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Breaking the camel's back: Can cognitive overload be quantified in the human brain?

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Abstract

Reductionism lies at the heart of science, yet this pre-occupation with the *trees* may mean that cognitive science is missing the *forest*. Based on the assumption that individual cognitive and perceptual processes interact to form bottle-necks of processing, which, in turn, have measurable detrimental effects on human performance, whole-head continuous EEG was recorded as participants undertook baseline, mild cognitive load and heavy cognitive load tasks. Behavioral measures (reaction times and error rates) showed significant performance decrements between the mild and heavy cognitive load conditions. Graph analysis and pattern identification was then used to identify a sub-set of cortical locations reflecting significant, measurable neural differences between the mild and heavy cognitive load states. This thus lays the foundation for future research into suitable metrics for more accurately measuring degree of global cognitive load as well as practical applications such as developing simple devices for measuring cognitive load in real time.

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1. Introduction

Science is, by nature, reductionist; that is the study of any object or process, whether simple or complex, is firstly deconstructed and examined at the smallest unit possible given the technical constraints of the time. For example, the advent and advancement of microscopy in the 1600s allowed the discovery of bacteria (around 7μm) and their link to human illness [1]. Since then, advances in technology have allowed the smallest unit to become increasingly smaller, to the point where medical research can now examine biological units less than 2 *n*m [2]. Cognitive science adopts similar principles even if the topic of investigation is sometimes more difficult to measure and/or define. For example, it is assumed, based on the results of various behavioral investigations in the 1950s [3], that humans have between five and nine chunks of available working memory (WM); the greater the number of chunks an individual has, the greater the individual capacity for cognitive processing involving WM [4]. More recently, 3T functional

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Magnetic Resonance Imaging (fMRI) was used to propose a continuous semantic space which encompasses specific cortical locations with mm^3 accuracy for category specific memory processing (e.g. boat, car, gas pump) [5].

Although reductionism is essential to the understanding of complex systems such as human cognition, it can come at a price; by focusing on the fine print, the big picture can become lost. As a result, despite increasing amounts being known about individual processes such as memory and attention [6, 7] the complex interactions of these processes and any subsequent impact on human performance remains largely conjectural. From a neural perspective, even less is known; for example, the difference between global cognitive load and global cognitive overload lacks clear definition and knowing where, when and how to measure such load in an individual has not been addressed in the open source literature.

1.1. Quantifying Cognitive Load

To be able to achieve quantification of global cognitive load and potentially apply that quantification in any practical sense would require three preliminary steps. The first of these would be to identify a small set of cortical areas where overall cognitive load is most likely to be expressed. Once such sites are identified, it would then be necessary to identify the most suitable metric for measuring such load in real time. Such a metric would need to be capable of capturing both the degree of load in an individual as well as accurately reflecting real time individual performance degradation. Finally, to be of any practical application, both the metric and the device measuring it, needs to be ambulatory, relatively inexpensive and non-invasive. For the purposes of the current paper, only preliminary results addressing step one will be discussed although it should be noted that electroencephalogram (EEG) is the only technology currently capable of also fulfilling the requirements of steps two and three [8].

1.2. Assumptions

It should also be noted that the paradigm that will be presented here is based on a number of assumptions. Firstly, it is assumed that the human brain has limited processing capacity in higher order cognitive processes such as WM [4]. Secondly, it is assumed that lower order sensory processes are similarly constrained [9]. It is further assumed that complex interactions between higher and lower order processes combine to create a global expression of cognitive load which is independent of the contributions of individual processes. Finally, it is assumed that such independence of global expression will compensate for individual variation within human brains [10].

1.3. Probable Sites of Interest for Measuring Cognitive Load

Due to the nature of the current investigation, it was necessary to identify *a priori* quantitative techniques capable of detecting deeply buried functional network change patterns. Based on previous research [11], it was concluded that graph theoretical analysis (GTA) and information theory (IT) would provide the finest grained examination of brain function relative to cognitive load variations. It was also necessary to predict cortical areas where global cognitive load was likely to be expressed in such a way as to be measurable by EEG. Based on the results of numerous previous studies (12, 13) six primary sites of interest were proposed.

The first of these is the anterior cingulate cortex (ACC), a neural structure known to be involved in both autonomic nervous system (ANS) function and higher order cognitive functions such as decision making [12]. It is further anatomically divided into dorsal and ventral areas, with the former being associated with cognitive functioning and the latter with emotional processing [13]. These areas have also been demonstrated as being functionally related [14], thus if loads on individual processes combine to create a state of global cognitive load, then the ACC should reflect this.

A second area of interest involves the thalamus. Sometimes known as the sensory gateway, the thalamus is a deep brain structure with an abundance of cortical connections [15]. In essence, the thalamus is the switchboard of the brain; incoming sensory information is fed forward to cortical areas for higher level processing, which may then be fed further forward to higher levels of processing, or fed back to the thalamus. This near continuous feed-forward/feed-back process (thalamo-cortical loops) is proposed as being the neural mechanism underlying oscillatory brain activity displayed in the alpha (8-13 Hz) range of human EEG [16]. Allowing that variations in alpha activity have also been associated with various cognitive activities [17, 18], this makes alpha a prime candidate for a suitable metric for measuring global cognitive load/overload; if alpha is indeed generated by thalamo-cortical loops, then variations in alpha should reflect variations in thalamic activity.

Other cortical areas where global cognitive load/overload may be able to be accurately measured include: the left parietal-occipital lobe boundary; the left superior temporal sulcus; and right, frontal areas.

1.4. Hypotheses

Based on both the assumptions and previous research mentioned here, the following two hypotheses were proposed. Firstly, limited processing capacity at lower, sensory areas should result in bottlenecks of sensory processing that impact on higher order processing under increased sensory demands. By concurrently increasing higher order cognitive processing demands, there should be significant decreases in performance measures such as increased error rates (ERs) and longer reaction times (RTs) in high load versus low load conditions.

Secondly, if the effects of interactions between higher and lower order processes combine to produce an expression of global cognitive load at a neural level, then the identification of cortical areas where lower and higher order processing bottlenecks are functionally connected should be possible. This would be examined using GTA and IT with degree of connection taken as a measure of degree of load. This would thus allow the identification of EEG electrode sites most suitable for further investigation as markers of global cognitive load/overload.

2. Method

2.1. Participants

As this paper is reporting on early results, only five participants (four male) were recruited under University of South Australia HREC approval 30855. Ages ranged from 32 to 63 years (*m*=47.6, *SD*=11.44), with all having attempted or completed some type of university education. All had normal or corrected-to-normal vision and none had a history of psychological, motor or neural disorder. All participants provided informed consent and were confirmed as being right handed using the Edinburgh Handedness Test [19].

2.2. Equipment

Continuous EEG was recorded at 1000Hz via 24 sintered silver/silver chloride (Ag/AgCl) electrodes mounted in a Neuroscan Quikcap connected to a 40 channel Nuamps EEG amplifier. A single Ag/AgCl electrode drop-down lead was also placed near the edge of the left eye to allow for the later removal of ocular artifacts. All EEG was acquired using Neuroscan V4.5, with post-processing (including ocular artifact removal) using CURRY V7.

Stimulus presentation was controlled, and behavioral responses (ERs and RTs) recorded, using STIM2 V4.1. Visual stimuli were presented on a Philips 227E monitor located approximately 50 centimetres from the participant. Auditory stimuli were played to participants on a Toshiba 4830 laptop through Seinheisser HD215 headphones. Behavioral responses were later analysed using SPSS V.21, while EEG data were examined, following post-processing, using MATLAB/EEGLAB.

2.3. Design and Stimuli

2.3.1. Condition One – Mild Cognitive Load (MCL)

In this first condition participants were required to undertake three tasks. The first of these, a 1-back Stroop Task [20], involved the participant viewing a visual stimulus which could be congruent (colour word such as “red” displayed in red font) or incongruent (colour word such as “red” displayed in blue font). The stimulus was replaced after 500ms with a printed question – either “Same?” or “Different?”. The participant was then required to respond to that question in reference to the previously viewed stimulus via either a yes or no response (“y” or “n” on a computer keyboard). The second task was a 1-back emotional Stroop Task. Using the same procedure as task 1, participants viewed a facial stimulus, either full face [21] or eyes-only [22], for 500 ms. They were then presented with an emotion word which could represent the same emotion as the facial expression previously viewed (for example ☺ followed by "Happy?") or different (for example, ☺ followed by "Angry?"). The final task was a visual perceptual search task where participants viewed alphabetic symptoms such as "Q" and "O" in arrays of various sizes. Participants then had to respond via button press if the target symbol was present in the array ("P" for present) or absent in the array ("A" for absent).

2.3.2. Condition Two – Heavy Cognitive Load (HCL)

In the second condition, a random selection of stimuli was taken from the three[1] tasks in the MCL. Participants were not reminded of what was required by each of these tasks in an attempt to load memory processing capacity. Participants were, however, instructed that not every visual stimulus would require a response. This was proposed as loading attentional resources as well as putting increased demands on error and conflict monitoring processes.

To further increase cognitive processing, participants were told that they would also see a variety of other visual stimuli. These images included neutral (e.g. furniture), aversive (e.g. war scene), threatening (e.g. someone holding a knife), and non-threatening stimuli (e.g. sleeping kittens). Participants were further told that in some instances these images would be followed by a question requiring a keyboard button press response and that they were to respond to every question based on the most recent image seen. Although STIM was programmed to wait for a response to each question, visual images were presented from 66 to 1000 ms. All stimuli were sourced from international news sites [23], or copyright free websites [24].

To further increase demands on sensory processing, participants also listened to a pre-recorded sound track whilst performing the tasks. This sound track was constructed using dichotic listening principles; that is, different sounds played to different ears at the same time [25]. In some cases these sounds were considered neutral (e.g. birdsong), while others could be considered aversive (e.g. a baby wailing). This soundtrack was constructed using a Toshiba 4830 laptop running Adobe Audition software and recorded in a 16 bit .WAV format at a 44 1000 Hz sampling rate. All sounds used were sourced from royalty-free websites.

2.4. Procedure

Upon arrival, participants were fitted for an appropriate sized Quikcap. Impedances were checked via Neuroscan, with no recording undertaken until all impedances were below 20kΩ. To reduce eye-blink artifacts, a VEOL threshold of 105 µV was also applied. Baseline continuous EEG was then recorded for two minutes while the participant stared at a fixation cross, followed by two minutes with eyes closed. Continuous EEG was then recorded as participants then undertook the MCL condition with the order of tasks counter-balanced across participants. Finally, continuous EEG was recorded as participants undertook the HCL task. Following data collection, the continuous EEG was band pass filtered (0.5Hz to 70Hz) with a 50Hz notch filter applied. Data were then down sampled from 1000 to 500Hz. and any eye blink artifacts corrected in Curry using Independent Component Analysis (ICA) [26]. Bad blocks were removed manually, with further bad data removal done with EEGLAB.

3. Results

3.1. Behavioral (ERs and RTs)Analyses

Due to paper length restrictions, error rates and mean reaction times were calculated for only MCL and HCL Stroop. As shown in Figure 1, all participants showed impaired performance in the HCL compared to MCL condition.

Paired samples t-tests were then performed between the MCL and HCL conditions. For ERs this was not significant, $t(1,4) = -1.81$, $p>.05$, nor were mean RTs $t(1,4) = -0.645$, $p>.05$. Means and standard deviations are displayed in Table 1. Although there were no significant differences between conditions, there was a general trend as displayed in Figure 2.

1 In trialing the design, it became apparent that swapping response keys between "Y" & "N" and "P" & "A" introduced an unacceptable degree of head and hand movements. Task 3 stimuli were subsequently dropped from the HCL condition)

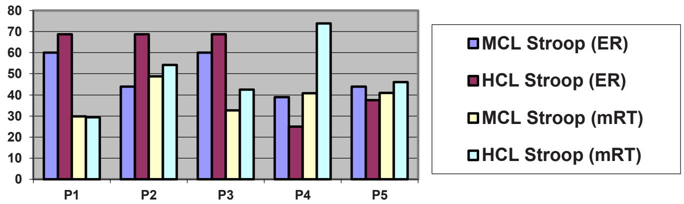

Fig. 1. Comparison of ERs and mean RTs between load conditions between participants.

Table 1. Means (*SDs*) for *t*-test analysis of load differences.

	MCL Stroop	HCL Stroop
ERs	49.4 (*9.89*)	53.75 (*21.01*)
RTs (ms)	3859.57 (*750.19*)	4921.98 (*1643.21*)

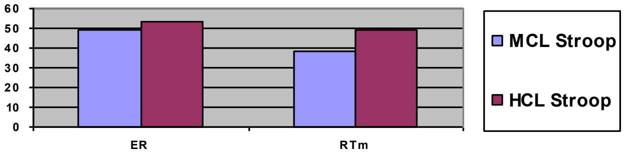

Fig. 2. Group comparison of ERs and mean RTs between conditions

It should be noted, however, that the small sample size (*n*=5) may have distorted results. It should also be noted that significance levels do not always translate into practical measures of performance, thus individual performance decrements were computed as percentage differences. These are displayed in Table 2.

Table 2. Performance change between MCL and HCL expressed as a percentage (+ = increase in HCL, - = decrease in HCL)

	P1	P2	P3	P4	P5
ER %age difference (MCL v HCL)	+14.6	+56.25	+14.6	-35.9	-14.8
RTm %age difference (MCL v HCL)	-1.43	+11.29	+30.26	+80.99	+12.5

3.2. EEG Analyses

3.2.1. Signal and Information Processing - Application of Techniques

The pre-processed EEG data from the four tasks (*eyes open, eyes closed, mild cognitive load, heavy cognitive load*) were used for this study. The Fast Fourier Transform (FFT) was used to transform the multi -channel EEG data into frequency domain. The EEG processing framework for analysis of functional brain networks is shown in Figure 3.

3.3. Graph analysis and Pattern Identification

The pre-processed EEG data for 100 seconds each for eyes open and cognitive load were transformed into component frequencies using Fast Fourier Transform (FFT). This transformation is useful because the transformation of EEG into respective frequency spectral patterns allows enormous compression in the display of data over time, providing easy visualization of temporal trends. The FFT spectrum (the magnitude and phase components) is analysed with emphasis given for phase.

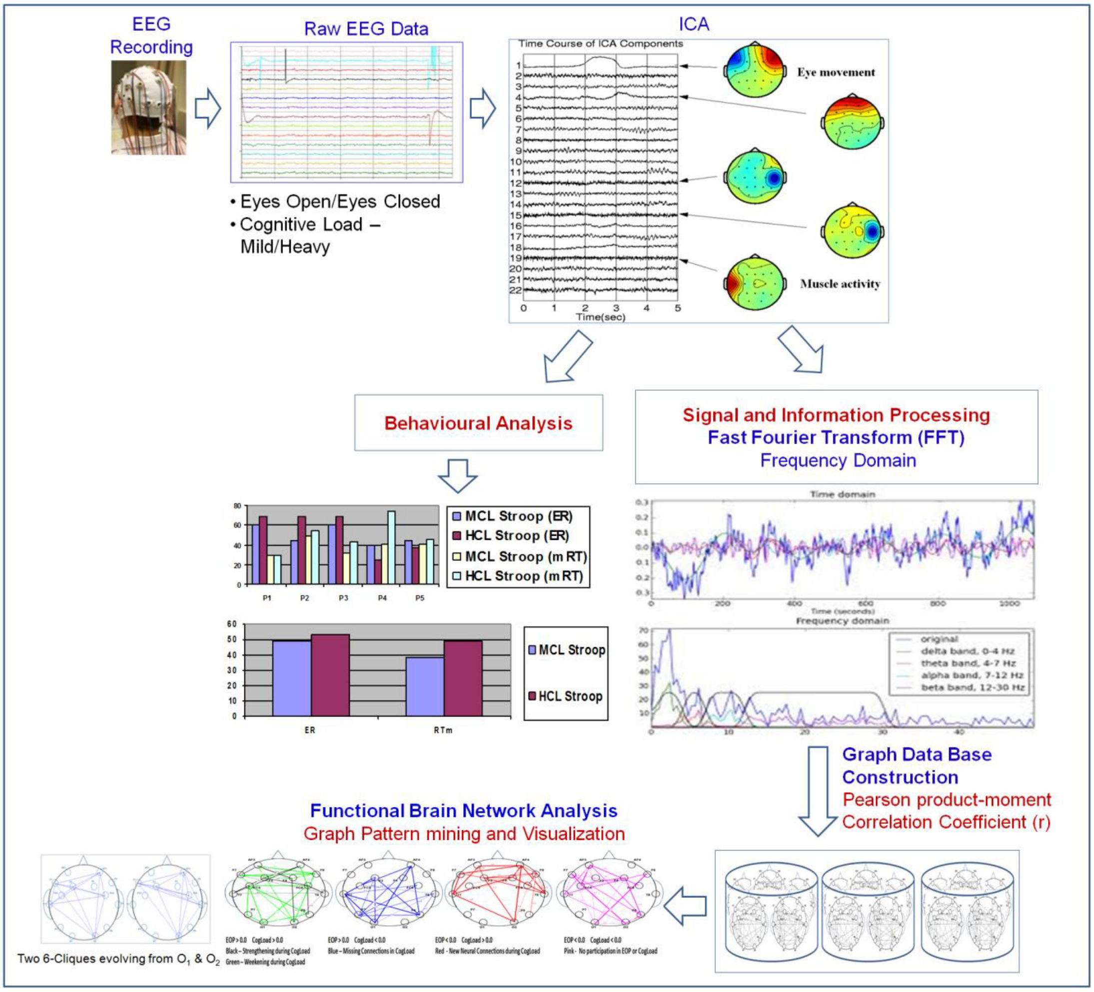

Fig. 3. Analysis framework for computing Functional Brain Networks during cognitive load

The critical task is to construct graph databases from the transformed EEG data. In the current study, 14 EEG electrode sites/channels were chosen for analysis. Data at electrode sites or nodes were treated as transactions and the pair-wise association between each node with every other node using the statistical measure of Pearson product-moment correlation coefficient *r* as edges on 10 sec EEG data constituting one graph.

$$r = \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

Given nodes *x* and *y,* the r value is computed as where *n*=1280. The *r* values depict the degree of correlation of the channels in the range -1 to +1. The resulting 10 phase correlation graphs for each event are stored in to a graph database. The eyes open and cognitive load states graphs are then analysed and compared using graph pattern mining algorithm for identifying characteristic patterns common in both the events, and those evolving during cognitive load. The prevailing hypotheses on functionally active brain regions during these events could be mapped closely with that of the results obtained during GTA. The graph databases are further analyzed using clustering, clique and frequent pattern mining algorithms and the functional behavior of brain during cognitive activities is effectively compared to that of the brain's resting state.

The GTA was done on averaged data from each event data set. The empirical results reveal information about the varying degrees of activities taking place at different brain regions. GTA of the EEG data displayed high degrees of correlation between certain brain regions during eyes open and cognitive load states. Temporal analysis of graph data revealed a degree of variability of the functional networks demonstrating the non-stationary nature of the EEG data; however, it was observed that the neuronal clusters during cognitive load were distinctively different from eyes open state. Figure 4 illustrates the strengthening of phase correlations between many of the associations and development of new positive neural correlations during cognition represented on the scalp diagram for better visualization.

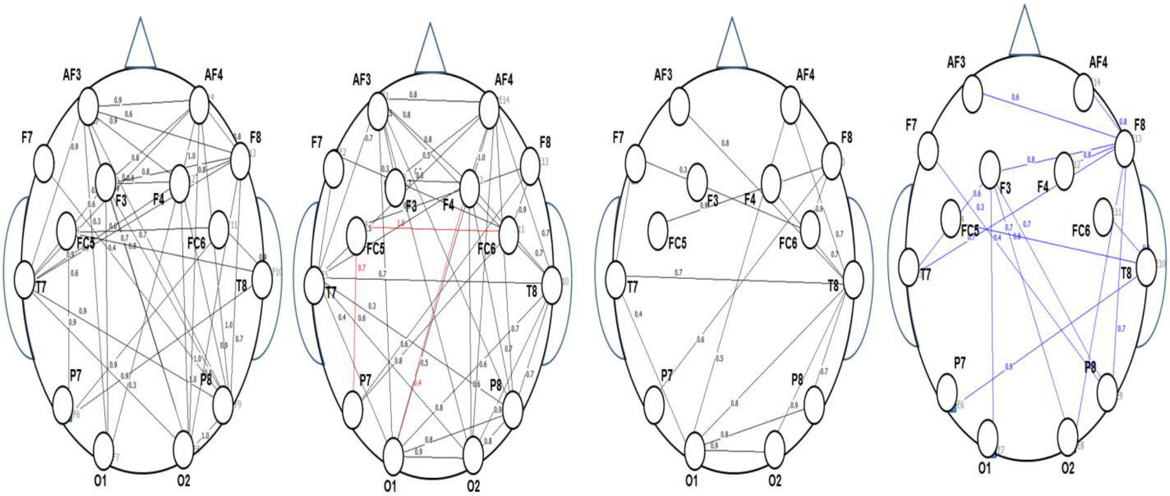

Fig. 4. (a) Eyes opened (b) Cognitive load with strengthened connections (Red) (c) New neural connections during cognition (d) Missing connections during cognition (Blue).

Further investigation on strong correlations and frequent pattern mining algorithms reveal that there are some interesting highly cohesive interactions taking place between the Occipital lobes O1 and O2 with a set of other 5 nodes during cognition forming 6-cliques as shown in Figure 5.

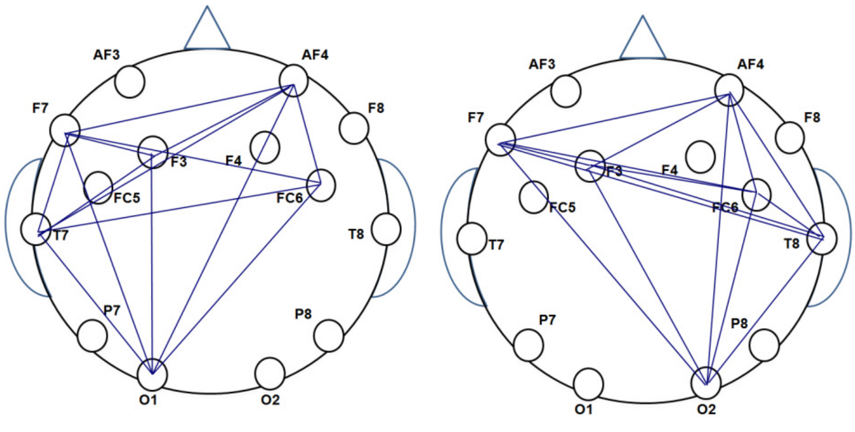

Fig. 5. Two 6-Cliques evolving from O_1 and O_2

The empirical results also demonstrate an increase of strengths of correlations among certain electrode sites increase up to 30% during cognition when compared to that of the baseline activity.

4. Discussion

As predicted, there were obvious decreases in performance measures in the HCL condition when compared to the MCL condition. Although these differences were not significant in a statistical sense, it is considered likely that this is a reflection of the small sample size rather than a lack of effect. As previously mentioned, statistical significance does not always equate to practical significance, and although statistical significance was not achieved in the current study, performance decrements of up to 56% for error rates and 81% for reaction times would be unacceptable in numerous situations. This suggests then that the current study paradigm was adequate in demonstrating that the HCL condition was indeed heavier cognitive load than the MCL condition.

Also confirming predictions, a number of electrode sites were clearly identified as sites of interest for further investigation of global cognitive load measurement. The first of these were T7 and T8. Although temporal lobe sites are generally associated with sound processing, T7 and T8 represent cortical areas considered likely to reflect thalamic activity due to their relative structural adjacency. As thalamo-cortical loops are thought to underlie oscillatory alpha activity, the authors of the current study are now more closely examining activity within the 8-13 Hz range to determine if changes in oscillatory activity are reliable metrics for gauging cognitive load variations.

Electrode sites F3, FC6, F7 and AF4 were also identified as being sites of interest for further investigation. Of these, site F3, and to a lesser extent F7, are considered likely to reflect ACC activity. This was well in keeping with original predictions that the ACC was likely to display measurable differences in activity directly related to cognitive load variations. Sites FC6 and AF4 are considered likely to be associated with higher order cognitive functioning, thus the current authors are in the process of designing and implementing a more sensitive paradigm design to delineate finer grained degrees of cognitive load.

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