Educ Psychol Rev (2010) 22:425–438
DOI 10.1007/s10648-010-9130-y

REVIEW ARTICLE

Using Electroencephalography to Measure Cognitive Load

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Published online: 29 April 2010

Abstract Application of physiological methods, in particular electroencephalography (EEG), offers new and promising approaches to educational psychology research. EEG is identified as a physiological index that can serve as an online, continuous measure of cognitive load detecting subtle fluctuations in instantaneous load, which can help explain effects of instructional interventions when measures of overall cognitive load fail to reflect such differences in cognitive processing. This paper presents a review of seminal literature on the use of continuous EEG to measure cognitive load and describes two case studies on learning from hypertext and multimedia that employed EEG methodology to collect and analyze cognitive load data.

Keywords Electroencephalography · Cognitive load · Educational psychology

Researchers working in the context of cognitive load theory (CLT; Paas *et al.* 2003a, b; Sweller 1988; Sweller *et al.* 1998) have been concerned with analyzing the effects of cognitive load on learning and devising strategies and tools to help learners maintain an optimal level of load in various learning contexts. As a consequence, measurement of cognitive load plays a key role in CLT research (Paas *et al.* 2003a, b). In this article, we will discuss new possibilities for cognitive load measurement offered by neuroscience, focusing in particular on (EEG).

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Cognitive Load Theory

CLT is based on a cognitive architecture that consists of a working memory that is limited in capacity and time when it comes to holding or processing novel information (Miller 1956; Peterson and Peterson 1959) and a long-term memory with virtually unlimited capacity (Sweller *et al.* 1998). Working memory limitations regarding novel information are a bottleneck when it comes to learning. Only 7±2 information elements can be held in working memory, and the number decreases (Cowan 2001) when information has to be not only remembered but also processed (i.e., when elements interrelate and have to be combined). For example, learning the grammar of a foreign language is more intrinsically complex than learning individual words because grammar involves the interaction of several information units (e.g., subject, predicate, and object), while vocabulary can be learned as a sequence of single information elements. Therefore, the higher the number of interacting information elements a task contains, the more difficult it is and the higher the intrinsic load it imposes on working memory. However, information that has already been learned, that is, stored in long-term memory in the form of cognitive schemata, reduces working memory load because a schema can be handled in working memory as a single information element. Therefore, having prior knowledge (or expertise) on a task lowers the cognitive load imposed by that task. Moreover, when a task or aspects of a task are repeatedly practiced, cognitive schemata become automated, and no longer require controlled processing (Shiffrin and Schneider 1977), which further frees up working memory resources.

Therefore, the intrinsic load imposed by a task consists of the inherent complexity of the content (i.e., interacting information elements) in relation to the learner's level of expertise. Next to intrinsic load, there is load imposed by instructional design of the task: germane and extraneous load. Germane load is defined as the cognitive resources required to handle intrinsic cognitive load (see Sweller 2010 in this issue for a detailed discussion of element interactivity and cognitive load effects and types). Germane load occurs when information presentation is designed to encourage assimilation or accommodation of new concepts and appropriately challenge the learner. For example, when learning a foreign language, germane load is likely to occur in situations where learners are asked to compare and contrast the native language with the foreign language (e.g., onomatopoeia or the linguistic conventions for animal noises in the two languages; Krashen 1982). Extraneous load, on the other hand, is the unnecessary mental burden that is caused by cognitively inappropriate design and presentation of information; in other words, cognitive processes that induce extraneous load do not contribute to learning. For example, if the teacher uses a diagram to explain a new grammar rule but places the diagram far from the examples that illustrate the use of this rule, the learners' extraneous load may be increased due to split attention (Chandler and Sweller 1992). The more working memory resources devoted to extraneous load, the less are available to deal with intrinsic load and so the less learned and the higher the total cognitive load (Sweller 2010).

Cognitive Load Measurement

Cognitive load is the load imposed on working memory by the cognitive processes that learning materials evoke and can be measured at different levels. Xie and Salvendy (2000) distinguish between instantaneous load, peak load, average load, accumulated load, and overall load. Instantaneous load reflects the dynamics of cognitive load, which fluctuates every moment from the beginning to the end of performing a task or set of tasks. In Fig. 1, the curve is a plot of instantaneous load versus time. This is the most basic level of measuring cognitive load because other levels are based on it and can be derived from it. Peak load is the maximum value of instantaneous load while executing a task. In Fig. 1, the peak load is the peak point on the instantaneous load curve for each of the two tasks. Peak load can be obtained by comparing the magnitude of all instantaneous load values. Accumulated load is the total amount of load that the learner experiences during a task; it is the area below the instantaneous load curve. Average load represents the mean intensity of load during the performance of a task. It is the average value of instantaneous loads that is equal to the accumulated load per unit of time. Since cognitive load relates directly to task duration, both average and accumulated load are necessary for estimating the effects of instructional interventions. Finally, overall load is the experienced load based on the whole working procedure; it is not equal to either accumulated load nor average load (Xie and Salvendy 2000). Overall load is believed to represent the individual's perception of mental effort. Most of the available subjective scales measure cognitive load at this level (see also Paas *et al.* 2003a, b).

Different techniques are available for measuring cognitive load. Most CLT research applies subjective rating scales to assess cognitive load (Paas *et al.* 1994, 2003a, b, 2008), such as an adapted version of the NASA-Task Load Index (NASA-TLX; Hart and Staveland 1988) or (an adapted version of) the 9-point symmetrical category mental effort rating scale developed by Paas (1992). Mental effort is defined as "the aspect of cognitive load that refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task; thus, it can be considered to reflect the actual cognitive load" (Paas *et al.* 2003a, b, p. 64). Subjective ratings typically consist of one question (e.g., "Please rate the amount of mental effort invested in the task"), and the responses range from "very very low mental effort" to "very very high mental effort" as in the widely used mental effort scale by Paas (1992). These ratings are collected immediately after each task (e.g., Paas 1992; Paas and Van Merriënboer 1994; Van Gog *et al.* 2006, 2008), in which case they presumably reflect the accumulated cognitive load. Sometimes, however, they are taken after a series of tasks (e.g., Kalyuga *et al.* 2001), in which case they presumably represent the overall cognitive load. Thus, subjective rating scales do not give insight into fluctuations in instantaneous load over time, unless they are applied repeatedly within a task, which has been done with tasks of varying duration (e.g., Ayres 2006; Experiment 1 by Van Merriënboer *et al.* 2002). But even when applied multiple times, it is unclear whether subjective methods provide a continuous measure of fluctuations in cognitive

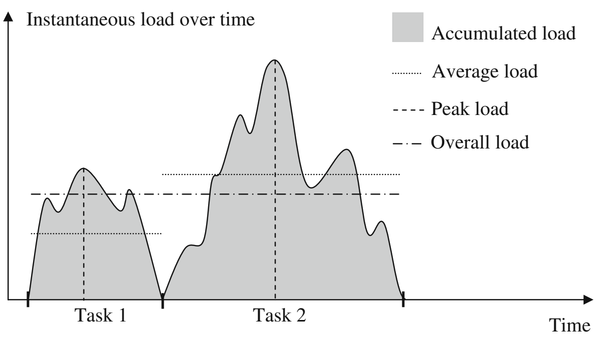

Fig. 1 Levels of cognitive load over time (per Xie and Salvendy 2000; Paas *et al.* 2003a, b)

load during task performance, because of the relatively large time intervals between presentations of the rating scale.

Objective measures of cognitive load have also been used in CLT research, although to a lesser extent. Objective measures include secondary task procedures, in which the amount of load imposed by the primary (learning) task is measured by the performance or response time on a secondary task (see Brünken *et al.* 2003). Like subjective rating scales though, secondary task procedures are not continuous, that is, response time measurements are taken at intervals, when the secondary task stimulus is presented.

Continuous measurement of instantaneous cognitive load allows looking at data for specific instances of time, which will allow a more detailed, and likely more accurate interpretation of the effects of instructional interventions on cognitive load and learning than a single measure of accumulated or overall load (see also Van Gog *et al.* 2009). Objective cognitive load measurement techniques that have been explored in CLT research, which can provide continuous measures, thereby allowing for "online" assessment of cognitive load at all levels (instantaneous, peak, accumulated, average, overall) are physiological measures such as heart rate variability (e.g., Paas and Van Merriënboer 1994), eye movement data (e.g., pupil dilation, Van Gerven *et al.* 2004; blink rate, blink latency, blink duration, Goldstein *et al.* 1992), and hormone levels (e.g., catecholamine Adrenaline and Noradrenaline; Wilson and Eggemeier 1991). Other physiological techniques that are used in neuroscience such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and electroencephalography (EEG) are coming within reach.

As is the case with all measures of cognitive load, physiological methods have their limitations. Some of these measures provide only a tenuous link to cognitive load (e.g., blink rate, blink duration); others are too slow for online measurement (e.g., hormone level), or insensitive to fluctuations of instantaneous load (e.g., heart rate variability; Paas and van Merrienboer 1994). Measures that are sensitive and consistently reflect cognitive load are often too intrusive and cumbersome to deploy in ambulatory settings—for example, PET and fMRI, which are neuroimaging techniques that register changes in blood flow related to neural activity using scanners. Pupil dilation, which has none of these limitations, has been shown to be unsuitable for tasks that involve continuous reading (Iqbal *et al.* 2004; Schultheis and Jameson 2004). There are also indications that the sensitivity of pupillary responses to changes in cognitive load diminishes with participants' age (van Gerven *et al.* 2004).

Unlike other physiological devices, which require subjects to lie in restricted positions (fMRI), or to ingest hazardous materials (PET), EEG can noninvasively measure brain activity in authentic, real-world settings. EEG is a popular neuroimaging technique that measures electrical activity produced by the brain via electrodes that are placed on the scalp. These measurements vary predictably in response to changing levels of cognitive stimuli (Anderson and Bratman 2008; Klimesch 1999). This makes EEG an appropriate choice for assessing cognitive load in educational psychology. Wireless EEG solutions like the B-Alert system (Berka *et al.* 2004; Stevens *et al.* 2007) appear especially promising because they offer better ecological validity by reducing the overall size of the equipment and allowing collection of data from multiple participants at the same time. Lee and Tan (2006) demonstrated that cognitive performance can be measured using a low-cost electroencephalograph (USD $1,500) and without extensive medical expertise.

While the application of EEG in educational psychology offers the above advantages, it has to be noted that, as most physiological indices, EEG research collects data in highly controlled experimental settings and requires data on a large number of trials. Unlike fMRI, EEG has low spatial resolution (in the cm range), making it difficult to draw precise inference on the activated brain areas. EEG is also susceptible to motion artifacts, such as blinking and movement. These actions create artifacts or noise in the data which are, in some cases, stronger than the signal from the neural activity (Berka et al, 2004). Noise is also introduced into the EEG signal from electrical interference and the subjects' breathing and heartbeat.

Despite these limitations, EEG is a promising tool for the continuous measurement of cognitive load. Most of the contemporary EEG systems are equipped with robust software that streamlines signal filtering, removal of unwanted artifacts like eye blinks, and data analysis. In contrast to fMRI, EEG benefits from high temporal resolution, enabling it to measure changes in cognitive activity on the millisecond scale. Therefore, EEG measurements are continuously reflective of a participant's cognitive states (Berka *et al.* 2004).

A solid theoretical and methodological framework is necessary to reliably interpret EEG data. Three of such frameworks on the use of continuous EEG to measure cognitive load are described in the section below: Basar's theory of neutral oscillations (1999), functional significance of alpha and theta oscillations (Klimesch 1999), and the event-related (de-) synchronization measure for the quantification of oscillatory EEG dynamics (Pfurtscheller and Aranibar 1977).

Measuring Cognitive Load Using EEG

The continuous (also called spontaneous) EEG signal is composed of oscillations in various frequencies, which are assumed to reflect information representation and transfer within and across neuronal assemblies (e.g., Klimesch *et al.* 2005). This oscillatory frequency information has long been neglected as the majority of neurocognitive EEG research focused on Event-Related Potential (ERP) indices. ERPs reflect brain responses to certain events and are calculated by averaging the continuous EEG signal over many trials so that the oscillatory background activity, considered as noise, is cancelled out. In the past two decades, however, the growing interest into how functional networks in the brain are formed and interact with each other has moved the dynamics of brain oscillations again into the focus of attention. Basar (1999), for instance, proposed a brain theory of neural oscillations. He traced the development of this theory over several decades and showed the functional significance of the brain's electrical activities. This theory explains how EEG can be used to detect brain wave rhythms and how these rhythms can be considered an "alphabet for brain functions" (Basar 1980). Wavelike potential changes can serve as direct and measurable indices of specific brain activities correlated with multiple functions that include sensory registration and tracking, perception, movement, and cognitive processes related to attention, learning and memory (Basar 1999).

At present, it is believed that electrical activity in the brain generates at least four distinct rhythms (Basar 1999). Figure 2 shows that brain waves are a continuum from the large, slow delta waves to smaller and faster (i.e., higher frequency) beta waves.

Two of these oscillatory components of the continuous EEG have been reported as sensitive to task difficulty manipulations—alpha and theta (Gevins and Smith 2003; Klimesch 1999; Klimesch *et al.* 2005). *Alpha* is the dominant brain wave rhythm in the

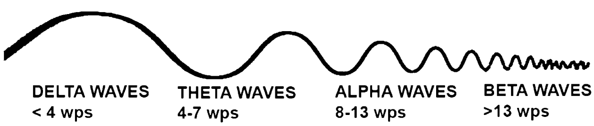

Fig. 2 Human brain wave rhythms (waves per second)

normal human EEG and consists of oscillations in the 8–13 waves per second range (referred to as Hertz or Hz; Andreassi 2007). It is especially pronounced when wakeful participants are asked to relax with closed eyes. When the eyes are opened, a suppression (or desynchronization) of alpha activity occurs indicating alert attention (Fig. 3). Theta, in contrast, is less prominent in the normal adult EEG and comprises oscillations of about 4–7 Hz (Andreassi 2007). Klimesch (1999) provides a detailed review of the functional topography for alpha and theta oscillations relative to cognitive performance. The general consensus is that the localization of recording sites is determined by where these brain wave rhythms are most prominent—parietal areas for alpha and frontal midline location for theta (Klimesch *et al.* 2005).

Measurement of the changes in the alpha and theta brain wave rhythms reflects what is happening in the participant's information processing situation, even if the participant is unaware of the changes or is unable to verbalize them (Basar 1999; Klimesch *et al.* 2005). Several researchers have repeatedly observed that alpha and theta activity is related to task difficulty or cognitive load in a variety of task demands. An interesting description of alpha blocking was provided in an early study by Penfield and Jasper (1954) for Einstein who showed continuous alpha rhythm while conducting complex but for him fairly automatic, mathematical operations. Suddenly, Einstein's alpha waves dropped out. He reported that he had found a mistake in the calculation he had made the day before. Sterman *et al.* (1994) analyzed EEG data obtained from 15 Air Force pilots during air refueling and landing exercises performed in an advanced technology aircraft simulator and found a progressive suppression of alpha with increasing amounts of cognitive load (see also Gale and Christie 1987). Gevins *et al.* (1997) examined changes in cortical activity during spatial and verbal working memory tasks in eight participants and observed lower alpha activity in the difficult as compared with the easy task version. In addition, theta activity increased in magnitude with higher task difficulty. Similar results were reported by Gevins and Smith

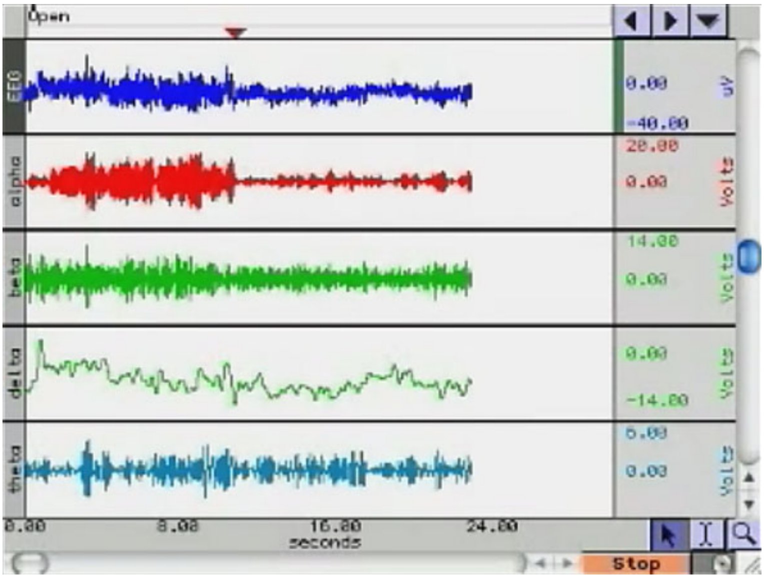

Fig. 3 Alpha suppression. Alpha activity (second waveform from the top) becomes visibly suppressed 10 seconds into the experiment when the participant opens her eyes and engages in a mental arithmetic task

(2000) in a comparably large sample of 80 participants. The difficult version of a spatial working memory task elicited lower alpha but higher theta activity than the easier task condition. These results suggest that alpha and theta oscillations are differentially related to task difficulty. As task difficulty increases, alpha activity decreases (desynchronizes), whereas theta activity increases (synchronizes).

Because brain wave behavior varies as a function of age (Niedermeyer 1993), brain volume (Nunez 1995), and individual differences (Klimesch 1999), it was proposed to analyze the changes in the EEG signal induced by a certain event or task rather than looking at the absolute power of a given frequency band. A well-established rate-of-change measure for oscillatory EEG dynamics is event-related (de-) synchronization, which was originally developed for the quantification of changes in the alpha band (Pfurtscheller and Aranibar 1977). It reflects the percentual decrease (event-related desynchronization; ERD) or increase (event-related synchronization; ERS) in band power during a test (activation) interval compared with a baseline (reference) interval (for a review, cf. Pfurtscheller and Lopes da Silva 2005). The baseline interval typically reflects a pre-stimulus time period without any task demands, whereas the activation interval refers to the time period while working on the experimental task. The ERD/ERS index is then calculated using the formula

$$ERD/ERS\% = \frac{\text{baseline interval band power} - \text{test interval band power}}{\text{baseline interval band power}} * 100$$

This is done for each electrode and EEG trial and then averaged over the trials to increase reliability. A positive ERD/ERS value indicates a decrease in band power (ERD), whereas a negative value indicates an increase in band power (ERS).

The ERD/ERS index for alpha and theta has also turned out to sensitively respond to different levels of task difficulty in a wide variety of tasks, ranging from motor (e.g., Pfurtscheller and Berghold 1989) to cognitive tasks (e.g., Neubauer *et al.* 2006). For instance, Neubauer and Fink (2003) presented 58 participants with three one-digit numbers and asked them to indicate whether the triplet matches a specific rule or not (e.g., "Is the first digit the largest?"). They found that the amount of alpha ERD increased with higher task difficulty, even though significant differences were only observed between the easiest and the more complex task conditions. Stipacek *et al.* (2003) investigated the sensitivity of alpha ERD to different memory components and increasing levels of memory load. Participants had to solve a short-term memory task and a working memory task, each with five levels of memory load. They found a linearly increasing ERD in the upper alpha band with ascending cognitive load.

Case Studies of Applying EEG to Assess Cognitive Load during Learning

We will now present two studies that provide evidence of the viability of using EEG in educational research to collect and analyze cognitive load data for the purpose of testing the effectiveness and improving the design of learning materials: a recent one on hypertext (Antonenko and Niederhauser 2010) and an earlier one on multimedia learning materials (Gerlic and Jausovec 1999).

Cognitive Load and Learning From Hypertext

The basic difference between learning from traditional text and learning from hypertext is the fact that while in a traditional text, the author typically presents a series of coherent arguments in the text and conceptually guides the reader, the central feature of information presentation in hypertext—linking—requires that the reader bears responsibility for selecting the concepts to learn and creating a situation model of the content (Antonenko and Niederhauser 2010). Specifically, the reader must hold representations that involve a concept from the previous node in working memory, while considering how the information from a new node might relate to the first. The reader then selects another node by following a new link that, in the reader's opinion, will lead to additional promising information. This process continues until the information is rendered sensible and the reader's situation model of the text is updated.

A fundamental problem with processing information in this manner is that human cognitive architecture constrains readers to optimally integrate concepts from working memory into long-term memory when reading is interrupted (Glanzer *et al.* 1984). For each disruption, critical text information must be reinstated in working memory if the reader is to successfully continue building a situation model (Lorch 1993). In the case of learning from hypertext, situation model development is disrupted by the presentation of information in physically separate nodes, when readers' attention is divided between novel information encountered in a new node and the concepts integrated from the previous nodes.

One tool that may reduce this instance of split attention and the resulting extraneous load in hypertext-assisted learning is the *lead*. Leads function as a preview or advance organizer to orient and prepare the reader for information contained in the linked node while the current node is still visible. In the context of hypertext, a lead provides a brief summary of the content that follows in the linked node and may occur in the form of a mouse-over balloon that pops up next to the selected link. Thus, in a lead-augmented hypertext system, the reader has the opportunity to get an idea of what is coming in the next node without having to leave the current node.

Antonenko and Niederhauser (2010) investigated the effects of leads on cognitive load and learning in an experiment with 20 teacher education students, who read lead-augmented and traditional hypertexts (i.e., without leads) of comparable conceptual difficulty (i.e., within-subjects design). Their browsing behavior was tracked with screen-capture software, and EEG was recorded and analyzed using a Biopac MP30 psychophysiometrical unit. Electrode placement followed the Modified Combinatorial Nomenclature expanded 10–20 system, as proposed by the American Clinical Neurophysiology Society (Jasper 1958) and was confined to one set of electrodes over the frontal cortex (F7) and one over the parietal lobe (P3) in the left hemisphere of the right-handed participants. The sampling rate was 500 Hz. Brain wave rhythms were recorded as separate channels, allowing identification of the raw EEG signal, alpha rhythm (8–13 Hz), and theta rhythm (4–7 Hz). Each participant's data were decontaminated from eye blink and muscle activity using the built-in artifact removal tools like an Infinite Impulse Response (IIR) bandpass filter. Band power values of the participant's alpha and theta brain waves were estimated with the Area function of the Biopac software. ERD/ERS values were then computed for each participant's alpha and theta rhythms under each of the two experimental conditions (leads or no leads). Because the purpose of this study was to determine the effect of leads on reducing split attention at the point of entering new hypertext nodes, it was expedient to measure *accumulated instantaneous* cognitive load of learners by using the 10 seconds spent reading the primary hypertext passage immediately before the selection of links, and the 10 seconds spent reading after clicking the link (in the lead condition participants processed the leads before accessing links).

Results showed that acquisition of conceptual and structural knowledge was significantly better in the lead-augmented hypertext condition. The self-report measure of mental effort expended on reading each hypertext did not detect any differences in the experienced cognitive load for the entire hypertext. This indicates that performance in the leads condition was more efficient (see Paas and Van Merrienboer 1993; Van Gog and Paas 2008): with the same amount of effort, better performance was reached. Presumably, this is due to the fact that students in both conditions engaged in different cognitive processes, that is, both experienced the same amount of overall cognitive load, but the processes causing this load were likely to differ. Functioning as advance organizers, the leads must have decreased the number of interacting elements in the experimental hypertext and thereby reduced the participants' extraneous load associated with split attention. More working memory resources were then available to the participants to deal with intrinsic cognitive load, resulting in higher levels of germane load (see Sweller 2010 in this issue for a detailed discussion of element interactivity and cognitive load effects and types). The EEG data provide support for this interpretation. A repeated measures multivariate analysis of variance and univariate analysis of variances on alpha and theta ERD/ERS demonstrated that leads indeed significantly decreased alpha ERD (from 44.67 to 36.08%) and theta ERS (from 16.90 to 11.80%) during the 20 seconds of reading the leads and initial processing of new hypertext nodes. Since higher alpha ERD and theta ERS have been associated with higher cognitive load, these results suggest that accumulated instantaneous cognitive load was lower when participants were accessing new nodes that included leads, presumably due to the reduction of split attention (Antonenko and Niederhauser 2010).

This case study shows how EEG can serve as an online, continuous measure of cognitive load detecting subtle fluctuations in instantaneous load, which can help explain effects of instructional interventions on learning when measures of overall cognitive load fail to reflect such differences in cognitive processing. The fine temporal resolution of EEG allowed Antonenko and Niederhauser (2010) to detect differences in the participants' cognitive load while they were accessing hyperlinks, and coupled with the results of learning tests, this showed that the design of educational hypertext can benefit from node previews.

Cognitive Load in Learning With Multimedia

Changes in the power of neural oscillations measured with EEG was also the method of choice in a study that examined cognitive processes in multimedia learning (Gerlic and Jausovec 1999). Thirty-eight psychology students (19 gifted and 19 average) learned new material in a text format (Text), text, sound, and picture format (Picture), and text, sound and video (Video). The researchers hypothesized that differences in alpha power would be observed in relation to the format of the presentation and learner's cognitive ability. Specifically, it was expected that multimedia instruction in comparison with text instruction would involve less alpha activity (i.e., increased cognitive load) in the temporal and occipital brain areas of all students because the temporal cortex is responsible for the processing of auditory input, while vision is "the exclusive function of the occipital lobe" (Gerlic and Jausovec 1999, p. 7).

The second research question focused on testing the neural efficiency hypothesis relative to the cognitive performance of gifted students. According to the neural efficiency hypothesis, intelligence is not a function of how hard the brain works but rather of how efficiently it works (Haier *et al.* 1992). This efficiency may derive from a more focused use of brain areas relevant for proficient task performance. Other studies demonstrated that in problem solving, the gifted or more intelligent students exhibited a higher alpha power (less mental activity) than did average students (e.g., Neubauer *et al.* 1995). O'Boyle *et al.* (1995) found that during word processing, gifted individuals activated frontal regions, whereas average-ability individuals activated temporal regions. Based on these findings, Gerlic and Jausovec (1999) hypothesized that gifted students would exhibit higher alpha power and therefore reduced cognitive load during all three formats of the presentation because their brain would process information more efficiently, activating frontal regions of the cortex, as opposed to "working harder" with higher activation in the temporal regions.

The procedure consisted of showing each participant a 1-minute, Text, Picture, and Video presentation; the order was determined randomly for each participant. The text presentation was presented on a sheet of paper, while the two multimedia presentations were presented on a computer monitor. Brain wave activity was recorded using an ECI Electro-cap (Blom and Anneveldt 1982) over 16 scalp locations of the cortex: five frontal, four temporal, three central, two parietal, and two occipital. The digital EEG data acquisition and analysis system (FlexComp) was configured to record brain waves at the 256-Hz sampling rate and had a bandpass of 0–100 Hz. Alpha power average (μV) was computed using Fast Fourier Transformation built in the FlexComp software for each presentation type and electrode location.

Repeated-measures analyses of within-subjects effects (i.e., presentation format and electrode location) produced two important results. First, for the Text presentation, the alpha power was higher (i.e., less mental activity) over the occipital and temporal lobes than with Picture or Video over the frontal lobe. Second, less alpha power was recorded over the frontal lobe in the Text condition, than in the Picture or Video conditions. In other words, the Video and Picture presentations increased the activity of the occipital and temporal lobes, whereas the Text presentation increased the activity of the frontal lobes. These results support the researchers' hypothesis that the Video and Picture presentations induced visualization strategies (a basic function of the occipital cortex), while the Text presentation mainly generated processes related to verbal processing in the frontal cortex. The analysis of between-subjects effects (giftedness and gender) further showed that gifted students displayed higher alpha power (i.e., reduced cognitive load) during all three formats of presentation. These differences were especially pronounced for the Video format (12–16 electrode locations). The authors concluded that multimedia presentations of learning content might be less effective for gifted students, although no learning performance data were reported to support this conclusion. Alternatively, it is possible that gifted students had higher levels of prior knowledge in the subject matter than the average students.

This study demonstrates that EEG is useful for determining cognitive load induced by various multimedia formats relative to the areas of the cortex involved in processing verbal, visual, and auditory input. It also shows that EEG can be used to detect variations in cognitive load as a result of differences between students, which is in line with studies that have shown that individuals with higher levels of intelligence show lower ERD in the alpha band (Gevins and Smith 2003; Grabner *et al.* 2004, 2006).

Caveats

The aforementioned studies suggest that the continuous tracking of brain wave activity and the analysis of changes in alpha and theta band power can be useful for measuring cognitive load and thus allow a better test of hypotheses concerning effects of instructional manipulations. However, even though these outlined EEG indices are promising candidates for neurophysiological measures of cognitive load, some theoretical and methodological points need to be clarified in future studies before they can be applied widely. First, previous EEG studies suggest that the theta and alpha bands are sensitive to different task demands. Klimesch and colleagues (Klimesch 1997; Klimesch *et al.* 1997) have repeatedly emphasized that alpha activity, especially in the higher frequency range (10–13 Hz, referred to as upper alpha), is associated with semantic information processing, in particular with searching, accessing, and retrieving information from long-term memory. Since most cognitive tasks draw on these processes, alpha ERD can be observed in a wide range of task demands (Klimesch *et al.* 2006). Theta activity, in contrast, has been frequently related to episodic and working memory as theta ERS increases parametrically with working memory load and is sustained during the retention period (e.g., Jensen and Tesche 2002; Kahana *et al.* 2001). Thus, the cognitive processes and nature of the learning task used in the research need to be taken into account when interpreting experimental effects on alpha and theta activity.

Directly related to the functional significance of alpha and theta oscillations is their differential topography. While (upper) alpha ERD primarily emerges over parietal and occipital brain regions (Klimesch 1999), theta ERS is often observed over frontal cortices, presumably reflecting the involvement of anterior cingulate cortex in supporting working memory processes (Kahana *et al.* 2001). In addition, there are some studies reporting increases in alpha activity (alpha ERS) over task-irrelevant brain regions, which are assumed to facilitate the cortical activation (alpha ERD) over task-relevant brain regions (e.g., Neuper and Pfurtscheller 2001; Sauseng *et al.* 2005). In light of these phenomena, it is highly recommendable to use electrode configurations that cover the entire cortex in order to identify task-relevant brain regions and to create a valid index of cognitive load from this topographical information.

A central advantage of EEG over behavioral indices and other neuroimaging methods lies in its high temporal resolution, which also allows for the assessment of the time-course of cognitive load during execution of the learning task (instantaneous cognitive load; Xie and Salvendy 2000). However, it needs to be kept in mind that ERD/ERS values require averaging over time or trials to yield a satisfactory reliability (cf., Pfurtscheller and Lopes da Silva 2005). In other words, less reliable information on the time course can be obtained when only a few trials (problems) are available for analysis than when the task consists of a larger number of trials (e.g., 30–50). Consequently, whether reliable indices of instantaneous or average load can be calculated depends on the number of trials in a task.

Finally, it needs to be emphasized that EEG, like any other method, does not allow to distinguish whether the load measured is evoked by processes that are germane or extraneous to learning. Therefore, it remains important to analyze the results of EEG measures of cognitive load in the context of the associated learning performance.

Conclusions and Outlook

In sum, EEG provides a reasonably good time resolution to allow tracking of changes in cognitive activity as complex learning behaviors unfold, which offers educational researchers the opportunity to measure subtle fluctuations in brain activity associated with cognitive load and focus on analyzing only those time instances that are of special interest. As mentioned previously, recent advances in EEG hardware, like wireless EEG systems (Berka *et al.* 2004; Stevens *et al.* 2007), appear promising because they remove the limitation of dealing with cables and allow collecting data from multiple participants at the same time in a natural setting. EEG systems nowadays also come furnished with advanced recording and analysis software that allows amplification of the incoming signal, differentiation of band components like alpha and theta, streamlined removal of eye blink, movement, and amplifier saturation artifacts, tracking of the temporal data, and automation of spectral power analysis. Additionally, integration of data acquired from EEG analysis software and other sources like server logs and screen capture videos allows mapping of EEG-derived indices to behaviorally relevant aspects of the cognitive processes in real-world learning contexts.

While some scholars have criticized the increased interest of educational researchers in neuroscience and psychophysiology citing the lack of useful, translatable research findings (e.g., Bruer 1997), this review has shown that employing EEG methods like ERD/ERS and relating them to educational psychology can be helpful in understanding the cognitive processes in various learning contexts. However, empirical studies employing physiological methods in educational research are scarce, and much conceptual and experimental work is still needed to improve the translation of physiological research findings to educational research and to provide educational researchers with practical guidelines for implementing neuropsychological research methods and interpreting results.

Acknowledgement During the realization of this work Tamara van Gog was supported by a Veni grant from the Netherlands Organization for Scientific Research (NWO; grant nr. 451-08-003).

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