Unsworth, N. (2019). Pupillometry tracks fluctuations in working memory performance. *Attention, Perception, & Psychophysics*, *81*, 407–419. <https://doi.org/10.3758/s13414-018-1618-4>

- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48, 1–36. Retrieved from <http://www.jstatsoft.org/v48/i02/>
- Schmiedek, F., Oberauer, K., Wilhelm, O., Süß, H.-M., & Wittmann, W. W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General*, 136, 414–429.
- Unsworth, N., Redick, T. S., Lakey, C. E., & Young, D. L. (2010). Lapses in sustained attention and their relation to executive control and fluid abilities: An individual differences investigation. *Intelligence*, 38, 111–122. <https://doi.org/10.1016/j.intell.2009.08.002>
- Unsworth, N., & Robison, M. K. (2016). Pupillary correlates of lapses of sustained attention. *Cognitive, Affective, & Behavioral Neuroscience*, 16, 601–615. <https://doi.org/10.3758/s13415-016-0417-4>
- Unsworth, N., & Robison, M. K. (2017). The importance of arousal for variation in working memory capacity and attention control: A latent variable pupillometry study. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 43, 1962–1987. <https://doi.org/10.1037/xlm0000421>
- Unsworth, N., Robison, M. K., & Miller, A. L. (2018). Pupillary correlates of fluctuations in sustained attention. *Journal of Cognitive Neuroscience*, 30, 1241–1253. https://doi.org/10.1162/jocn_a_01251
- Walker, J. (1971). Pain and distraction in athletes and non-athletes. *Perceptual and Motor Skills*, 33, 1187–1190.

- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The panas scales. *Journal of Personality and Social Psychology*, 54, 1063.
- Weinstein, Y. (2018). Mind-wandering, how do i measure thee with probes? Let me count the ways. *Behavior Research Methods*, 50, 642–661.
- Wickham, H., François, R., Henry, L., & Müller, K. (2018). *Dplyr: A grammar of data manipulation*. Retrieved from <https://CRAN.R-project.org/package=dplyr>
- Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, 18, 459–482.