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RACE: A Real-Time Architecture for Cognitive State Estimation, Development Overview and Study in Progress

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Abstract Cognitive load management is important in successful learning, referring to working memory and other factors related to accomplishing instructional tasks. Cognitive overload and underload are induced when challenges provided to the student exceed or underutilize working memory capacity, leading to suboptimal learning. The link between cognitive load and successful learning is well established. However, current educational technologies fail to utilize cognitive load effectively to personalize learning and fail to adapt to the student's learning pace. Neuroadaptive interfaces, specifically Brain-Computer Interfaces, are slowly transforming the traditional educational landscape offering promising possibilities to enhance and improve learning experiences by enabling direct communication between the brain and a computer to adapt instructional content in real-time based on the assessment of cognitive load brain states. This research-in-progress paper discusses the development, following a design science research methodology, of *RACE*: a novel artefact consisting of a Closed-Loop Brain-Computer Interface that measures cognitive load in real-time applied to a memorization-based learning task to adapt the learning Interactive User Interface in real-time based on assessed and classified levels of cognitive load. Specifically, this artefact adapts the speed of information provision and response time to the learner's pace to make learning more personalized and effective.

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1 Introduction

The development and integration of technologies into teaching practices have begun a trend toward transitioning from the more traditional classroom pedagogical models to online models [1, 2]. Research has shown that the use of technological tools in learning helps promote engagement and motivation as predictors of success [1, 3]. While technological tools in education have been designed with user Cognitive Load (CL) as a design consideration [4, 5] very few of these technologies utilize direct real-time measurements of CL to adapt in real-time, potentially making learning less personalized [6].

Neuroadaptive technologies, specifically Brain-Computer Interfaces (BCI), are tools to overcome physical impairments and augment specific cognitive capacities [7]. Rapid improvements in sensor technologies such as electroencephalogram (EEG) and methods of classifying brain activity into specific states have shown BCI to be a useful assistive and interfacing technology [38] for human–machine systems [8]. BCI technology has been defined as "*a device that reads voluntary changes in brain activity, then translates these signals into a message or command in real-time*" [9]. BCIs are a core component of systems that utilize the user's neurophysiological data as input to a computer system, which then performs actions to adapt, assist or provide feedback to the operator. A common application of BCI technology is to measure and classify CL under various conditions. Studies have found correlations between CL and variance in brainwaves expressed as increases or decreases in α (8–12 Hz) and θ (4–8 Hz) in pre-frontal brain regions [10].

In this work-in-progress manuscript, we answer a call for research to investigate neuroadaptive technology using NeuroIS methods [11, 12] and discuss the integration of a design science approach to developing a research BCI artefact that monitors and classifies CL in real-time to drive interface adaptions to improve learning outcomes in an education context. We provide an overview of the requirements analysis, design choices and overall architecture of the BCI artefact and provide a study methodology that utilizes the BCI artefact to adapt an interface in two ways: speed of information presentation and response time, to investigate if these adaptations improve learning outcomes.

As the means from which to derive requirements for the BCI artefact that meet the needs of the study, we posit the following research question, "*To what extent does utilizing a real-time BCI that adapts the speed of information provision and response times based on cognitive load improve learning outcomes in a task involving memorization of astronomical constellations?*".

2 Background

Cognitive Load and Learning

Many factors influence learning; however, CL remains a central concept for understanding and improving the learning process [5, 13, 14]. Cognitive Load Theory (CLT), proposed by Sweller [15], posits a cognitive architecture to investigate how information is processed and retained and centers around the interactions between Working Memory (WM) and long-term memory [6, 14–16]. It defines CL as the management of the WM's limited capacity, i.e. the amount of mental effort an individual allocates to a task [6].

Cognitive overload or underload during the completion of online or computer-based learning tasks may occur when WM's capacity is exceeded or underutilized, potentially leading to slow learning progress or poor performance [17]. Current educational technologies consider CL as only one of many factors influencing learning outcomes and do not emphasize its centrality to the learning process or how modulating CL may lead to improved learning outcomes [4, 5].

Previous methods of quantifying CL in both research and developing educational technologies consisted of batteries of subjective measures administered through questionnaires [14, 18]. However, while these measures provide the learner's perspective on their experience, they cannot quantify the amount of mental effort invested throughout the entire learning process [14]. One solution to this problem is to measure CL directly and in real-time through the brain's electrical activity using BCI.

Brain-Computer Interfaces

As discussed previously, BCIs are systems that allow the human brain to communicate directly with a computer [19]. BCIs transform brain activity into control signal data for computer interaction [20, 21]. BCI research has gained in popularity in the last decade due to its potential clinical application [20]. These systems allow bypassing the peripheral nervous system for neurorehabilitation in cases of brain injury, motor disabilities and other medical purposes [19, 22, 23]. BCI technology has also been used in studies investigating video games [24–29], marketing and advertisement [30, 31], neuroergonomics and smart environments [32–37], and work monitoring and safety [38–43]. There are currently three categories of BCI: *Active*, where users voluntarily and consciously control their brain activity to directly control an application [8, 25]; *Reactive*, a hybrid of *Active* and *Passive* paradigms, where users indirectly modulate their brain activity in response to external stimuli, using Event-Related Potentials (ERPs) derived from brain activity, to control an application [8, 25]; and *Passive*, wherein spontaneous brain activity is automatically monitored to differentiate or quantify mental states, where the user provides no active control and where feedback is provided as a response from the system [8, 25, 44].

Interest in neurotechnology and more specifically passive BCIs has grown rapidly in the last decade [45]. In a passive BCI, brain activity is classified, then these classifications are sent to a computer system, which then adapts content or provides visual feedback, which in turn encourages changes in brain activity as part of a biocybernetic loop [46]. There are several examples of passive BCIs in the literature which have been used to support learning tasks [47], increase engagement [48], and increase performance [49] of learners.

While interest in BCIs has grown substantially, few research papers exist regarding BCI technologies focused on learning and measuring learner's CL in real-time. Furthermore, while the theoretical relationship between learning and cognitive load is strong, and several research studies [40–42, 47, 48] have been conducted to develop BCIs to detect levels of CL, none specifically focuses on utilizing CLT and BCI technology to monitor CL and adapt learning content to the user in real-time.

Speed of Stimulus Presentation in Learning

Learning pace, modulated by the speed of stimulus presentation, has been extensively studied for decades [50]. The need to adapt, personalize and present content to the learner's pace to increase information retention and improve learning has been noted many times [51–53]. In this context, a BCI could be utilized to monitor CL in real-time and trigger an interface to adapt and personalize the pace of learning. Most previous research using BCIs in an educational context applied the technology to assess mental state concerning interface complexity and CL while using a new interface and not directly adapting learning content [6, 14, 44, 50]. To our knowledge, the research presented here is the first of its kind proof of principle as it integrates BCI technology, real-time measurement of CL and speed of stimulus presentation to create a neuro-adaptive learning interface. It is, therefore, imperative to follow a rigorous *Design Science Research Methodology* to develop a complete and valid solution.

3 Objectives and Methodology

We created our neuro-adaptive artefact in accordance with Brocke et al. [54] and following Peffers et al.'s [55] Design Science Research Methodology (DSRM). The DSRM provides a valuable framework for our research use case, given its wide adoption [56] and iterative nature [55]. First, we formulated a problem statement: "*design an artefact that can regulate the level of cognitive load of users while performing a learning task*". Second, we performed a series of iterative development activities (*Activity 1–6*) to develop a valid artefact.

We began our methodological process with *Activity 1*, which consisted of an in-depth analysis of the current literature concerning our research problem: the absence of a reliable and valid system in the field of education to regulate the cognitive load of learners to improve their learning. This analysis was necessary to fully understand all aspects of the problem and to create a relevant and useful solution. Theoretical foundations were drawn from previous research on CL and BCIs (see other sections on CL and BCI), and were applied to our design.

In *Activity 2*, we explored the state of existing and potential solutions and formulated objectives (see next section) that could help solve the identified problem. To build our objectives, we examined the rigor of the different methodologies used in the previous research, thereby following a rigor and relevance process [55, 57]. Since there are very few studies about BCIs and learning, objectives were aligned with a *Type I* use case, which centers the BCI as a tool for research purposes [58].

Subsequently, we proceeded with the Design Cycle throughout *Activity 3*. We developed the solution following an iterative process through several research activities and design-related decisions until the solution fulfilled its objectives extended over an 8-month period. Specifically, we have conducted 12 main research activities related to the IUI and the neuroadaptive system through just over 50 pre-tests, resulting in approximately 45 design-related decisions and iterations.

We then continued with *Activity 4*, which allowed us to demonstrate with a small sample of participants that the artifact does indeed adapt in real-time according to a classification of CL, therefore confirming its feasibility and practical potential. We were able to test the solution on 10 pre-test participants.

Afterwards, we assessed the quality and validity of the artifact through simulations to demonstrate that (1) the adaptations occurred as expected and (2) that it met all the initial design requirements as part of *Activity 5*. In future steps, we plan to test the artifact in larger-scale controlled experiments to assess its performance and effect on cognitive workload in a learning context. We also plan to communicate our DR and results to the scientific community through publication as part of *Activity 6*.

To achieve our goal and cover the broadest range of features required to fulfill a functional BCI artifact, we derived a series of four design objectives (DO).

DO1: *The interactive user interface (IUI) should support a learning task which displays an image of a star constellation with associated multiple-choice answers and capture feedback (as right or wrong answers) for a predetermined amount of time adapting to a user's level of cognitive load.* To create the learning task, we adapted Riopel et al.'s [59] constellation memorization study to create a valid task capable of inducing CL fluctuations. However, for this study, we selected 32 constellations based on unfamiliar names or confusingly similar visual forms (see Fig. 1). In our study, the adaptive parameter influenced by the user's CL is the speed of information provision, more precisely (1) the amount of time given to answer and (2) the amount of time for the answer feedback. Both should have the same duration and change on the IUI according to the level of the CL classifier. Right or wrong answers should not affect the speed of information provision. Thereby, the IUI should permit isolation of the effect of the speed of information provision to adequately measure the CL. According to the current literature on CL, the IUI should be as clear as possible by avoiding too many different elements (figures, colors, etc.) and redundant text to minimize extraneous processing and by avoiding complex sentences to minimize

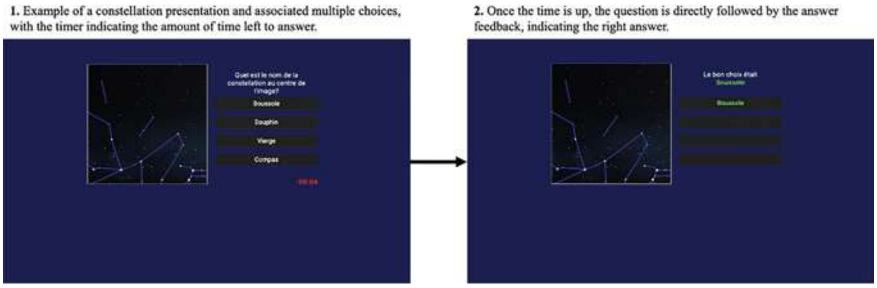

Fig. 1 Design of the Interactive User Interface (IUI) following the Design Objective 1 (DO1) and 2 (DO2)

intrinsic processing and maximize germane processing [60]. The IUI should also show the right answer even when the user answers correctly. Previous research shows that even if a right answer is obtained, following feedback is important for better information retention and to avoid making future mistakes [61, 62]. Finally, the task duration should be long enough to ensure CL fluctuations over time.

DO2: *The system should regulate cognitive load levels through neurofeedback by adapting the information presentation speed of an interface (i.e., stimulus speed of presentation) to improve users learning and enhance their performance.* The adaptation should not obstruct the learning task itself. Therefore, the IUI informs the user of how many seconds are left to answer the question with a countdown timer right underneath the multiple-choice answers (see Fig. 1). The countdown timer should be displayed in a way that is easily perceived by the user without creating anxiety or stress and without affecting recall performances [63]. Changes in the speed of information provision have to be relatively subtle to not interfere with the task and performances, but relevant enough to create a brain state change in the user. Thus, the amount of time given to answer the question and the amount of time for the answer feedback both increase or decrease with 1 s jumps at a time, going as high as 8 s and as low as 3 s each. The minimum was set at 3 s to avoid to avoid transient brain responses to novel information being confounded with CL classification. The maximum was established based on pretests and observations of time limits where participants begin to disengage with the task.

DO3: *The system should classify the level of cognitive load continuously and in real-time and communicate the level of cognitive load to the IUI.* To fulfill this requirement, we used a Lab Streaming Layer (LSL) to communicate CL classifiers to a Python script that sends the classifiers to the IUI through a Web Socket client. Classifiers were transmitted from the start to the end of the experiment every six seconds.

DO4: *The system should record and store raw neurophysiological data during use for post-hoc analysis.*

4 Design and Development

Interactive User Interface and Adaptation Logic

Figure 2 illustrates the proposed artefact's process flow, which follows the four design objectives and iterative design activities. The artefact was developed in Simulink MATLAB (version R2021b, Mathworks MA) and uses a wireless 32-channel active electrode EEG from G.Tec (g.Nautilus, Austria) to continuously measure brain activity. To act as a baseline for post-hoc analysis, a small and static black square in the middle of a gray screen for 1 min and 30 s was displayed before the experiment began. To train the artefact and set threshold values for a high and low workload classification, we developed an *n*-back task where $n = 0$ and $n = 2$. Used in many studies to induce high (2) and low (0) CL through the manipulation of WM [10, 64–67], the *n*-back task was deemed to be the most appropriate calibration task for CL classification because it requires the memorization and recall of presented visual stimuli, similar to the constellation learning task.

To support the instantiation of **DO3**, the artefact processes end-to-end the acquired brain signals and classifies CL as low (0), medium (1), and high (2) through a novel index calculation based on mean alpha band power in the parietal cortex over a 6 s sliding window, stabilized by comparing average CL calculated using a sliding window of 60 s. Classifications are sent via Lab Streaming Layer (LSL) to a Python script which then pushes the level of CL to the Interactive User Interface (IUI) every 6 s through a WebSocket client integrated into a dynamic Web app built with AngularJS. We implemented a rule "engine" to allow the web app to switch from active (experimental) to passive (control) conditions, whereby the neuro-adaptivity rules are provided through a JSON file on selecting "active". When either option is selected a personalized link is generated leading to the correct IUI for each participant, further generating placeholder database entries to store the behavioral and qualitative

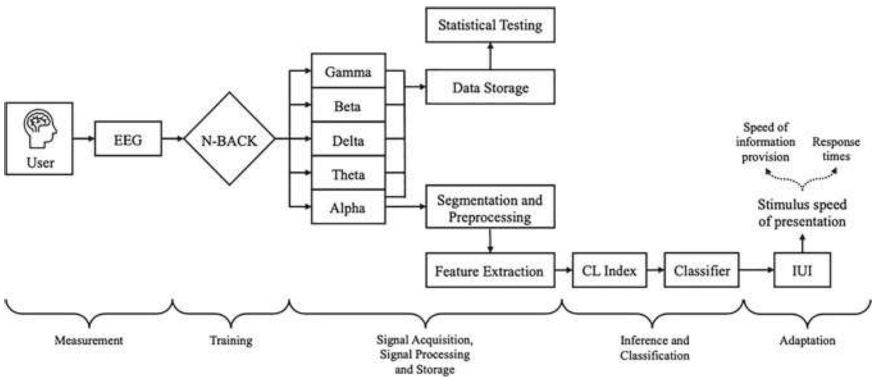

Fig. 2 Real-time Architecture for Cognitive State Estimation (RACE), Block process diagram of the BCI system, moving from User to the IUI

data for later analyses. The IUI was presented to the participants via Google Chrome. The IUI displays a constellation image and four multiple-choice questions with a timer indicating the remaining response time, followed by the correct answer (see Fig. 1).

The neuro-adaptivity model is integrated into the IUI; when CL is high (2), the artefact decreases the speed of information provision and increases response time each by one second (max 8 s). When CL is low (0), the artefact increases the speed of information provision and decreases response time by one second each (min 3 s). Starting time is set at 5 s, and no adaptation occurs when the IUI receives a "1".

5 Next Steps: Artifact Evaluation and Experimental Study

We have evaluated the artefact through pre-tests and confirmed that its development meets all the initial design objectives, demonstrates a high level of utility in learning, and has the potential to go beyond the boundaries of research and laboratory application [55, 56, 68]. Our next step is to evaluate the artefact in a controlled laboratory study with a larger pool of participants. To this end, we developed a between-subjects study design to isolate the effect of neuro-adaptivity. In group one (control), the speed of information provision is the same throughout each trial block (without neuro-adaptivity); in group two (experimental), the speed of information provision varies according to the participant's cognitive load level (neuro-adaptivity). The task involves learning and memorizing as many constellations as possible from a total of 32 constellations. The task consists of four trial blocks, separated by a 30 s break, where each constellation is presented two times per trial block. As per design specification, multiple-choice answers are randomly presented, and the correct answer's position between all four possible answers is also randomized. The presentation order of the constellations in each trial block has been pre-randomized and is identical for all participants. We evaluate participant performance throughout the experiment. Before the experiment begins, participants are asked to complete a short questionnaire including the 10-item *Edinburgh Handedness Inventory* to assess handedness [69], demographic questions and questions about prior level of interest and knowledge of constellations. A second short questionnaire is presented to the participants immediately after the experiment to gather self-repoted data on their experience, including the *NASA-TLX* to estimate perceived workload [70], the *System Usability Scale* (SUS) to measure the perceived usability of the system [71] and the 5 dimensions of Cognitive Absorption (Temporal Dissociation, Focused Immersion, Heightened Enjoyment, Curiosity and Control) of the *Psychologigal Ownership of IT* (POIT) [72]. The study is currently in progress, we have gathered data for n = 45 participants for evaluation and statistical testing and we look forward to sharing our preliminary results.

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