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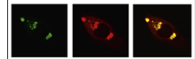
Research report

The impact of cognitive load on reward evaluation

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ABSTRACT

The neural systems that afford our ability to evaluate rewards and punishments are impacted by a variety of external factors. Here, we demonstrate that increased cognitive load reduces the functional efficacy of a reward processing system within the human medial–frontal cortex. In our paradigm, two groups of participants used performance feedback to estimate the exact duration of one second while electroencephalographic (EEG) data was recorded. Prior to performing the time estimation task, both groups were instructed to keep their eyes still and avoid blinking in line with well established EEG protocol. However, during performance of the time-estimation task, one of the two groups was provided with trial-to-trial-feedback about their performance on the time-estimation task and their eye movements to induce a higher level of cognitive load relative to participants in the other group who were solely provided with feedback about the accuracy of their temporal estimates. In line with previous work, we found that the higher level of cognitive load reduced the amplitude of the feedback-related negativity, a component of the human event-related brain potential associated with reward evaluation within the medial–frontal cortex. Importantly, our results provide further support that increased cognitive load reduces the functional efficacy of a neural system associated with reward processing.

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1. Introduction

When we learn, we do not learn in isolation. Typically, the neural systems that underpin human learning are forced to evaluate performance outcomes in complex environments that require several actions to be performed simultaneously. For example, the dangers brought about by talking on a cellphone while driving are well known (Horrey et al., 2006; Pickrell and Ye, 2013; Singh, 2010). Multi-tasking while we drive, or while we do any other activity in which we wish performance to be optimal, is well known to result in behavioral performance decrements for both tasks (Heenan et al., 2014; Kahneman, 1973; Ishigami and Klein, 2009; Ma and Kaber, 2005; McCarley et al., 2004; Strayer et al., 2003; Wickens, 1981). Here, we extend previous work (Krigolson et al., 2012) examining the impact of increased cognitive load on the neural systems that subserve human learning and demonstrate that the increased cognitive load brought about

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by multi-tasking reduces the functional efficacy of an error evaluation system within the medial–frontal cortex.

The impact of cognitive load on performance in general is a well studied phenomenon (Andersson et al., 2002; Broadbent, 1958; Kahneman, 1973; Knowles, 1963; Park et al., 2011; Sweller, 1994). In dual-task paradigms, cognitive load is induced by having people perform two tasks simultaneously that compete for cognitive resources (e.g., Wickens, 1981), for example, performing a visual stimulus-response task while at the same time having to listen for auditory cues. While typically the performance decrements associated with dual-task conditions are explained in terms of attention (c.f., Wickens, 1992), one can also simply think of a dual or multi-task condition in terms of cognitive load. In other words, in a dual-task condition a participant experiences greater cognitive load relative to a single-task condition and it is the increased cognitive load that leads to performance decrements. Of course, this is a moot point and one could also explain the performance decrement in terms of attention – the point, however, is simple – people perform worse in dual task conditions. Here, we are interested in how increased cognitive load impacts the function of neural systems other than attentional processes. For instance, a growing body of evidence suggests that human learning is principally driven by a reinforcement learning system within the human medial–frontal cortex that utilizes performance feedback to optimize behavior (Holroyd and Coles, 2002; Holroyd et al., 2005). Only recently has the impact of cognitive load on reward processing within the medial–frontal cortex been examined.

In a previous experiment (Krigolson et al., 2012) we sought to do just this – examine the impact of cognitive load on reward-processing within the human medial–frontal cortex. In our experiment, we had participants perform a simple time estimation task (c.f., Miltner et al., 1997) during which they learned to accurately guess the duration of one second via a trial and error feedback driven shaping process. The experiment was split into two separate counter-balanced experimental blocks, and within each the feedback provided to participants varied in terms of cognitive load – one feedback condition was considered to be "low-load" whereas the other was considered to be "high-load". In the low-load condition the feedback provided to participants simply consisted of a check mark that indicated a correct temporal estimate or a cross mark that indicated an incorrect temporal estimate. In the high-load condition the feedback following a participant's guess consisted of two integers – the participants mentally summed the numbers and an even sum indicated a correct temporal estimate whereas an odd sum indicated an incorrect temporal estimate. Not surprisingly, in terms of behavioral performance participants performed worse in the high-load condition relative to the low-load condition. Of principle interest however was the finding that the amplitude of the feedback-related negativity (FRN) – the difference in the event-related brain potentials (ERPs) evoked by positive and negative outcomes 200–300 ms following feedback delivery – was also reduced in the high-load condition relative to the low-load condition. In other words, increasing the cognitive load of the feedback stimulus reduced the functional efficacy of the medial–frontal learning system (Holroyd and Coles, 2002) – a result that suggests people may not learn as effectively in high

cognitive load conditions because the neural system responsible for learning is impaired.

In the present experiment, we sought to extend our original work (Krigolson et al., 2012) by examining the impact of cognitive load induced by multi-tasking on reward processing within the medial–frontal cortex. In the present experiment, we had two groups of participants complete a time estimation task similar to the one we employed in our previous work while we recorded both ocular and EEG data. To induce a higher level of cognitive load on one of the groups of participants we added a second task to their paradigm that they performed concurrently with the time estimation task. More specifically, while we instructed both groups of participants to try and keep their eye movements to a minimum and avoid blinking, we also told participants in the high-cognitive load group (HCL) that we would be tracking their eye movements and providing them with feedback in order to train them to not move their eyes while they performed the time estimation task. Our logic here was simple: while both groups of participants were given the same instruction to not move their eyes, we believed that because of the feedback induced training for HCL participants they would be performing two tasks simultaneously and thus would experience a higher level of cognitive load.

Given our previous results (Krigolson et al., 2012), we predicted that behavioral performance and the amplitude of the FRN would be impacted by increased cognitive load. More specifically, we predicted that behavioral performance and FRN amplitude would be reduced for HCL participants relative to LCL participants.

2.   Results

2.1.   Behavioral data

Given our performance based manipulation on the size of the response window (see Section 5 for more detail), mean accuracy did not differ between the LCL (49% [48% 50%]) and HCL (49% [48% 50%]) conditions ($p > 0.05$). We also examined the mean window size for both the LCL (139 ms [109 ms 165 ms]) and the HCL groups (163 ms [102 ms 224 ms]) and found that this did not differ, $t(13) = 0.40$, $p > 0.05$. In line with our previous work we examined the percent change in participants' estimates following correct and error feedback. Not surprisingly, we found a large effect of feedback valence – participants made larger changes to their temporal estimates following error feedback (25.6% [20.0% 31.1%]) as opposed to correct feedback (13.8% [11.0% 16.6%]) ($F(1,26) = 50.31$, $p < 0.001$, partial $\eta^2 = 0.66$). However, we observed no effect of cognitive load on the change on participants' estimates following error (LCL 251 ms [176 ms 326 ms] versus HCL 261 ms [173 ms 349 ms]) or correct (LCL 140 ms [95 ms 183 ms] versus HCL 136 ms [99 ms 174 ms]) feedback ($p > 0.05$).

2.2.   Ocular data

To examine the effect of eye movement feedback on eye movements, we calculated each participant's overall proportion of trials in which an eye movement occurred either 400–600 ms before feedback or while the time estimation feedback was displayed for 1000 ms. Not surprisingly, participants that
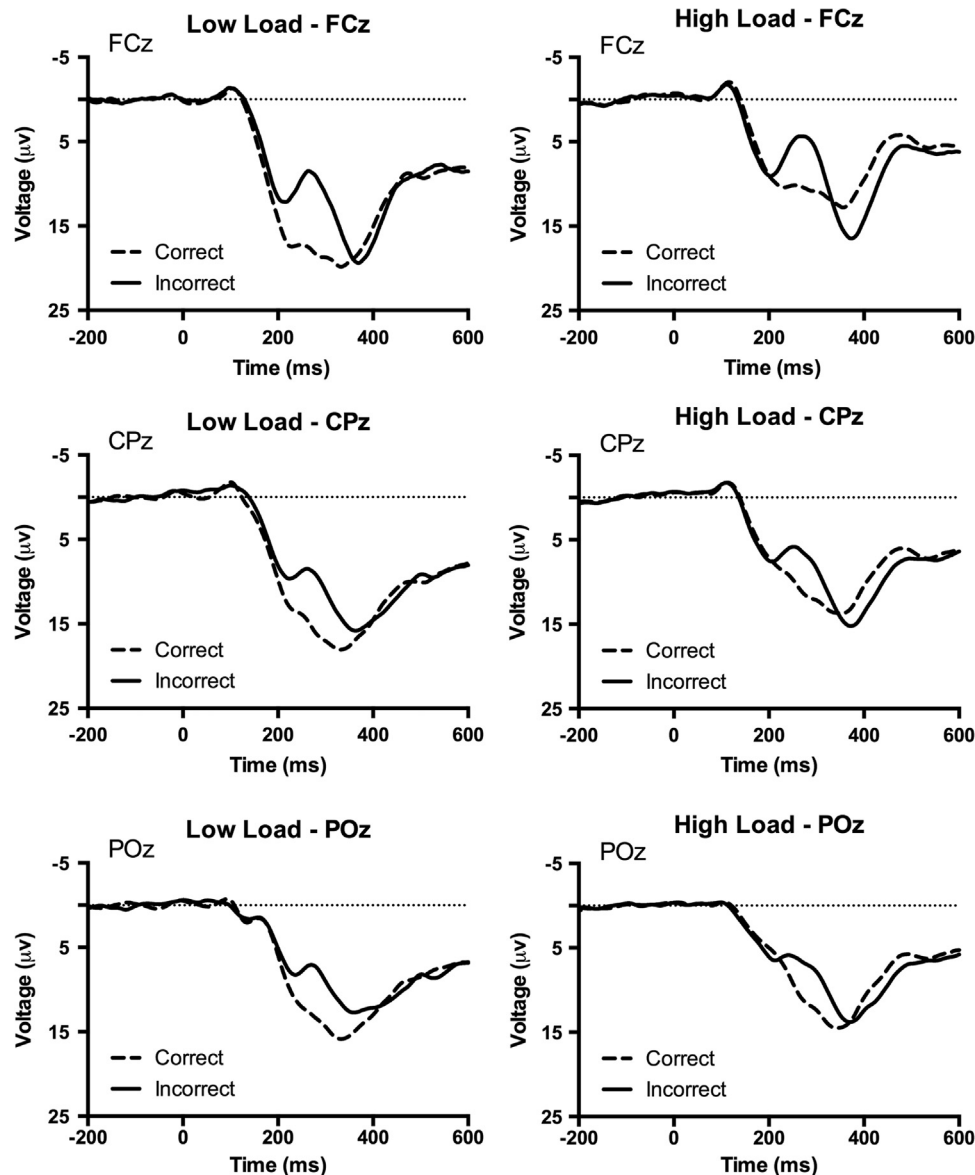
Fig. 1 – Grand average event-related brain potential waveforms time locked to the onset of the feedback stimulus at channels FCz, CPz, and POz for participants in the low-load group (a) and high-load group (b). Note, negative voltages are plotted upwards by convention.

received eye movement feedback (the HCL group) made fewer eye movements compared to participants who did not receive eye movement feedback (18% [6% 30%] of trials versus 40% [21% 60%] of trials) ($t(13)=2.21$, $p<0.05$).

2.3. Electroencephalographic data

In line with our previous work, we found that increased cognitive load decreased FRN amplitude (see Figs. 1 and 2). Specifically, we found the amplitude of the FRN in the HCL condition (−7.4 uV [−5.2 uV −9.4 uV]) was less negative than the FRN in the LCL condition (−11.0 uV [−9.1 uV −12.9 uV]) ($t(26)=2.65$, $p=0.01$) (Cohen's $d=1.006$; a large effect). The FRN in both conditions passed the test of existence – the single sample t-test of the FRN difference score against zero to

determine whether a FRN was present or not (LCL: $t(13)=-11.4$, $p<0.001$; HCL: $t(13)=-7.3$, $p<0.001$).

Further examination of the FRN in both the LCL and HCL conditions revealed that the component did not differ in latency between the two conditions (HCL: 279 ms [264 ms 294 ms]; LCL: 273 ms [259 ms 286 ms]), $t(13)=0.51$, $p=0.67$[1]. Also, a topographical examination of component amplitude was in line with previous accounts of the FRN as the components in both the HCL and LCL conditions were maximal over medial–frontal

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[1]Readers may want to know that we also analyzed the FRN after implementing an ocular correction algorithm (Gratton and Coles) during pre-processing. The results of this analysis mirrored the results reported here, the FRN was smaller for HCL participants (−5.9 uV [−4.6 uV −7.4 uV]) than for LCL participants (−7.8 uV [−6.3 uV −9.3 uV]), $p<0.05$.
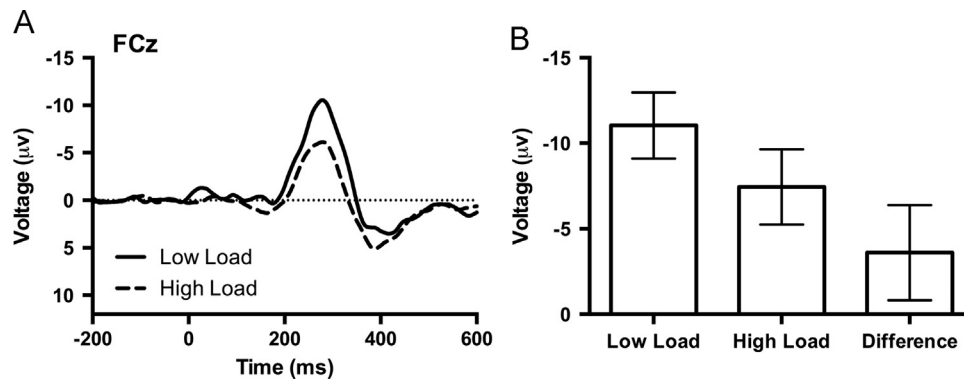
Fig. 2 – Grand average difference waveforms time locked to the onset of the feedback stimulus for participants in the low-load group and high-load groups (a). Also shown are the mean FRN scores for the low-load and high-load groups in addition to the effect (i.e., the difference in the group means). All error bars reflect the appropriate 95% confidence intervals.
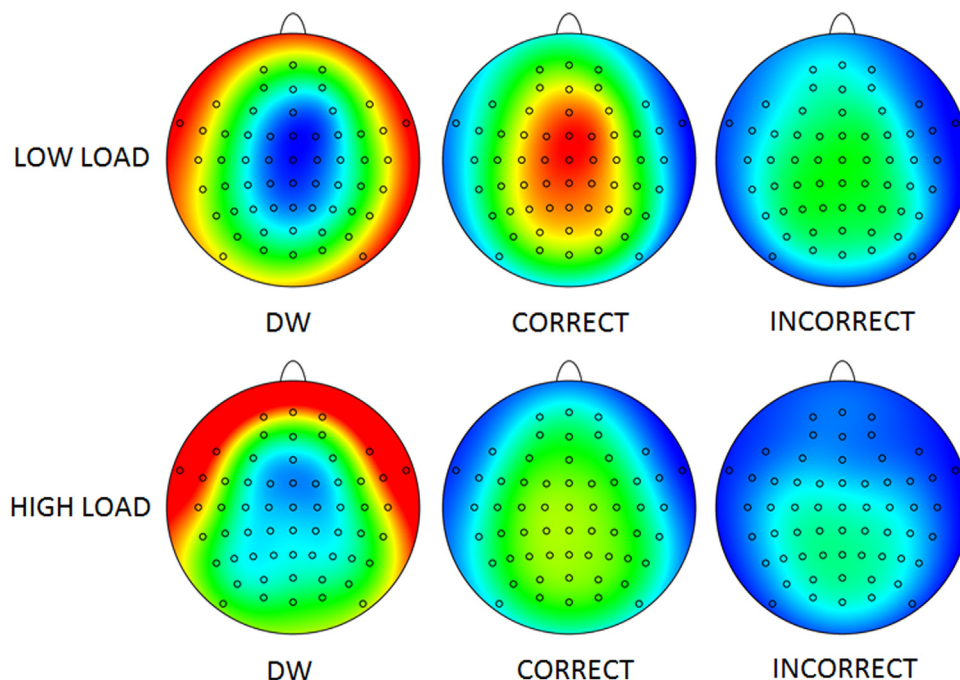

Fig. 3 – Scalp topographies for the feedback-related negativity taken at the time point of the maximal difference in the difference waveforms for the low-load group and the high-load group. Also presented are the scalp topographies for the conditional waveforms (correct, incorrect) at the time point of the maximal component amplitude.

cortex (see Fig. 3). An examination of component amplitude at each channel supported this and revealed that in both the HCL and LCL conditions the FRN was maximal at electrode FCz – a finding that, as stated above, is in line with previous accounts (Holroyd and Coles, 2002; Holroyd and Krigolson, 2007; Krigolson et al., 2009, 2012, 2014; Miltner et al., 1997).

3.   Discussion

In the present study, we examined how cognitive load induced by a dual-task paradigm impacted reward processing within the medial–frontal cortex. In line with our previous work (Krigolson et al., 2012), here we again found that increased cognitive load resulted in a reduction in the amplitude of the feedback related negativity – an event-related potential (ERP)

component thought to reflect a reinforcement learning prediction error generated within the anterior cingulate cortex (Holroyd and Coles, 2002; Holroyd et al., 2005; Krigolson et al., 2009, 2014). Recall that in our previous work we increased cognitive load for participants by increasing the complexity of the feedback stimulus participants relied upon while performing a time-estimation task, whereas in the current study we increased cognitive load by having participants perform a secondary task concurrent with their performance of a time-estimation task. Thus, in two studies now, we have seen a reduction of the amplitude of the feedback related negativity when participants experience increased cognitive load.

So why does cognitive load impact reward processing within the medial–frontal cortex? In our previous work we found evidence that increasing cognitive load increased the variability of feedback stimulus processing as evidenced by an increase in

the variability in the timing of the latency of the P300 ERP component (Krigolson et al., 2012; see also Duncan-Johnson (1981)). In that study, we proposed that an observed increase in variability of the latency of the P300 component in the high-cognitive load condition reflected an overall increase in the variability of the neural processes in general, and specifically in that experiment reward processing, when there is high cognitive load. The proposed result of the increased variability in reward processing was reduced functional efficacy of the medial–frontal system as seen in that study by the decrease in FRN amplitude. However, in the present study we found no evidence that there was increased variability in the timing of reward processes. Further, unlike our previous work, in the present study we did not observe a decrement in behavioral performance associated with increased cognitive load. As such, another explanation is needed to account for the findings of the present research in addition to potentially our previous work.

It has been apparent for quite some time that increased system "load" disrupts various neural processes. Indeed, in seminal work, Cherry (1953) reported that increased attentional load brought about by having participants listen to two tones bi-aurally resulted in a decrement in performance – a result that triggered a long series of studies on this issue (e.g., Broadbent, 1958; Moray, 1959; Treisman, 1963). Handy and Mangun (2000) provided a more recent extension to this work (amongst others) by using the ERP technique to show that increased perceptual load resulted in a disruption of attentional processing. In terms of the impact of cognitive load, less work has been done – but in a recent paper Nagamatsu et al. (2011) demonstrated that seniors performing a virtual reality street crossing task in high cognitive load conditions made more errors than when the same task was performed in low cognitive load conditions. Perhaps the best possible explanation for our work, and the other research mentioned here, stems from the resource theory as originally proposed by Wickens (1981).

Resource theory, as posited by Wickens (1981), proposed that when two tasks competed for and shared the same resources (e.g., attention) the tasks had the potential to disrupt each other if there were simply not enough resources to go around. Going back to an example we utilized at the start of this paper – resource theory explains why more accidents are observed when people talk on their cellphones while driving. In this example, we do not have enough attentional resources to be able to talk on the phone and drive with each task getting the full amount of needed resources. As such, one or both tasks has less resources than needed for full performance and as a result a performance decrement is observed – an accident in other words. Resource theory provides an explanation for the results of the current experiment. Recall again that we had participants perform a time-estimation task while they were also concurrently told to monitor and restrict their eye movements. We propose that both of these tasks competed for the same cognitive resources and that the sum resource requirement of both task was greater than the total available cognitive resources. As a result, we observed a reduction in the amplitude of the feedback related negativity in the high cognitive load group, and thus we suggest that the lack of available cognitive resources reduced the functional efficacy of the medial–frontal reward system. Interestingly, although increased cognitive load in the present experiment was

sufficient to impact the processes that underlie the FRN, behavioral performance was not impacted. As such, our data suggest that the reduction in the amplitude of the FRN was due to a paucity of cognitive resource availability even though the load manipulation did not have a significant effect on primary task performance. A final note we add here is that while we have framed our results and the relevant discussion around the FRN and with a difference waveform approach to analysis our results also support recent accounts investigating the reward positivity (see Holroyd et al. (2008) and Proudfit (2015) for review). Over the past 10 years of research investigating human reward processing with EEG it has become increasing apparent that the FRN is most likely a modulation of the positive as opposed to negative conditional waveform – hence a reward positivity as opposed to a feedback related negativity. With regard to the current paper, a close examination of Fig. 1 suggests that the specific impact of increased cognitive load is to reduce the amplitude of the correct as opposed to incorrect conditional waveform.

The results of the present study have implications for EEG research in general. Specifically, a key instruction in the vast majority of studies using EEG is typically something along the lines of "keep your eyes on the fixation point and avoid blinking" (Luck, 2014). As such, with the results of the present experiment in mind, participants in the vast majority of studies using EEG are experiencing higher than normal levels of cognitive load when they are performing their experimental tasks (see Klein (2014), for an interesting commentary on this very issue). While this will impact and reduce behavioral performance, perhaps more importantly, the higher than normal levels of cognitive load brought about by performing two tasks simultaneously – the base experimental task and the eye monitoring task induced by the experimental instructions – will reduce the functional efficacy of the neural processes that the experimenters hope to observe and will potentially reduce, wipe-out, or perhaps even reverse the effects the researchers hope to observe in the ERP waveforms. We cannot hope to offer a solution for this issue here – all that we can really say on this issue is that it suggests that researchers who use EEG will want to keep this potential confound in mind and perhaps think of ways to control for the eye monitoring induced cognitive load experimentally. It is worth pointing out that this issue was a confound in the present study – both groups of participants were given instructions to maintain a visual focus on a fixation point and to avoid blinking – we just emphasized this issue to a greater extent to participants in the high cognitive load group.

4. Conclusions

In the present study we demonstrated that increasing cognitive load by placing participants in a dual-task performance situation decreased the amplitude of the FRN – a component of the human event-related brain potential associated with reward processing (Holroyd and Coles, 2002; Holroyd et al., 2005; Krigolson et al., 2009, 2012, 2014). Importantly, this result extends our previous work (Krigolson et al., 2012) and provides more evidence that increased cognitive load disrupts reward processing within the human medial–frontal cortex. Our results are also of importance to researchers who utilize EEG

as they suggest that the typical instructions to "not move your eyes" and to "avoid blinking" by default put participants in a dual-task condition that disrupts or inhibits cognitive processes such as reward evaluation.

5.   Experimental procedures

5.1.   Participants

Thirty undergraduate students (16 male, 14 female; aged 18–29 years) with no known neurological impairments and with normal or corrected-to-normal vision participated in the experiment. All of the participants were volunteers who received extra-credit in undergraduate psychology courses at Dalhousie University as payment for their participation. The participants provided informed consent approved by Research Services at Dalhousie University and the study was conducted in accordance with the ethical standards prescribed in the original Declaration of Helsinki (1964) and all subsequent revisions.

5.2.   Apparatus and procedure

Participants were seated comfortably in front of a computer display (~75 cm distant) with their chin on a chin-rest affixed to the table the display rested on. Participants provided responses via a standard USB keyboard connected to an experimental computer in another room. For both of our experimental groups (see below), participants' eye movements were monitored and recorded via a desk mounted SR Research Eyelink 1000 eye tracking unit centered in front of and below the computer display. EEG data was recorded from 59 active electrodes attached to an EEG cap and 5 skin affixed active electrodes connected to a Brain Vision QuickAmp system (see below for all equipment and technical details).

During the experiment, participants performed a time estimation task (c.f., Holroyd and Krigolson, 2007; Krigolson et al., 2012; Miltner et al., 1997). In the time estimation paradigm participants performed a computer based task in which they learned to accurately guess the duration of one second via a trial and error shaping process. Each experimental trial began with the presentation of a centrally positioned fixation cross that remained onscreen for the duration of the trial. Participants were instructed to keep their eyes on the fixation cross at all times and to try and avoid blinking. A brief duration (500–700 ms) after the fixation cross was presented before participants heard an auditory cue (3000 Hz, 65 dB, 50 ms duration). Following the cue, participants waited until they thought one second had elapsed and then responded by depressing a response key on the keyboard. A feedback stimulus (either a "+" or "o"; see below) indicating the accuracy of the participant's estimate appeared 400–600 ms following a participant's response and remained onscreen for 1000 ms. Following the offset of the feedback stimulus, a blank screen was presented for either 1400, 1500, or 1600 ms (equivalent probability of each).

A participant's temporal estimate was considered correct if the participant's response was within a time window of ±100 ms centered on 1000 ms. Thus, a participant's estimate on the first trial was correct if their response occurred 900–

1100 ms after the auditory cue and incorrect if their response was outside this window. Following each correct trial the size of the time window decreased by 10 ms and following each incorrect trial the size of the time window increased by 10. This manipulation adjusted the time window to a participant's performance and thus ensured that over the course of the experiment a participant's accuracy was approximately 50%. Importantly, adjusting the window in this manner and roughly equating correct and incorrect trials helps to avoid contamination of the amplitude of the FRN by stimulus frequency effects (i.e., modulation of the N200 and P300, c.f., Holroyd and Krigolson, 2007; Holroyd et al., 2008; Krigolson et al., 2012). As noted above, the feedback stimuli were a "+" and a "o" that were randomly counter-balanced in meaning across participants. In other words, a "+" was correct and a "o" was incorrect for Participant One whereas a "o" was correct and a "+" was incorrect for Participant Two, and so on.

Two groups of participants performed the time-estimation experiment – one group in a "low" cognitive load condition (LCL) and the other in a "high" cognitive load condition (HCL). In the LCL condition, participants performed the time estimation task as outlined above and were given the "typical" EEG experiment instructions to keep their eyes on the fixation cross and try and blink as little as possible. In the HCL condition, participants performed the time estimation task and were given the same instructions to keep their eyes on the fixation cross and blink as little as possible – but HCL participants were also explicitly told that their eye movements would be monitored on each trial via the eye-tracking system. Further, HCL participants were told that in addition to performing the time estimation task they had a secondary goal which was to minimize eye movements and that the experimental program would indicate to them when they had moved their eyes. Specifically, on trials in which HCL participants moved their eyes following the standard feedback stimuli (i.e., a "+" or a "o") they saw an "X" that indicated they had moved their eyes. Thus, in the HCL condition, participants were performing two tasks which we believed would require more cognitive effort and thus place a higher load on the system than would be experienced by participants in the LCL group. Participants in both groups completed ten blocks of 20 trials. We treated the first two experimental blocks as practice sessions and removed these blocks from post-experiment analysis to discard task task related learning effects. Participants relaxed during self-paced rest periods between each block.

5.2.1.   Behavioral data acquisition
The time estimation task was programmed in and ran in the MATLAB software environment (Version 2012B, Mathworks, Natick, USA) with the Psychophysics Toolbox extension (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007). The experimental program recorded participant accuracy (correct, incorrect) and the magnitude of each temporal estimate (ms) for each trial as behavioral measures of performance.

5.2.2.   Ocular data acquisition
Eye position was monitored throughout the experiment using a desk-mounted eye tracking system sampling at 250 Hz (EyeLink 1000, SR Research, Ottawa, Ontario, Canada). We employed the eye tracker to detect whether or not blinks or saccades more than three degrees from a central fixation

point had occurred at any point throughout the experimental trial – and if they did, the blinks/saccades were then recorded and utilized by the experimental program.

5.2.3. Electroencephalographic data acquisition

EEG data were sampled at 512 Hz, amplified via 64 active electrodes attached to a QuickAmp amplifier (Brain Products, GmbH, Munich, Germany), and recorded with Brain Vision Recorder software (Version 1.20, Brain Products, GmbH, Munich, Germany). The electrodes were mounted in a fitted cap with a standard 10–20 layout – see www.neuroeconlab.com for an exact montage. During recording, the amplifier applied a built in average reference to the EEG that was subsequently re-referenced post-experiment. The vertical and horizontal electrooculograms were recorded from electrodes placed above and below the right eye and on the outer canthi of the left and right eyes, respectively. Electrode impedances were kept below 20 kΩ at all times throughout data collection.

5.2.4. Behavioral data analysis

We calculated mean accuracy (%) and mean size of the response window (ms) for correct and error trials for each experimental condition and participant as measures of task performance (c.f., Holroyd and Krigolson, 2007; Krigolson et al., 2012). We also calculated the percent change in the estimate for the trial following error feedback (%) for each experimental condition and participant, the logic with this measure being that we anticipated participants would make changes to their estimate following error feedback to improve subsequent performance (c.f., Holroyd and Krigolson, 2007).

5.2.5. Ocular data analysis

Based on the data recorded by the Eyelink 1000, for each participant we calculated the proportion (%) of trials in which they moved their eyes or blinked prior to or during time estimation feedback. We then computed the mean proportion of eye movement-contaminated trials for each experimental condition (LCL/HCL).

5.2.6. Electroencephalographic data analysis

The EEG analysis was done as follows for both experimental groups (LCL, HCL). First, the EEG data were filtered offline through a (0.1–30 Hz passband) phase shift free Butterworth filter and re-referenced to an average mastoid reference. Next, epochs for each feedback valence (correct, incorrect) were extracted from the continuous EEG (200 ms before feedback stimulus onset to 800 ms after feedback stimulus onset). Epochs were then baseline corrected using the mean voltage for the 200 ms preceding feedback stimulus onset. Subsequent to this, epochs were then examined for artifacts and removed from the data set if any data point within an epoch exceeded ± 75 uV. For the LCL group, 28% [15.1% 40.1%] of the data were discarded per participant on average, for the HCL group, 16% [5.7% 26.4%] (note, artifact percentages were high as we did not employ an ocular correction algorithm before artifact rejection – see below). For interest, we directly compared the number of artifact trials that were rejected for the LCL and HCL and found that they did not differ, $t(13)=1.97$, $p>0.05$. One participant from the HCL group was removed from further analysis due to an excessive number of artifacts in their EEG data (88%). One participant from the LCL group was removed due to missing data (EEG markers were not recorded). Further, unlike a standard ERP analysis we did not employ ocular correction during data pre-processing (e.g., ICA, Gratton and Coles) as we were intentionally manipulating eye blinks via the experimental instructions and feedback in the HCL group.

After preprocessing, ERP waveforms were created by averaging the EEG epochs for each feedback valence (correct, incorrect) for each participant for both experimental groups. Next, difference waveforms were created by subtracting the correct ERP waveform from the incorrect ERP waveform for each participant (Holroyd and Krigolson, 2007; Holroyd et al., 2008; Luck, 2014). The FRN was quantified as the most negative deflection on the difference waveform between 200 and 400 ms following feedback stimulus onset at channel FCz. We focused our analysis on channel FCz given previous work (Holroyd and Krigolson, 2007; Holroyd et al., 2005, 2008; Krigolson et al., 2008, 2009, 2012) and an examination of the FRN topographies that supported our decision (see Fig. 3). The logic of our difference waveform quantification of the FRN was as follows – if the processing of correct and incorrect feedback did not differ cognitively, at least in terms of effects observable in the ERP data, then the peak analysis of the difference waveforms would not statistically differ from zero. Extending from this, if cognitive load did not impact FRN amplitude, then the comparison of FRN amplitude would not differ between the two experimental groups (LCL, HCL). For a final visual comparison, we also computed the difference waveform of the two difference waveforms (LCL minus HCL). On this difference waveform we plotted the 95% confidence intervals for each time point to allow a simple visual examination and interpretation of our data (see Cumming (2013), for full details on the validity and logic of this approach). EEG analyses were done with Brain Vision Analyzer (Version 2.0.4, Brain Products, GmbH, Munich, Germany) and custom code written in the Matlab programming environment.

5.3. Statistical analyses

Single sample t-tests were used to test for FRN existence (see above) and between subjects t-tests were used to to examine accuracy, percent changes in participants' estimates, and FRN amplitude differences between groups. The percent change in temporal estimate was tested via a 2 (group: LCL, HCL) by 2 (feedback valence: correct, error) mixed analysis of variance. An alpha level of 0.05 was assumed for all statistical tests. Error measures for descriptive statistics and in figures reflect 95% confidence intervals (Cumming, 2013).

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